SIMULATION AND CONTROL OF A LARGE-SCALE LOGISTICS SYSTEM WITH APPLICATION TO FOOD CRISIS MANAGEMENT

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ABSTRACT

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Logistics has always been a part of relief operations. But balanced distribution, meaning the need to keep supply and demand in balance for the entire domain of operations and optimal allocation and use of existing resources are not usually considered. Unbalanced distribution of food and a waste of resources have always been the cause of more fatalities than the scarcity of aid. These problems could be greatly alleviated by efficient planning and development of strategies for rational management and optimal allocation of available resources. In this dissertation, a simulation model of a logistics system is presented as one approach to the above planning and control problems.

The design of the logistics system in this study has been based more on temporal structure and economics than spatial. The model is composed of six major parts. The port, regional warehouses and roads, supply and demand, information and data acquisition, capital development process, and the cost function. The model is equipped to simulate various ship arrival patterns, population movements and road breakdowns with possible transshipments. Ship arrivals, docking, and the information acquisition process are modeled in discrete time, where the rest of the system is continuous time. The information sampling component enables the model's "true" variable values to be disturbed with specific

measurement error statistics. Sampling frequency, sampling error and processing delays are applied to model variables, thereby simulating surveillance sampling results received by system managers.

Available information plays a vital role in the successful implementation of the designed policies. Due to a general lack of data on famine, there is an immense need to extract maximum benefit from the gathered information. Two estimation methods resulted from an extensive search in the literature, keeping in mind the characteristics of the process generating the data. These were the Extended Kalman filter (parameter identification via state augmentation) and the adaptive α-β tracker (time-varying β parameter). When high uncertainty exists regarding the initial values of the demand model's state variables or its trajectories are partially known (common conditions in famine relief efforts), the adaptive α-β tracker performs much better than the Extended Kalman filter.

Logistical policies are composed of two different but highly interconnected decision rules, these being food allocation and capital acquisition. The model has been used for the design and experimentation of various policies. There are several performance measures based on the level of service and total cost, which are used for policy evaluation.

Several general principles for relief logistics emerged from the study. "Well" stocked regional warehouses speed up grain shipments out of the port, thus reducing ship waiting time and providing better service at the regional level by compensating for errors in information. A more uniform arrival of aid reduces port congestion hence lowering the total cost. The expected rate of food arrival and the level of the port's silos are important variables in capital acquisition

policies. The existence of several conflicting objectives poses new difficulties in the search for Pareto optimum control strategy. By systematically investigating policy alternatives and the range of choice of important state variables, grounds have been laid for further optimization work. The dissertation concludes by indicating major results, areas for further research and possible extensions.

To my parents,

who have always made decisions as if

their children were their only objective

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CHAPTER I

INTRODUCTION AND PROBLEM DEFINITION

When food is abundant, it is wasted or treated as a commodity. But when food is scarce, it is regarded as the staff of life and its distribution becomes a highly emotional issue. Food production worldwide is increasing faster than the population, but distribution is uneven, reserves are limited, and bad weather conditions could lead to widespread famine (1).

While food production may expand 90% (that is optimistic) by the year 2000, the per capita increase will be less than 15%. This global estimate disguises regional disparities; food availability and nutrition levels may scarcely improve in South Asia and the Middle East and may actually decline in the poorer parts of Africa (46). The likelihood of man-made catastrophe is growing, and even many of the so-called natural disasters such as famine are caused at least in part by people (31).

Despite all efforts, the history of man is punctuated by frequent famines. There has been a serious famine somewhere practically every year since the end of World War II (78). Except perhaps for nuclear war, nothing in our time so threatens a majority of the world's people as does the specter of hunger and starvation. In spite of all the development programs, the technology transfer, and the "miracle seeds" of the so-called Green Revolution, the prospects for eating a reasonably nutritious diet seem increasingly dim for hundreds of millions in the 1980's and beyond (44).

Catastrophic results of a famine can be seen in the recent Cambodian one. At least two million people were believed to be on the verge of death by starvation or disease. Many had been reduced to eating the leaves off trees peeling the bark and boiling it, and digging for tubers and roots. Malaria was commonplace, as was a severe form of bleeding dysentery (4). One of the worst famines in modern history struck Honan province in 1943, and as many as five million Chinese perished (126).

Famine usually comes with widespread crop failure; but the factors which cause this failure are different and diverse. Natural disasters such as floods, earthquakes, droughts, crop diseases or pests form one group and another is formed by the impact of wars and civil disturbances on both crops and farmers. Some examples of famine and its causes are: successive crop failure due to drought and flood in India, Sahelian drought as desert advances, earthquakes in Latin America and Asia like Iran, civil war in Africa, locusts in Middle East, and a conflict of superpowers in Cambodia.

Food crisis can be thought of as a consequence of ecological crisis. In the poorer countries of the world, hunger is often directly connected to the deterioration or the destruction of ecological systems that could provide a harvest of plenty instead of continuing food shortages (44). One of the major factors contributing to the Sahelian drought is the disruption in the ecological system caused by centuries of improper land use and ever-increasing pressures of both human and animal populations on available land resources (38). In most of the famine prone countries, ecological deteriorations which have caused the evolution of periodical droughts, have been direct consequences of years of colonialism and international capitalism (19), (44).

French politics in Sahel resulted in chronic hunger. Production of cash crops meant a reduced production of food. When less was grown, there was less to store as a reserve in case of a natural or economic disaster (44). The ecological destruction has been widened by desertification, deforestation and woodcutting which have been a much more serious threat to the ecosystem, (38), (93), (124).

Drought causes at the same time crop and income failure for those populations whose main source of income is subsistence agriculture or grazing. Assuming that there is food for purchase outside the affected area, income failure prevents the affected populations from acquiring it (21). The following problems can be discerned in a drought-stricken state: great suffering, damage to the local economy, widespread migrations of people and animals, and cities dangerously overcrowded with thousands of helpless immigrants, bent on finding jobs that will allow them and their families to survive (36).

The relationship between ecological destruction and food production is thus direct and close. Whenever an environment is degraded, deprived of its basic resources, or often of even one of the key resources, that environment becomes a part of the world food crisis, and the people who live there become its victims. These observations show that if famine is to be understood and controlled, there must be an understanding of it's ecology (96). It is apparent, however, that famine has major ecological roots and impacts. We must therefore examine these, and seek ecologically sound short-term responses to alleviate occurring famines, and long-term programs to prevent future famines (25).

A food crisis is not only a matter of food shortages, inadequate nutrition, economic conditions, and population policies. It is also a matter of politics, both national and international. Indeed, in many ways politics is one of the underlying causes of the current food crisis (69). Politics have also been an obstacle to relief operation in one way or another. The classic example is the case of famine in Ethiopia between 1973 to 1975. Two coverups took place. The first by the government of Haile Selassie and the second by the international relief agencies and donor nations. The latter group remained silent as the Selassie government requested, despite what its members knew was happening to the Ethiopian people (105).

The literature is filled with examples of influences of internal or national policies on relief operations. Refusal of aid by host governments (45), their hesitation to ask for aid (39), (126), and internal corruption (37), (42), (71), (89), (119). As prices rose, at one point the Ethiopian government offered to sell 4000 metric tons of grain it had in storage to the United States, which could then donate it back for relief inside Ethiopia (105). It is important to recognize that internal policies and politics contribute to shortage. Poverty is caused by uneven distribution of resources which in part is an offspring of internal corruption of governments. "Famine is a vogue word, the problem is poverty (123)". Poverty has been an contributing element in famine (130). The real problem faced by the Sahelian countries is not the possibility of a recurrence of the drought but their overall poverty year in and year out (124).

Despite a growing population and increasing demands of that population for improved diets, it appears that the world is not close to universal famine. That people are malnourished or starving is a question of distribution, delivery, and economics, and not agricultural limits.

The problem is putting the food where the people are and providing an income so that they can buy it (128).

Famine affects both individuals and the society as a whole. It has sociological, psychological and physiological effects (62), (130). Large-scale starvation, increase in death rate of both human beings and large farm animals, social disruption, spread of epidemics, and destruction of seeds for future crops have been devastating consequences of famines. It has uncureable and permanent physiological effects on individuals. The physiological response of the human body, in its broadest nature, is one which reflects adaptation to the patterns of food availability and shortage that characterizes man's evolutionary history (25). DenHartog describes different kinds of adjustments in detail (29).

The psychological state of people deteriorates rapidly causing an increase in mental restlessness and crimes. Obsession with food and apathy and despair become widespread (130). In some cases cannibalism also happens (126). The stress of the destruction of the familiar environment causes perceptual abnormalities, the illusion of centrality, a reduced sphere of awareness, etc. Sections of society most vulnerable to famine depend very much on the circumstances of the famine, rural or urban setting, cultural factors, physical work requirements, etc.

It has also long-lasting influences on culture and social behavior of the people of stricken regions. In extreme cases of starvation, the breakdown of family units occur and food taboos spread (130). The drought and subsequent famine caused serious long-term damage to Ethiopia. Traditional patterns of society have been broken; in some areas there was little for the Ethiopian peasant to return to; whole villages dead, a way of life shattered. A vast population of abandoned mothers with children roam the land (105).

Unfortunately, the threat of famine is still with us and its primary causes are operative. A series of crop shortfalls in the U.S.S.R., South Asia, and North America in early 1970's and the failure of the major producing and consuming countries to prepare for the event shows how much susceptible the nations are to famine (100). The Global 2000 Report (46) offers a gloomy view of the world 20 years from now if governments fail to act. The result of three years' analysis of probable changes in world population, resources and environment through the end of the century, the report warns that unless nations do something now to alter the trends, the earth's capacity to support life will decrease while population growth continues to climb; there will be a steady loss of croplands, fisheries, forests, and plant and animal species; and there will be degradation of the earth's water and atmosphere, all in the next 20 years. It suggests that sufficient resources of basic food should be available for prompt response to a major shortage.

Prediction is that population - food collision is inevitable, and imminent famines in Latin America, Africa and Asia are expected (23), (28), (44), (45). Famine in the Horn of Africa is not an event of the past, but of the future; it is cyclical (105). If rainfall in the Sahel is regarded as a stationary random variable, normally distributed, then a further drought with four or five consecutive years with below-normal rainfall can be expected by the turn of the century (129).

Already the news about the drought is coming from Sahel countries. Reports from Senegal, Mali and Mauritania show that rainfall is already delayed in the region (32), (90), (98). There is little doubt that regions in these countries are seriously short of food and that unless supplies are expedited, there is the danger that as the hungry season continues, later seeds and other stocks in villages will have been completely consumed by people and livestock scratching around for anything on which to subsist (75). "Conditions now are worse than those of the early seventies in several western Sahelian nations, which face a crisis of critical proportions (97)".

Both the potential of famine and the capacity of human society to avoid it are greater today than ever before. So whatever the primary cause of famine, we must be able to offset it. Because of the urgency for action following a disaster there is little time available for planning, assessment and coordination, personnel may be inefficiently utilized and scarce resources misdirected. It is, however, possible to provide a constructive approach to effective relief planning and administration for future disasters in developing regions of the world (23).

Food shortages may have different origins but famine differs from most other disasters in that it is usually predictable well in advance and is often, theoretically, preventable. The disaster could be greatly alleviated by efficient pre-planning by a government agency (76). The basis for relief is to obtain and make available sufficient food to stop the developing famine, maintain the population in body weight balance, and eventually rehabilitate the population (78). Planning and development of strategies for rational management and optimal allocation of existing resources play an important role in reducing catastrophic results of famine. Indeed, having a better strategy to make better use of available food can lead to significantly higher survival rates in the afflicted population (73).

It is obvious that the whole process of disaster relief is carried on in totally unconventional and emergency circumstances which in modern times, at least, has tended to infiltrate the total life of the nation. There is a wide range of problems encountered in planning and implementing the relief operations depending on size and duration of disaster and the region in which it is happening.

With much of the structure of society broken down, lack of information and data, different political obstacles, it becomes very hard to have a clear picture of the most pressing needs and the scale of them. The poor transportation system of less developed countries and breakdown of main bridges due to earthquakes or floods which also wash away the roads and rails, make distribution of available foods and communication with stricken regions difficult (82). The desperation of the people and the deteriorating situation throughout the Sahel zone made it clear that even the largest of relief operations undertaken by the national governments could not meet more than a small part of the growing requirements. Not only did the governments lack food, feed and other supplies, as well as funds, but they also lacked the infrastructure and distribution facilities for massive relief operations (33).

Frequent occurance of famine in less developed countries and longer duration of crisis, relative to the other forms of disaster such as floods and earthquakes, allow more lead time for better prediction and preparation in order to reduce the impact and results of famine. Yet the problems encountered, the assumptions, techniques and forms of organization required vary, depending upon country and the type of crisis. In general, disaster relief activities are characterized by a lack of understanding of the under development context, by lack of planning and by an obsession with emergency. Some donors are self-interested, disregard national sovereignty, ignore the villager's need for self-determination, and are incapable of using local resources.

Disaster relief operations can have numerous objectives. Minimization of the total number of deaths has been cited as the ultimate goal (25), (78). Equitable and timely distribution of food, optimal use of existing resources, improvement of nutritional status of people while disrupting cultural patterns as little as possible, adjustment to the nature of the local crisis (25), higher survival rates, safe keeping of the food, and preventing the spread of epidemics are other desirable ends. Attainment of these objectives is constrained by limited aid, time, money, equipment and personnel.

The basic problem in food shortage is the optimal allocation and distribution of existing food to those who need it and in times when it is needed with minimum cost. Different systems are necessary to fulfill this task. Goals of relief operations set the priorities and clear the way in which these systems should interact. Major support systems are information and resource acquisition, logistics, and communication. Education and training programs at field levels are also required.

The effectiveness of operations is in direct proportion to the degree of integration and coordination achieved among the various support systems. Support which is disjointed obstructs existing capabilities. Interdependency of support systems requires recognition and application at all levels of relief operations by personnel involved. By keeping in mind the other support systems, the emphasis in this dissertation will be on logistics systems.

Structure of Logistics System

The USAID Report to Congress on Famine in Sub-Sahara Africa summarized the enormous problems of transport and communication in the following terms: "In 1973 there were times when ships were hard to obtain because of massive world-wide grain movements. Ports in West Africa are poorly equipped to handle huge shipments and there have been port congestion problems, particularly this year. Railroads were often inadequate to move food inland on a timely basis. There are few paved roads. Ferries are slow and inefficient. River transport is important but capacity has been inadequate for the amounts involved. Roads leading to many outlying distribution points where nomads are congregated are difficult at best, impassable when the rains come. Few trucks, and problems of their maintenance, have often caused difficulties. Lack of storage has been a problem. The complexity of managing relief operations of this nature, involving six recipient governments and a number of donors under extremely difficult physical conditions, is without precedent (41)".

The significance of logistics in disaster relief operations is clear. Economics limits the available food and resources for relief, logistics limits the mobilization and use of resources which are available. Modern logistics is defined as the process of strategically managing the movement and storage of commodities from point of supply, through facilities involved, to the point of consumption (11). Logistical activities consist of transportation, inventory, facility location, communication, handling and storage.

Figure 1.1. illustrates the general structure of famine relief logistics system. Blocks show the major sub-systems involved. Three important linkages are recognizable. Necessary information such as storage levels, demand for food and other commodities, movement of the population, orders of shipments and transshipments flow through the communication link. Transportation link contains air, railroads, river

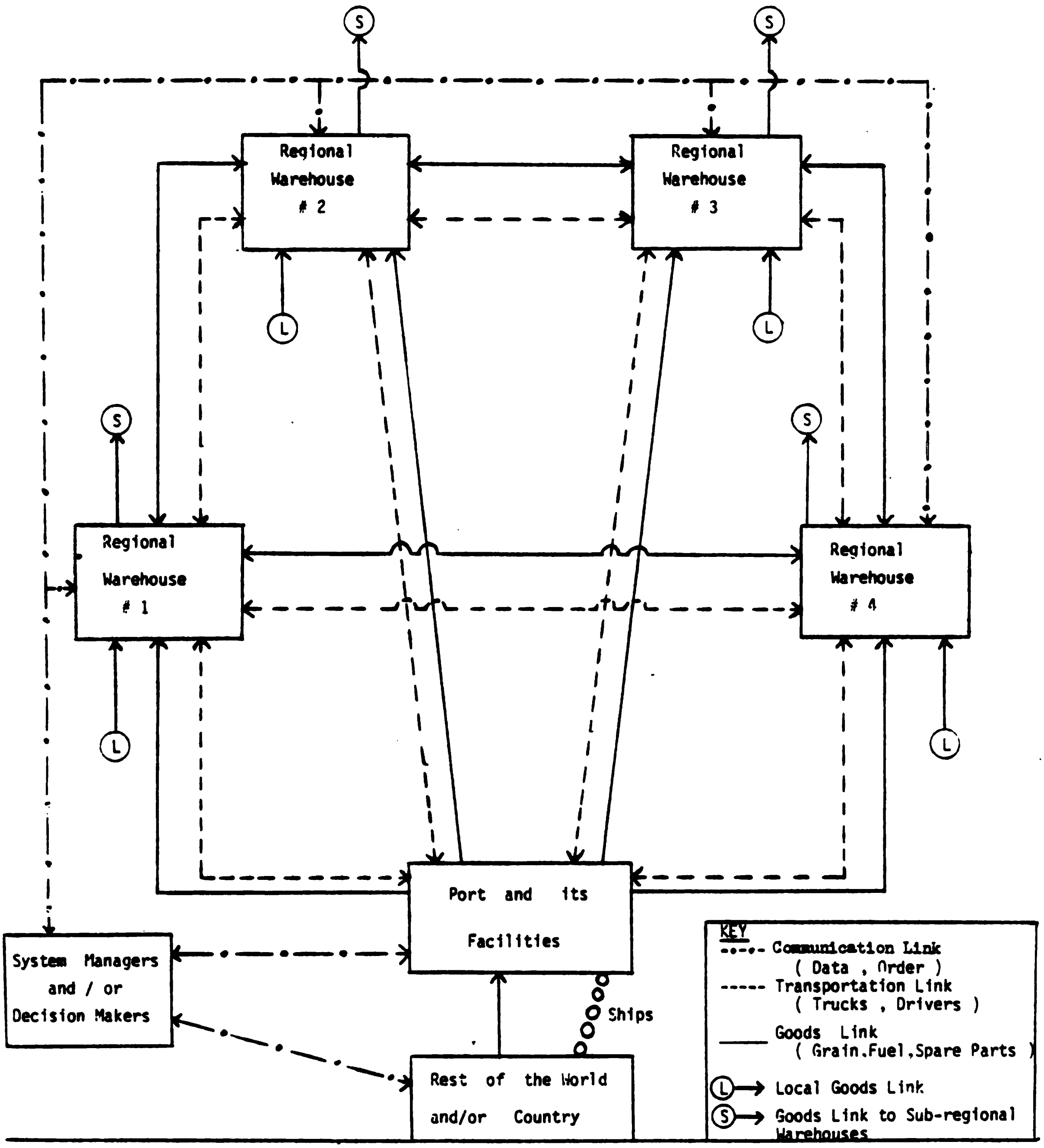

Figure 1.1. Major Sub-systems and Linkages in Famine Relief Logistics System.

transport, trucks and drivers. Movement of food, fuel, spare parts, and maintenance personnel form the goods link. Arrows show the direction of flow movement, either unidirectional or bidirectional. The local goods link symbolizes the help from the region itself which is mostly local food reserves and production. The goods link to sub-regional warehouses is the connection with field offices and final destination, which is affected people.

Design of logistics support systems can be considered as an aid for system managers and decision makers who are responsible for total relief system. The process of movement of supplies from ship to affected people entails a series of highly synchronized functions, the failure of any one of which could have a resonant effect, reverberating along the entire line of communications. At no time are all the components of the structure in perfect balance. Indeed, the elimination of one limiting factor sometimes creates another at a different point. The elimination of the deficiency in one of the transportation links, for example, makes the forward storages one of the main strictures, for they are unable to receive the large tonnages which the link has become capable of forwarding. "For the donor countries, the major problem has been to select the best means of transporting huge quantities of relief supplies (40)".

The history of logistics operations seem characterized by a succession of alarms over one critical deficiency or another, and the theater has been occupied at all times with efforts to eliminate some bottleneck and to bring the system into balance. As already stated, the inadequacy or the breakdown of the delivery system is one of the main problems. Whatever the food commitment on the part of the international community and whatever consignments have reached the points of entry of the affected country, the food deficit has usually reached such a degree that existing intra-country delivery systems are in most instances, inadequate to deliver on time sufficient food to families and individuals in the affected areas (2), (21), (44), (71).

"August 6th, 1973. Report from the Field: 10,000 in Bati, and 15 per day dying of starvation at the relief center ... Farmers eating seeds in Werababu ... 50 Danakils in the province of Tiger are dying daily of famine. They have grain, but no means of getting it to the Danakil region (105)." Total disruption of communication and transport system following a disaster always hampers the relief operations (92), (94). Logistical difficulties are often the major limitation of a relief operation (3), (48), (84). Existence of adquate transportation infrastructure is a key factor to prevention of famine (25). "The material development of Africa may be summed up in one word - transport (124)." In his classification of different types of famine, Dando (28) identifies "transportation famine" as one of the basic ones.

The earth is ringed with a disaster belt south of the equator, Dr. Rudolf Frey of the Club of Mainz points out (31). Within this disaster prone region are many undeveloped countries which lack the financial resources, expertise, and equipment to respond to emergencies. Sahel countries are the best example. The territory is vast and sparsely settled, distant from seaports and lacking in railroads and adequate highways; it has been exceedingly difficult to get food, medicine, and other emergency supplies to the places where they are most needed (35). Transport generally - road, rail, river and by other means - is the biggest bottleneck (27), (33), (41).

Selection of the best means of transportation is another important issue. Air transport has some advantages. Relief supplies can be delivered quickly when speed is critical. Aircraft can transport food, medicine and other commodities to the interior where it is urgently needed. But air transportation has high operating costs (per unit of cargo) and limited capacity. The aircraft also requires elaborate support facilities for optimum service: airports and landing strips; technical personnel able to handle tower control and ground directions; and, above all, quantities of fuel readily accessible.

In order to appreciate the logistical problems, it is important to remember that of the six Sahelian states only two have direct access to the sea. Others have to rely on the port and transit facilities of neighboring countries (40). Although ships carry far more cargo per voyage and at cheaper rates, they also pose different problems. One of the main problems is congestion. Underdeveloped countries have ports with a very limited handling capacity. Congestion causes another problem, meaning the shortage of suitable storage facilities. Perishability of bulk of supply items intensifies this problem (33), (40), (91), (105).

When regular warehouse storages are full of grain, relief supplies are stacked in the open where they start to rot. "The rats feed well at Dakar," cabled a reporter to the Guardian on July 24. "Some of those stocks will still be on the wharves in November," he wrote of the transport tie-up, "if the rats - the only fat animals I saw in West Africa - leave any at all (104)." "The estimated 1985 production of 450 million tons of cereals will, at 2000 calories a day, give us 45 billion person-days of food. At least it would if it all got into people's mouths. Unfortunately much of it goes to insects, rodents, and microorganisms (51)." Security of food is another task. There is need for adequate protection to prevent excessive losses from moisture, insects and theft.

Railroads offer by far the cheapest means to transport commodities inland. It is estimated that shipping by rail costs 25-30 percent less, on the average, than trucking, the next cheapest means of transport (40). Ability to haul bulk commodities, all weather functioning are other advantages. Yet there are problems here too. The railroads are fairly antiquated, single-track systems, with different gauges, and any malfunctioning seriously disrupts traffic. This happened in July 1973 when a derailment prevented trains from reaching Mali, depriving that country of one-half of its normal supplies at a particularly critical time (40).

River transport should be considered in the design of relief operations. Although it is a viable alternative in some parts of the world like north-eastern India and Bangladesh, it has not been an important mode in relief logistics in Africa. In a drought situation, the rivers are usually below normal levels. Also, owing to the river's shallow channel, it takes only light barges.

Road transport has played an important role in the effort to deliver relief supplies. Although the road quality varies from country to country they usually connect the capital cities with administrative centers and major coastal ports and many remote towns and villages. Usually underdeveloped countries have trucks and other types of vehicles which can be utilized. Since they are driven by local drivers which are familiar with the region and roads, it has the advantage of creating jobs for a substantial number of people. Also, trucks critically complement the railway systems. "In the long run, the most effective way of getting relief to the Sahel's interior is by road (40)."

Road transport has its own bottlenecks. Bad and incomplete infrastructures of road networks, weather dependability, long distances between cities, lack of sufficient number of trucks and maintenance are some of the problems encountered.

No two disaster relief operations will necessarily be faced with identical requirements (25), (45). While their logistics problems will contain many similar aspects, there will always be important differences. In all cases the logistics will have certain critical items, certain important issues, and a vast amount of subsidiary detail which may easily obscure the critical and important factors. Almost never will all logistic requirements be satisfied in an exact balance, and as long as that is true some phase of logistics is bound to be the limiting factor.

In all operations, transportation, fuel, technical spare parts, and technical repair personnel will be critical (17), (33), (40). "There is no point in sending lorries without supplies of spare parts and perhaps without directly ensuring their fuel supplies ... in Chad, for example, twelve lorries ... were meant to be distributing relief food but were immobilized by a shortage of fuel (41)." There will be a conflict between demand for transportation to carry food and the spare parts. Mayer suggests that "maintenance personnel are as critical as logisticians and drivers; spare parts may have to take priority over food (78)." System managers should have prior knowledge of the logistics limitations.

Every logistics endeavor must be guided by a clearly stated objectives. The objective to the greatest extent possible, must be so specified as to permit continuous measurement of the degree of accomplishment of the endeavor toward the objective. The logistics objective is valid only in so far as it supports the overall objectives. Therefore, the propriety of the logistics objective must constantly be reappraised in the light of the intentions of total relief operation.

There must be a flexibility of logistics support. Responsiveness to the needs is most readily assured through adaptability of logistics which is the basic measure of flexibility. The capability to react rapidly and reliably to changing situations, is a mark of effective logistics.

One of the chief problems which usually follows disaster is a lack of organization and coordination of the relief efforts made by the various agencies involved. To improve the efficiency of relief operations, it is essential that every country should prepare a national disaster relief plan (8), (88), (111). Many difficulties stem from lack of coordination among individual efforts undertaken by various national and international groups, and by failure of these groups to work effectively with local governments (25). "The difficult logistical problems involved in supplying the more remote areas of Mali with food, medicine, and other essential commodities are further complicated by the inefficient use that is made of existing transport facilities (34)." Weak administrative organization and management in the rural areas of India is one of the causes for creating problems in devising and implementing effective food policies (43).

Coordination is one of the main stumbling blocks. Referring to relief operations in Biafra, Western (125) found an extreme lack of coordination between agencies and haphazard distribution methods such that some areas were receiving aid regularly from several agencies and others were not receiving any. It is not enough merely to have the right resources; rather the right resources must be at the right place at the right time. This is a foremost objective of logistics flexibility. It is an objective to be attained through responsiveness, a condition of flexibility.

Control of the performance of logistics involves a management effort. A measurement of logistics to assess its efficiency in terms of economy and effectiveness must be made internally and externally. Although internal measurement of the logistical activity may give considerable emphasis to cost minimization, external measurement must emphasize effectiveness. Of these, the latter is the only reason for logistics.

The essence of successful logistics is to do more with less through an economy of resources. Economy of resources seeks to avoid depletion while assuring that needed resources are readily available. It is achieved not only through an exchange of quality for quantity but is predicated on a continual striving for the most effective management of resources.

People, supplies, and facilities may be designated as basic resources. Services, transportation, and communication constitute functional resources. The virtue of accomplishing a logistics task with the least quantity seems obvious. Yet there is danger in interchanging the words "economy" and "least". The latter may be too little while the former suggests providing no more than the minimum amount and degree of support needed to do the job effectively. "Least" implies, primarily, quantity, "economy", on the other hand, involves a combination of quality and quantity. The nature of "economical logistics" is not necessarily that of least quantity but involves an input of quality so that mission accomplishment is in fact enhanced rather than jeopardized.

Money, time, and technology are to be thought of as "determinant resources" in that they determine to a large extent the quantity and quality and proportions of basic functional resources which will be available for different support systems. Timing of relief is a very important factor. Often priorities are inadequately worked out and by the time supplies have reached the area, needs have changed (44), (105). The transport problem was largely due to the fact that aid was not provided quickly enough and at the proper times of year to ensure distribution before the rains struck (97).

Experience during the recent famines in arid areas of Africa has shown that the main limiting factor has been the lack of funds for the intra-country transportation, storage and distribution of supplies. The foods made available at the points of entry of the affected countries have been in excess of the funds available for transportation, storage and distribution. Donors have been more generous with foods than with funds. Voluntary agencies have been unable to locate sufficient funds for the intra-country delivery of their planned food aid programs. Some local governments in fact were unable to allocate funds for the distribution of relief foods and large quantities of supplies were left at the ports of entry or in the warehouses, undistributed (31). So, acceptable operating cost, low capital cost, and minimum per unit cost of delivering to final destination are desired characteristics of logistics system. Of course, there exists the trade-off between mentioned attributes and speed and consistency of operations which are also desired.

Logistics systems should be designed such that it minimizes the deterioration of normal activities at main port and transportation network. Since the fundamental purpose underlying the very existance of relief operations is to provide adequate food for the people in need, safeguarding of food is a very important issue. Contamination, humidity, insects and animals such as rats, and corruption are some of the problems which can be encountered.

System managers decisions are based on available data. The importance of an information support system is easily realizable. Existence of it is essential for keeping the total operation in balance and making distribution and allocation decisions. Knapp (64) demonstrates that optimal policy implementation varies with information quality and quantity. He discusses the importance and crucial effects of consumption patterns on relief policy and prediction of famine duration.

There is usually inadequate and unreliable data regarding the crisis (49). In times of disaster due to disruption of communication it is difficult to obtain information (27). Acquisition and assessment of information have been advocated for a long time, but have not been applied (2), (91). The most conspicuous failure of the relief efforts from 1968 through 1973 was the failure to gather, retrieve, and use information. At every stage of disaster every piece of information missing added up to yet a larger void. The absense of information paralyzes planning (104).

Some of the causes for general lack of information in less developed countries are: meager budgets for statistical research; lack of trained personnel; vast distances and critical lack of infrastructure; limited internal communications system; poor record-keeping in outlying districts; and, above all, a population to a large extent illiterate and often profoundly distrustful of anyone seeking information (39).

In disaster we are in need of knowing all about different support systems. Appropriate and relevant information will lead to effective management and balance distribution of resources. Of course, we should keep in mind the trade-off between the cost and quality of data. The design of an early warning system is an effective device for famine prevention. If we recognize the signs of disaster early, a whole range of preventive and protective measures can be applied (52). There is a need for early warning indicators that can provide substantial advance warning of food crisis with low probability of false alarms (72)."

The United Nations (2) prescribes continuous monitoring of information on the following four aspects, along with the evaluation and interpretation of information. First, is that "geographical zones" where disasters occur should be mapped. Secondly, "meteorological data," that means climate and rainfall, on different regions, in order to identify various conditions and anticipate trends. Third is to report on "the agricultural situation and food supplies, crop conditions, factors responsible for not planting, harvest, bottlenecks in crop movements, food imports/exports, food security, and food relief stocks." The fourth consists of "monitoring political events, wars, civil disorders, and anticipation of probable effects." Capone (21) and Currey (26) also give a list of early warning indicators.

During an emergency, the relief foods are scarce and should be given to the people in the greatest need. So we need rapid and objective measurement of nutritional status. Also surveillance of communicable disease must be carried out as part of nutritional surveillance (48). Information on size and trends of demand, population movements, storage levels at different regions, back-logs, transportation network, conditions of roads and vehicles, fuel and spare parts provide better management of logistics system and optimum use of resources. Not having enough knowledge of the situation leads to catastrophic results. In short, an information system is the "nerve system" of overall operation.

Field offices are in direct connection with affected people. Here is where the effects of a relief system can be seen. They are in charge of distribution of food, operation of health clinics and food kitchens. The results of their efforts and the data which is collected by them are used by system managers for ever improving the balance of the total system. For operational efficiency the field unit should be kept small, generally with no more than five or ten persons. Depending on the task and size of the population served, multiple units should be used to provide the services (2). Camps must be properly administered. Auxiliary personnel should be from the local people and receive fixed and clearly defined monetary or non-monetary salaries. Key personnel should not be from the population affected (48).

Field offices are responsible for gathering information and transmitting it to the system managers. So data feed back by them is very important for the stability of the total operation. The followings are typical field reports. These are from the 1973 famine in Ethiopia (105). June 20th, "Merca, 30 kms south of Weldiya. The situation is very serious. People were seen dying of starvation ... cattle, sheep, and goats have almost all died." July 2nd, "Medical situation: Bati health center has 100 patients suffering from Amoebic Dysentery, and eight per day die from it."

The goal of the logistical mission is to achieve a predetermined level of support at the lowest possible cost expenditure. Clearly service performance policy and logistical cost have a direct relationship. The attributes of high availability, fast and consistent capability, and high quality have associated costs. The higher each of these aspects of total performance, the greater the cost of logistical operations.

Reasonable balance between performance levels and total cost expenditure is typically the best. Rarely will either the highest service performance system or the least total cost constitute the best logistical goal. Measurements of cost performance trade-offs are good aids in comparison of different logistics system designs. The estimates of expenditures are needed for alternative levels of system performance. In turn, alternative levels of system performance are meaningless unless viewed in terms of overall relief goals and objectives.

Logistical performance is, in fact, a question of priority and cost. With respect to total performance, almost any level of logistical service can be obtained if we are able to pay the price. For example, a fleet of trucks could be held in a constant state of delivery readiness. Logistical performance is measured with respect to availability, capability, and quality.

Availability involves the system's capacity to consistently satisfy material or goods requirements (11). Availability deals with inventory level. It can be measured by either the total stock-out time or percentage of stock-out time. We should remember that the consequence of any stock-out is the possible increase in the total number of deaths, and reduction of it is the prime goal of total relief operations.

The capability of logistical performance refers to the elapsed time from receipt of an order to inventory delivery (11). Performance capability consists of the speed of delivery and its consistency over time. Here, the following measurements may be identified. Delivery time, or accessibility, which reflects the time required, on the average, for the goods to reach the affected people through the logistical system once the order has been received.

Variance in delivery time and accessibility is another measurement which may be more critical that the average time. Idle times of trucks, drivers and different facilities are good measurements in reflecting where design could be made more efficient. Waiting time for ships to unload is a good indicator of efficiency and stability of the system.

Performance quality relates to how well the overall logistical task is completed with respect to damage, correct quantity of goods (i.e. low error rates), and resolution of unexpected problems (11). There is no use in speedy and consistent delivery of wrong orders. Total amount of goods transshipped, excluding those transshipments which are due to break down in the transportation link, is a good index for quality of logistical performance.

Regional equilibrium and balance distribution is another important performance criterion for logistics support systems. Unparallel supply and demand will increase the possibility of stock-outs and idle times of trucks, drivers and different facilities. Increase in the variance of delivery time and waiting time for ships are other consequences of unbalanced distribution. Sum of the squares of the differences between supply and demand, integrated over the period of operations is an index which should be minimized to achieve optimum balance.

Figure 1.2 shows the logistical system identification. It tries to clarify the relationship between goals and the obstacles which must be removed in order to reach these goals.

Logistical performance provides time and place utility. Such utility represents an important aspect of operations. The basic purpose is to assure that the quality and quantity of food and other necessities are in desired locations, in the time and condition needed to successfully fulfill the relief task. The responsibility here is to design a logistics system to control the flow and strategic storage of food, spare parts and other commodities to the maximum benefit of the entire relief system.

Depending on the striken country the feasibility of logistics

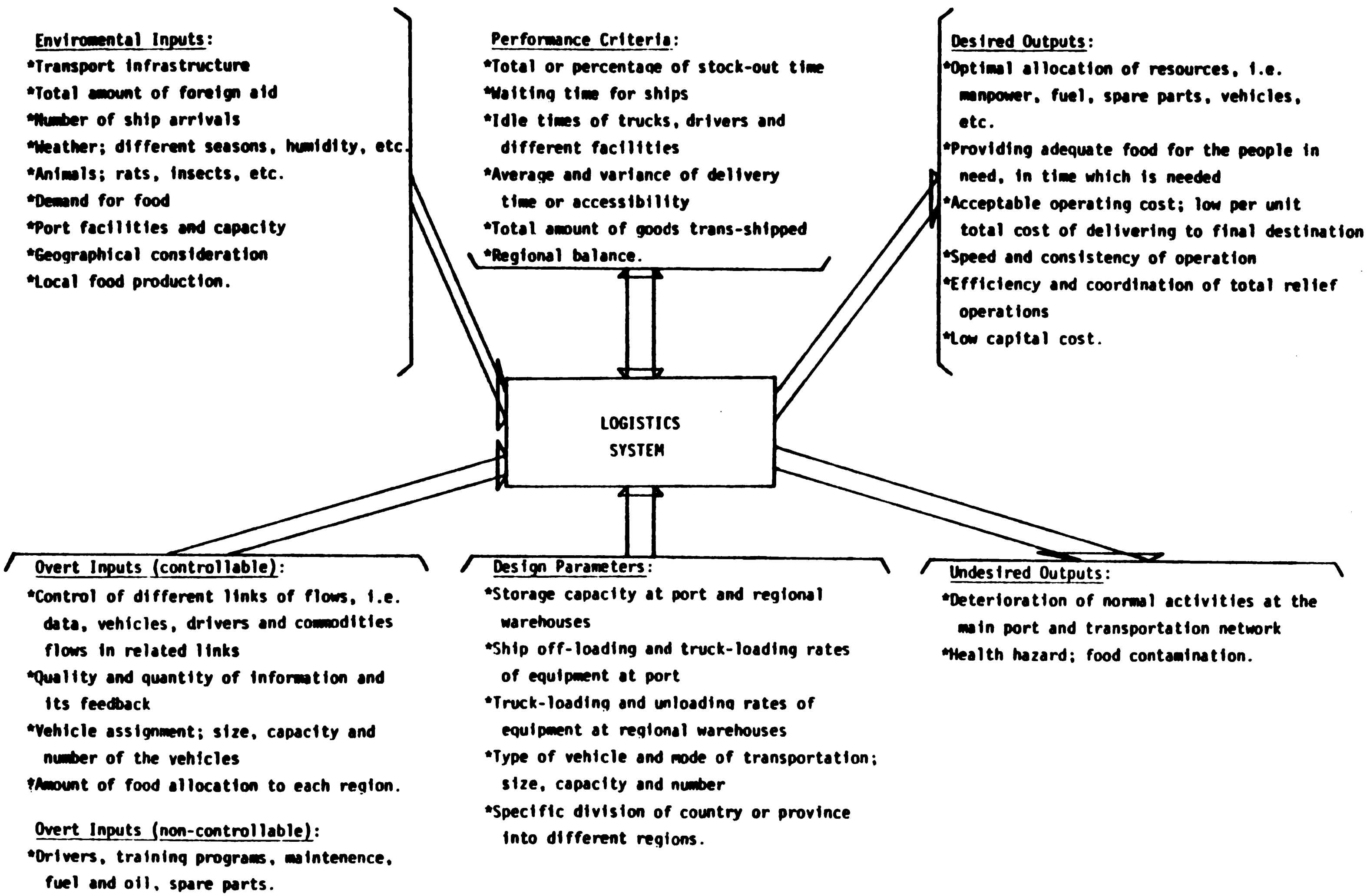

Figure 1.2. Logistical System Identification

system changes. As the country becomes less developed and poorer the implementation of it becomes harder. Most of the time the major hauler in rural and in many urban areas is the animal cart. Man himself is a major carrier of food, fuel, and other commodities in rural areas, crowded city lanes, and roadless mountain sections. For example, the International Red Cross in Wollo (Ethiopia) used camels to haul grain as far as 150 kilometers from storage points along the Addis-Asmara highway (105).

FAO/OSRO (Office for the Sahelian Relief Operations) financed and organized camel caravans to areas that had become impassable to vehicles. Some 5000 camels were used in this operation, each carrying a load of 250 Kg. They were sent out in trains of 50 to 100, accompanied by two soldiers of the Niger Camel Corps and the number of drivers required to keep the line under control and moving. Another expedient adopted to ensure deliverence of supplies was to have teams of porters carry bags of grain across flooded points where truck transport was dislocated (33).

Political, social and cultural obstacles must be taken into consideration. As relief grain arrived at port, red tape delayed shipment inland. The Ethiopian government refused permission to use storage facilities, and relief grain rotted in the rain (105). Cultural and religious factors often exacerbates the problems. Food taboos and dietary habits are very important. Officials of USAID were surprised by a Washington Post report from Timbuktu that nomads were unable to digest American-donated sorghum and diarrhea is rampant (104).

There are more factors in the real world than what appears in Figure 1.1. For example, warehouse location patterns. Locational decision in a logistical system design usually centers on warehousing.

Determination of the number and geographic locations of them is determined by port location and distribution of affected population. The warehouse location is justified only if it increases the capability of reaching more people or reduces total cost. Locational impact on inventory is worth mentioning. More locations reduces the uncertainty of stock-outs as a result of a shorter replenishment-cycle. Much more thought is needed for richer appreciation of the complexities involved in design of support systems.

Design of Logistics Support System

The relationships within a logistical system can be classified as spatial or temporal. The spatial structure relates to the combination of facilities and linkages. The temporal structure of the logistical network relates to inventory levels and flow rate (11). Logistical system design could be based on either spatial or temporal economics but the interaction of spatial and temporal factors should be evaluated on a simultaneous basis. In this dissertation the design is more on temporal structure and economics.

It is assumed that the population of the stricken country or province is about sixty million, which is divided into four regions. The bulk of the aid from different agencies and donors around the world comes in the form of grain by ships to the closest port. System managers and decision makers analyze the information received from different regions, the amount of promised aid from foreign donors, and available logistical capability and then decide about appropriate allocation of aid to each region. Assigned aid then will be carried by trucks to corresponding regional warehouses. Transshipments allow for needed flexibility in the case of breakdown of transportation links between two points, or unexpected demand in one region. Available food in regional warehouses is then carried by different means to sub-regional silos and field offices. The affected people will receive food from field offices which in turn provide reports of necessary data to the system managers. Three echelon inventories exist in the system.

Port sub-system consists of incoming ships and dock, ship unloading facilities, grain silos and storages, truck and driver pools, truck loading facilities, maintenance and repair shops. Each regional warehouse is composed of truck unloading and loading equipment, silos and storages, repair shops, and information surveillance units.

The design of logistical support systems involves two policy considerations: (a) service performance, and (b) total cost expenditure (11). The challenge is to establish a balance between performance and cost that results in attainment of the desired return on specified goals. This balance is the logistical policy which in turn provides the managerial mandate for guiding system design.

Logistics has always been part of relief operations. But balance distribution which means the need to keep supply and demand in balance, and optimal allocation and use of existing resources have not usually been considered. "Application of the latest knowledge and tools for the monitoring and control of relief operations will help to facilitate the most efficient deployment of available resources as well as the effective distribution of relief aid (2)." Having a good control subsystem not only increases the performance levels but also decreases the cost. Minimizing the transshipments reduces the cost and minimizing the total time of stock-outs leads to higher survival rates which mean lower total number of death which was prime goal of disaster relief system.

One of the factors contributing to the relative inefficiency of disaster relief work is low cost effectiveness due to logistical difficulties and the necessity for speed in operations. Forty percent of the value of the relief supplies may be spend on their transport (3). In an interview in LeMonde in mid-1973, Niger's then president said that the cost of transporting 20,000 tons of cereals to the relief areas came to three to four times the cost of the grain (35). DuBois (40) gives a good cost-benefit analysis in using aircraft or trucks in Sahel drought. "Trucks at normal commission rates would have cost roughly 1/14 of what it cost to ship by air."

Fuel, manpower, spare parts and maintenance constitute the most important elements of total cost. Fuel is very critical considering the world wide energy crisis and that the high prices of fertilizers and energy have made the poor countries more vunerable to famine. "Rising fuel costs added to the road transport problems (62)."

Efficiency, effectiveness, and economy are not forever synonymous. They co-exist where related activities are meshed, where duplication is avoided, and where the process flow from one activity to another and through the entire system approaches a simple pattern. Minimum requirements, limitations and undesired outcomes of each design should be well considered in selection of logistics system.

Monitoring relief supplies is a key operation. "Any interruption of supplies to the remote areas would have immediately affected thousands of people who depended for their daily food ration on emergency deliveries. This necessitated the internal monitoring of food movements from the ports to the ultimate points of destination by rail, road and desert tracks, to ensure a continuous flow (33)." Logistics design with a better control system is highly preferred. Unbalanced distribution of food has usually been the cause for more fatality and death than the scarcity of aid.

The Approach

The discussions in previous sections should have shed some light on famine relief efforts in general, and the logistics system in particular. In coming chapters, an attempt has been made to model a logistics system for which various strategies for managing available resources can be experimented with. The generation of different control alternatives is a standard part of cost-benefit analysis. It leads to an understanding of the choices available. The common cost-benefit form converts all constraints and benefits to a monetary base for comparison purposes. Here, however, constraints and benefits could be measured in units of the limiting resources: man-hours, time, equipment units, etc.

Computer simulation has been used to represent the logistics system, its environment, and to evaluate the overall relief system's performance. It should be noted that a computer model has definite limitations. All the important factors influencing the system under study cannot be included. Different relationships and interactions can be modeled to the extent that they can be converted to numerical relationships. Another important factor limiting the scope of the model is cost. If every detail and element affecting the system is included, the cost of such a model is going to increase. The most complex model is not necessarily the best one. After all, the simulation is one of the analyst's tools in design. Models should be simple enough to disclose the inevitable design errors and sufficiently flexible to allow for corrections and evaluation.

The organization of this dissertation consists of the following chapters roughly leading to the development of the logistics system components represented by Figure 1.1. An application of the approach to a hypothetical country is followed through the individual steps, including major findings, pitfalls, and areas for further research. Chapter II covers the generation and simulation of the logistics system and its various components. A cost function and several performance measures have been developed which are used to evaluate different policy structures. To make effective use of gathered data, a detailed discussion on various information filters and estimation methods has been conducted in Chatper III. The chosen technique of this chapter complements the information system model of Chapter II. Testing and validation procedures and results are discussed in Chapter IV.

Experimentation with various logistical policies, their results and analysis has been reported in Chapter V. Experiments include several control policies and investigation of the sensitivity of policy results to changes in certain parameter values. This chapter, in essence, describes the decision making process and managerial aspects of logistics system. Finally, Chapter VI presents a summary and conclusions, and outlines areas for further work in refining, improving and extending the model.

Summary

The approach and design presented in this dissertation is by no means complete and can only be considered an initial attempt to address the logistics of relief operations. No specific country has been intended and the model is in general form. More work is needed to improve the model and to connect it to an overall famine relief model.

CHAPTER II

THE LOGISTICS MODEL

A computer simulation is an excellent tool for the systematic study of complex problems which are composed of several large, interconnected, dynamic systems. A famine relief system is of this type. Different management strategies can be tested in a relatively short period of time without the need of experimentation in the real world.

This chapter is a description of the famine logistics model. Various building blocks and their relationships have been described. These blocks are models of different functions and activities which form the logistics operations or influence these operations directly. Each of the components of the logistics model is discussed in some detail in the next sections. A copy of the computer program displaying all equations, parameter values and initial conditions used in these components and their related subroutines is shown in Appendix B.

Ship arrivals, docking, ship unloading facilities and information surveillance processes have been modeled as discrete time systems. The rest of the model is continuous time.

The Port Model

The basic port model addressed in this section was originally developed by Dr. A.G. Knapp (65). A detailed description of that model with its extensions and modifications is provided here. These changes enable the port to interact with the rest of the logistics system and add new important features that were not discussed or assumed given in the basic model.

The port system is defined to include ships from the time they enter the harbor, the ship offloading service facilities, grain silos and storage areas, and truck loading facilities. Truck and driver pools, and maintenance and repair shops are new additions. Subroutines EXGEN, FACPORT, DOCKY, ARAIVAL, and CHOICE of the simulation model are related to different functions at the port which will be discussed in the next few pages.

One of the most important indications of a port's ability to handle grain shipments is the relationship between thruput and input in grain tonnage. Hence the model is constructed to follow the flow of grain through the port. The block diagram in Figure 2.1 depicts the form of the model.

Ships are assumed to arrive with a Poisson distribution, thus the interarrival times will be exponentially distributed. The capacity of the ships is assumed to have a two level uniform distribution, based on data obtained for Bangladesh. The service time needed to offload a ship's cargo is based on docking time, machinery rates for offloading, and the capacity of the ship.

The availability of trucks and drivers to carry the grain into the country's interior is an important part of the overall transportation picture. Truck loading rate depends on the number of trucks and drivers available at port, rate of machinery for loading, available grain in silos, and regional demand for food. Integration of the difference between the ship offloading rate and the truck loading rate gives the net input to storage, and integration of the truck loading rate results

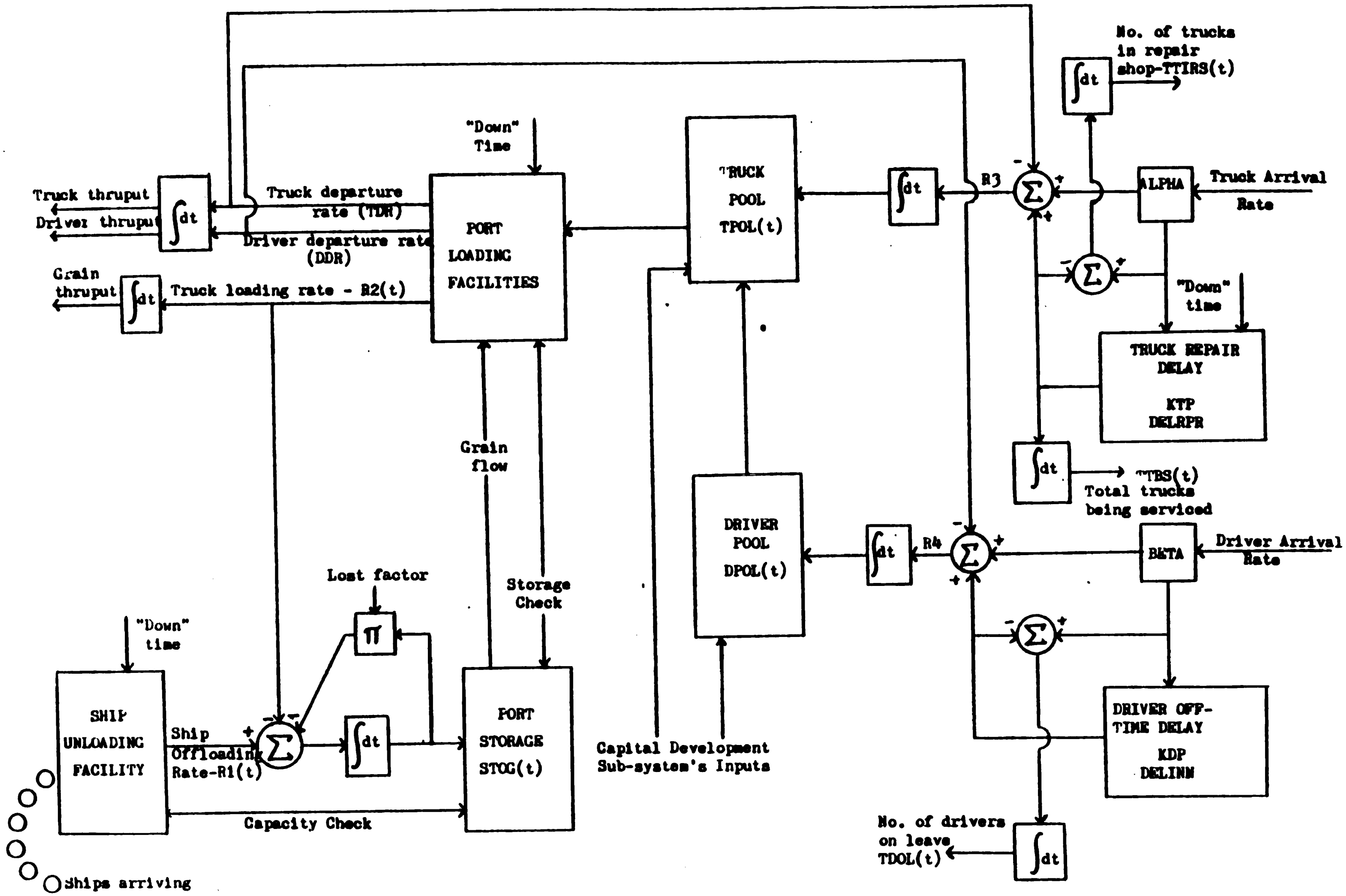

Figure 2.1. Model of the port and its facilities

in the amount of grain passed through the port into the country. Two factors which affect the overall port capacity are availability of storage and frequency of "down-times" at the port when no work is done. Too little grain in storage causes trucks and drivers to be idle, while too much in storage implies that ships no longer unload, thus the ship service center is idle. During a "down-time" period neither the ships nor the trucks are serviced. Even though the model can handle "down-times", it has been assumed that due to the emergency circumstances, there will be no "down-time" at any component of the logistics system.

The interarrival times for ships has been assumed to be exponentially distributed. The time varying mean of the distribution is calculated from a system parameter and one state variable. In Knapp's model this mean was assumed to be constant.

$$EAT(t) = AVTONS / YRTONS(t) \tag{2.1}$$

where:

EAT = expected value of interarrival time (years)

AVTONS = mean tons of grain per ship (tons/ship)

YRTONS = tons of grain arriving (tons/year)

t = time index.

To reduce the error caused by different patterns of grain arrival, EAT is recalculated at (t + EAT(t)/2) and is used in this form which can handle a cyclical arrival rate. Then the interarrival time is computed stochastically as

$$AT(t) = -EAT\ (\ t + EAT(t)/2) * LOG(R) \tag{2.2}$$

where:

AT = length of time before next arrival (years)

R = random number uniformly distributed in range (0,1)

LOG = Natural logarithm.

AT(t) is calculated in subroutine EXGEN each time a ship arrives. A simple counter is incremented by AT(t) to note the time at which the next ship arrives. YRTONS is computed using a supply model which is discussed in later sections.

The cargo weight and service time requirements of a given ship were used to be calculated in the basic model, by separate subroutine at the time the ship enters the offloading facility. In the current model, the cargo weight is modeled in the EXGEN subroutine and is computed when the ship enters the harbor. This modification is necessary for calculating the cost of ship waiting time. The service time requirements are modeled in the FACPORT subroutine and is calculated as the ship enters the offloading facility.

Calculations for cargo weight are based on specific data from Bangladesh.* Figure 2.2 illustrates the histogram of cargo weights. These tonnage figures approximated a two stage uniform distribution, with 86% of the weights falling in the interval 4000-27000 tons, and the remainder distributed in the 27000-55000 ton range. Using the above data, the dividing percentage, P1, for Bangladesh was calculated as follows.

$$\text{Expected tonnage} \approx 19000 = (4000 + 23000/2) * P1 + (27000 + 28000/2) * (1-P1)$$

$$P1 \approx .86$$

Thus, to generalize the Bangladesh case, two equations are

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* From "World Food Programme - Bangladesh, Foodgrain Digest," 12 May, 1976.

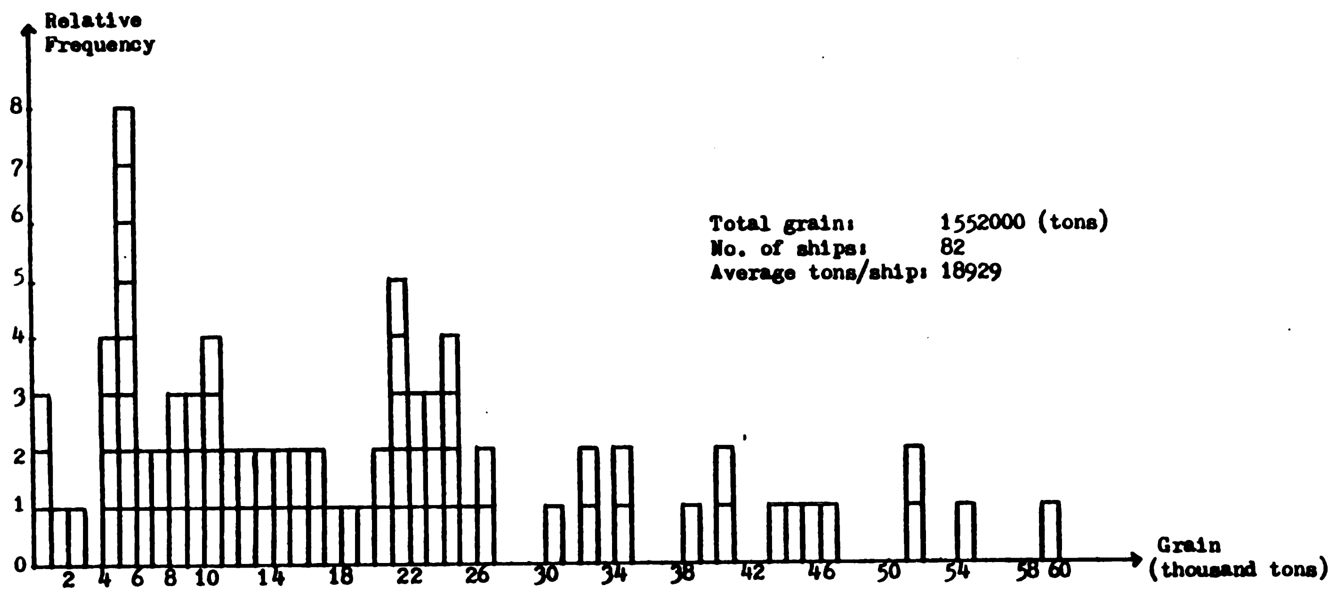

Figure 2.2. Histogram of Grain Weights by Actual Ship Arrivals (Bangladesh)

available, and the choice on which to use is based on comparison of a random number, R, with system parameter P1 as a dividing line, for $R \geq P1$

$$TONSH_i = A2 + \frac{(1 - R)}{(1 - P1)} * (A3 - A2) \tag{2.3}$$

and for $R \leq P1$

$$TONSH_i = A1 + R * (A2 - A1)/P1 \tag{2.4}$$

where:

TONSH = amount of grain on ith ship (tons)

A1, A2, A3 = smallest, middle, and largest tonnages in distribution (tons)

R = randon number uniformly distributed in range (0,1)

P1 = percentage of ships that have cargo weight in interval (A1, A2)

i = ship index.

Figure 2.3 shows the probability distribution used in the model to approximate the actual tonnage.

Service time required for offloading is based on a constant docking time plus the time needed to empty the ship, which is based on the offloading rate of the equipment available:

$$ST(t) = C1 + TONSH/RMS \tag{2.5}$$

where:

ST = service time remaining for ship in service center (years)

C1 = docking time required (years)

RMS = offloading rate of port equipments (tons/year)

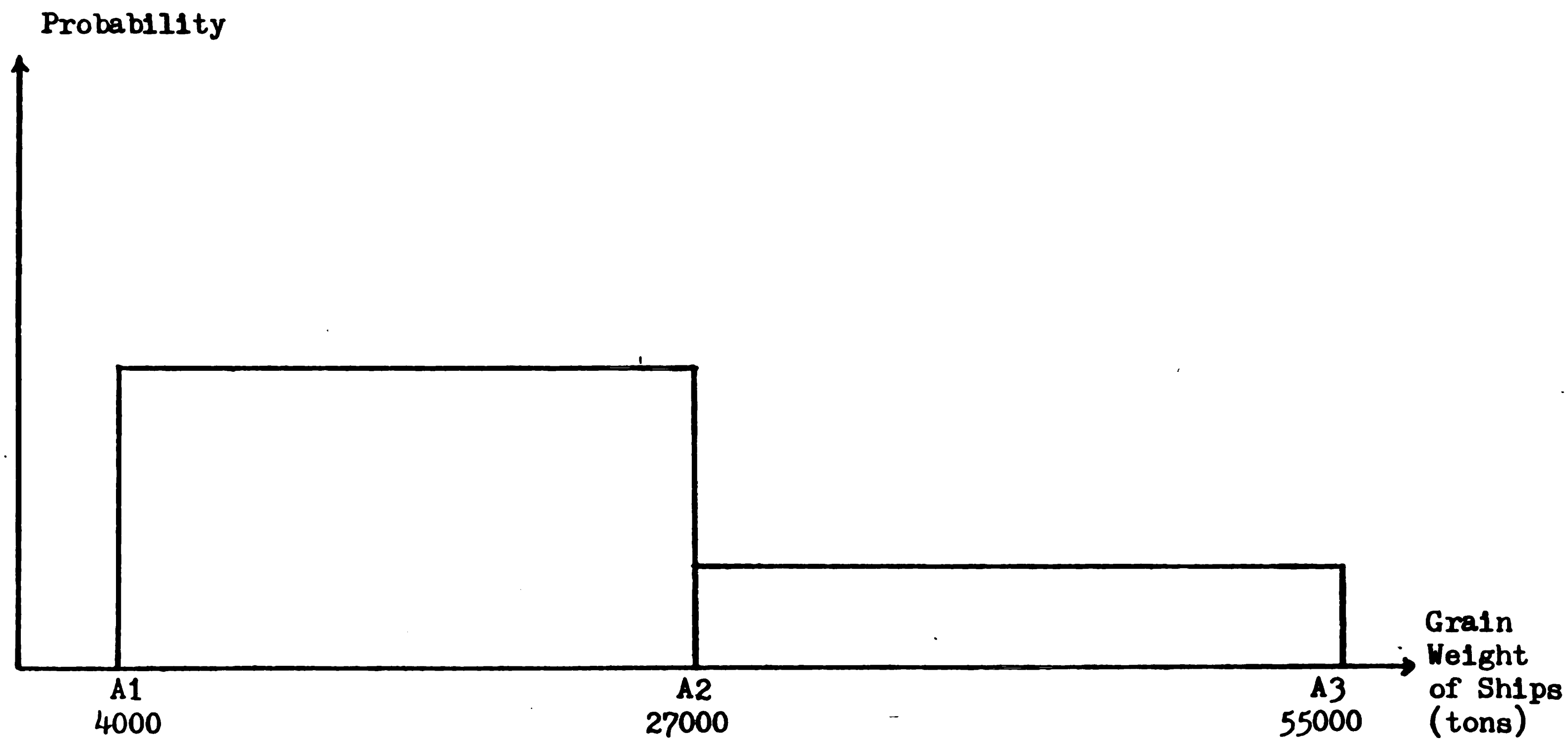

Figure 2.3. Probability Distribution Approximating the Actual Tonnage

TONSH = amount of grain on ship (tons).

As the ship is unloaded, ST(t) is decreased by the time increment, DT, once each time iteration.

Note that AT(t), the interarrival time of ships, is an exogenous variable; it can thus be calculated at times set by a single counter. But ST(t) is affected by several factors within the model (e.g. storage capacity, "down" times) and is defined as a time remaining, to allow for time periods during which no offloading occurs. ST(t) = 0 is the key used to indicate that the current ship is empty, a new ship can enter the service center, and a new ST(t) needs to be calculated.

The ship service facility modeled in subroutine FACPORT keeps track of two main items; the waiting line of ships and the offloading rate of grain, which is calculated each period and is defined as the average rate (tons/year) of grain movement in the time period (t, t + DT). Some parts of the offloading rate are computed by the subroutine DOCKY.

Observing the waiting line over time gives an indication of the stability of the port system and whether it can handle the tonnage that is arriving without tremendous backups. Note that the length of the waiting line (IWL(t)) changes only when AT(t) and ST(t) are calculated. AT(t) indicates arrivals, so IWL(t) is then increased by one. ST(t) = 0 indicates a departure from the service center and availability for the next ship, so if a ship is waiting (IWL(t) > 0), IWL(t) is decreased by one. If no ship is waiting, the service center will be idle and the performance statistic, TIDT(t), is increased by DT. Thus TIDT(t) gives the total idle time (years) of the service center during the period (0,t). The total waiting time of ships in the harbor can be calculated as

$$TWT(t + DT) = TWT(t) + DT * IWL(t) \qquad (2.6)$$

where:

TWT = total ship waiting time in period (0,t), (years)

IWL = length of waiting line at time t

DT = length of time increment (years).

And by keeping track of the number of ships that arrive, another useful performance measure is reached.

$$AVTWT(t) = TWT(t) / INTOT(t) \qquad (2.7)$$

where:

AVTWT = average waiting time for ships in period (0,t), (years/ship)

TWT = total waiting time in period (0,t)

INTOT = number of ships arriving in period (0,t).

Generally when a ship is in the service center, the average off-loading rate for period (t, t + DT) is equal to the rate of the equipment, meaning

$$R1(t) = RMS \qquad (2.8)$$

where:

R1 = average offloading rate for period (t, t + DT), (tons/years)

RMS = offloading rate of port equipment (tons/year).

A utilization measure of the unloading facility, TIDRMS, is incremented by DT. There are three exceptions to this. First, if the storage silos at the port are full, no unloading can be done. A check is made by comparing STOG(t), the storage in the silos at time t, with CAPWH, the capacity of the silos. If STOG(t) $\geq$ CAPWH, then no offloading is done (R1(t) = 0) and the performance variable TIDCAP(t) is incremented by DT. TIDCAP(t) is the idle time (years) in period (0,t) of the offloading equipment due to storage limitations.

The second case in which R1(t) does not equal RMS occurs when the ship is not in port for the full DT time increment; that is, when ST(t) < DT. For this case R1(t) is equal to a portion of RMS.

$$R1(t) = (ST(t)/DT) * RMS \tag{2.9}$$

where:

R1, RMS = as in Equation 2.8

ST = service time remaining (years)

DT = length of time increment (years).

Note that the occurrance of this second case is the appropriate time to signal that a ship has left port, the service center is now empty, and a new ST(t) should be calculated if a ship is waiting.

The last case for modification of R1(t) corresponds to the time allowed for docking manuevers, C1. A counter, TEMPC1(t) is defined to be the remaining docking time at t. TEMPC1(t) is set to C1 when a ship enters the service facilities and is decreased by DT each time loop. So if TEMPC1(t) $\geq$ DT, all of the period (t, t + DT) is spent in docking, no unloading is done and R1(t) = 0. But if TEMPC1(t) < DT, partial unloading can take place, and again the rate equals a portion of RMS:

$$R1(t) = \frac{DT - TEMPC1(t)}{DT} * RMS \tag{2.10}$$

where:

R1, RMS, DT = as in Equation 2.9

TEMPC1 = remaining docking time at time t (years).

After being in the country's interior, the returning trucks and drivers enter their pools at the port and form the queue for loading. From the total number of trucks and drivers coming back to the port, ALPHA% and BETA% respectively, will go out of the system temporarily. Trucks go to the repair shop and drivers take a leave. Subroutine ARAIVAL handles the above processes and computes net input to the truck and driver pools. These are new additions to the basic port model.

The choice of ALPHA and BETA parameters and the length of delay in which the trucks and drivers are out of the system are important design questions. Significant factors affecting ALPHA are the general conditions of trucks and roads in the country under study. If trucks are old and roads are out of shape, as is the case in most of the third world countries, ALPHA increases accordingly. There is not much the decision makers can do about ALPHA other than to try to assign a value for it. But they can have some flexibility in the choice of BETA, meaning that, by some means, asking the drivers to stay on the job longer. Of course there is some limit that BETA can not be lower than. Tired and unhappy drivers can interrupt the delivery system by either accidents or slow work.

The decision about the length of the delays involved more or less resembles and to some extend depends on the ALPHA and BETA selection and their values. If the trucks are new and in good shape, fewer numbers of them need repair and the frequencies of major and minor repairs are lower than when not too many good trucks exist in the system. The length of time for which a truck is out of work depends on the extend of the repairs it needs. Also, the drivers can have different delay times depending on the distances they have travelled and other human factors such as age, sickness, etc.

In the current model, it has been assumed that constant percentages of trucks and drivers leave the system and there exists an average delay for the repair shop and the length of the time in which a driver is out of the system. The following are the prime reasons for such a decision. As mentioned earlier, these parts of the system have been modeled in continuous time form, thus it is difficult, if not impossible, to single out each truck and driver. Secondly, this model is just a general representation of the real world and does not belong to any specific country, but the choice of the above parameters and delays is determined case by case and is country dependent. At last, these assumptions eliminate the need for detailed modeling of the above processes, and it is believed that the model preserves its integrity and generality. The above delays have been modeled using a Kth order distributed (continuous) delay process DELVF (74) which will be explained later in a more appropriate place. No constraints have been assumed on fuel, spare parts, and maintenance.

The average rate of change of the truck pool in the port for period (t, t + DT) is

$$R3(t) = TRUCKAR(t) + TRUCKRD(t) - TRUCKRN(t) - TDR(t) \quad (2.11)$$

where:

R3 = average rate of change of the truck pool in period (t, t + DT), (#/years)

TRUCKAR = total rate at which trucks enter the port, (#/years)

TRUCKRD = rate at which trucks leave the repair shop, (#/years)

TRUCKRN = ALPHA percentage of TRUCKAR which enter the repair shop, (#/years)

TRD = total rate at which full trucks leave the port (#/years)

t = time index (years) .

Then the total number of trucks at the port ready to be utilized, TPOL, is obtained by integrating R3. By integrating TRUCKRD, total trucks which have used the repair shop can be calculated. The average rate of change of the driver pool in the port for period (t, t + DT) is

$$R4(t) = DRIVEAR(t) + DRIVERD(t) - DRIVEIN(t) - DDR(t) \qquad (2.12)$$

where:

R4 = average rate of change of the driver pool in period (t, t + DT), (#/years)

DRIVEAR = total rate at which drivers come back to the port (#/years)

DRIVERD = rate at which drivers come back to the system (#/years)

DRIVEIN = rate at which drivers take a leave (BETA percent of DRIVERD), (#/years)

DDR = total rate at which the drivers leave the port with full trucks, (#/years)

t = time index (years).

Here, again, the total number of drivers in the pool, DPOL, can be obtained by integrating R4.

The truck loading rate from the storage silos is limited by RMT, the rate of the loading equipment, by the quantities of grain in storage, STOG(t), drivers at pool DPOL(t), and trucks available to be utilized, TPOL(t). When adequate supplies of grain are in storage, trucks and drivers exist to carry them, the average loading rate is given by Equation 2.13. In the basic model, a steady supply of vehicles and drivers were assumed.

$$R2(t) = RMT \tag{2.13}$$

where:

R2 = average truck loading rate in period (t, t + DT) (tons/year)

RMT = loading rate of silo equipment (tons/years).

A utilization measure for the loading facility, TIDRMT, is incremented by DT. If any of the above supplies, i.e. grain, truck, or driver, is not available the loading rate will be zero and an appropriate performance statistic is incremented by DT. These measures are: TIDGR for shortage of grain, TIDTR for shortage of trucks, and TIDDR for drivers.

If enough supplies do not exist, then R2(t) must be a fraction of RMT corresponding to the amount of supplies available at time t divided by the time over which it is loaded. But first, an inventory check should be made to see which one of the supplies is least available. Then R2(t) is calculated based on that type of supply and an appropriate performance measure is incremented. If grain is the limiting factor, then,

$$R2(t) = STOG(t)/DT \tag{2.14}$$

where:

R2 = average loading rate in period (t, t + DT) (tons/years)

STOG = storage in silo at time t (tons)

DT = length of time increment (years).

and TIDGR (t), the idle time of trucks, drivers and loading equipment due to shortage of storage, is increased by DT. When trucks are the least available, the loading rate becomes

$$R2(t) = TGRC * TPOL(t)/DT \qquad (2.15)$$

where:

TPOL = total number of trucks in the pool at time t (#)

TGRC = grain capacity of one truck (tons)

R2, DT = as in Equation 2.14.

and TIDTR which is the idle time of drivers, loading equipment due to unavailability of trucks, is incremented by DT. For the time when drivers are not available, the loading rate becomes,

$$R2(t) = TGRC * DPOL(t)/(TDRC * DT) \qquad (2.16)$$

where:

DPOL = total number of drivers available at time t (#)

TDRC = number of drivers required to operate a truck (#)

R2, TRGC, DT = as in Equation 2.15.

Here TIDDR, the idle time of trucks and loading equipment caused by shortage of drivers, is incremented by DT. R2(t) computations are carried out by the subroutine CHOICE.

Once the ship offloading rate R1(t) and the truck loading rate R2(t) are computed, the amount of storage and thruputs of grain, truck, and driver are derived by simple integrations. A lost factor models loss of grain due to animals, moisture, etc. The following equations explain all these relationships:

$$THRUPUT\ (t + DT) = THRUPUT(t) + DT * R2(t) \qquad (2.17)$$

$$TTRUPUT(t + DT) = TTRUPUT(t) + DT * R2(t)/TGRC \qquad (2.18)$$

$$DTRUPUT(t + DT) = DTRUPUT(t) + DT * TDRC * R2(t)/TGRC \quad (2.19)$$

$$STOG(t + DT) = DT * (R1(t) - R2(t) - STGLST * STOG(t)) \quad (2.20)$$

where:

THRUPUT = amount of grain thruput in period (0,t) (tons)

TTRUPUT = number of trucks which have been utilized in period (0,t) (#)

DTRUPUT = number of drivers which have been utilized in period (0,t) (#)

STGLST = grain loss factor due to insects, moisture, etc.

R1 = average ship offloading rate in period (0,t) (#)

STOG = storage at time t (tons)

R2, TGRC, TDRC, DT = as in Equation 2.16 .

Several idle times which have already been mentioned, are a result of random endogenous events (e.g. TIDT(t), TIDCAP(t), TIDTR(t), etc.). The port model also contains the capability to include planned, regular "down" times. This would correspond to those periods of the day when no work is done (e.g. night, delays, between work shifts, etc.). Counter NSP is incremented by 1 for each iteration of the time loop, and all work activities are skipped when NSP = NDTSKIP, a positive integer constant. NSP is then reset to 0. Note that ship arrivals and waiting lines will be unaffected. The effect on the model of this feature is to cause a "down" time equal to $\frac{1}{NDTSKIP}$ of the total run time. As mentioned earlier, this feature of the model meaning the "down" times, is not activited in the current study. Hence it is assumed that everything works around the clock.

Regional Warehouses and Roads

Grain from the port is taken by truck into the country's interior and to the prespecified regional warehouses. Figure 2.4 shows the model of a regional warehouse (RWH) and its connections to the rest of the system. Each RWH consists of truck unloading and loading facilities, silos and storages, and an information surveillance unit. The model handles four RWH as it was assumed, but by some small changes in array sizes can handle any number of them. Subroutines SILOS, DELAY, and TRNSHIP simulate the total activities related to each RWH.

Demand is the driving force for grain flow through each RWH and actually the total system. It has been assumed that loading and unloading rates are functions of demand and accomplished by manpower. This assumption is based on rational that at famine time and in an underdeveloped country, there will usually be enough labour to unload any number of trucks which are coming. In many cases manpower is the only mean even in normal conditions. In spite of this fact it has been assumed that there exists a maximum limit for unloading rate. By the above assumptions the service time at RWH's becomes variable, hence the standard queuing theory cannot be used to model truck arrivals. Thus, loading and unloading rates are time-varying.

The grain received by each RWH is either distributed to the area which is covered by and is close to that RWH or is carried to smaller sub-regional silos or field offices. The carrying process is done by different means. Small carts, manpower and animals are usual carriers. Thus, it is unnecessary to unload the trucks into storage facilities when they arrive at an RWH. At any time, when food arrives, the trucks are directly unloaded into the other means of transportation for distribution throughout the region. The modeling process goes as follows.

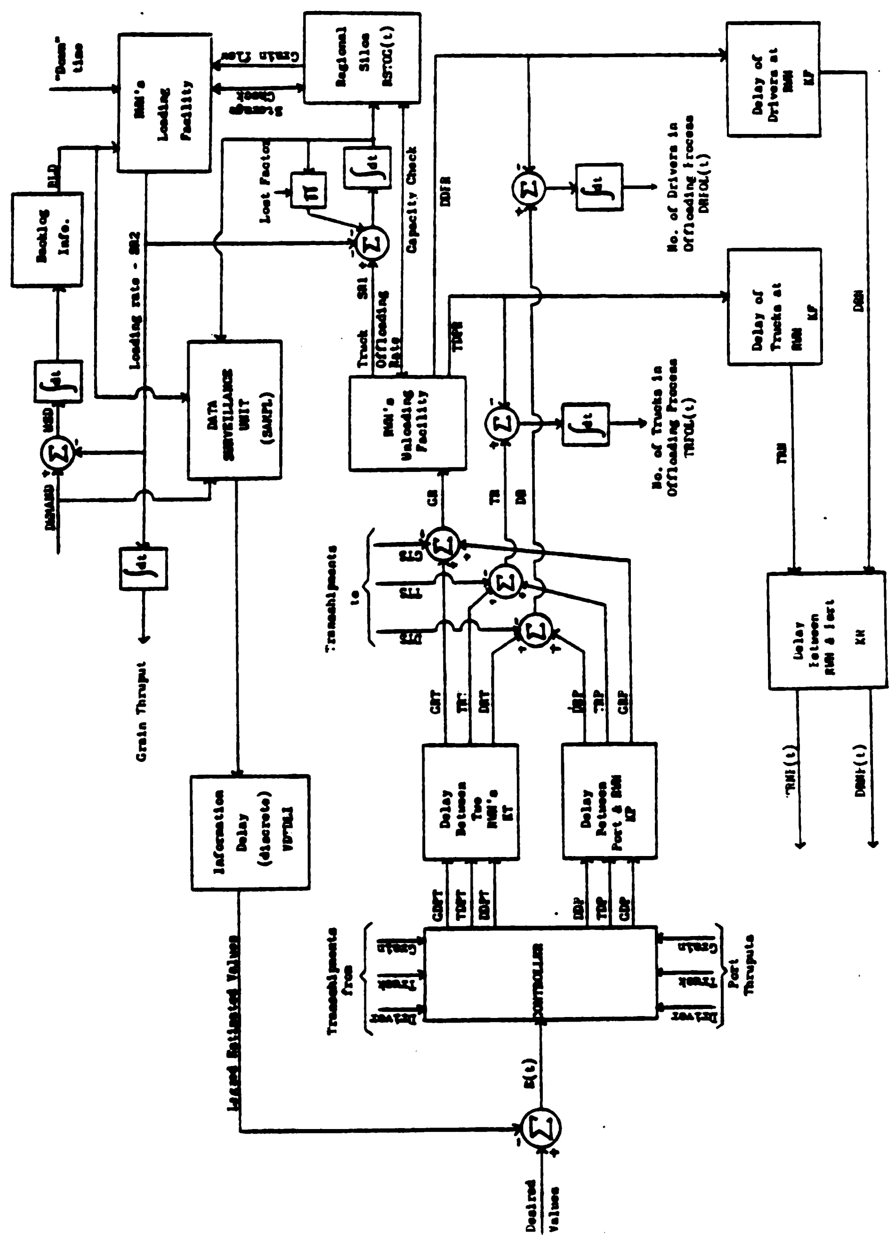

Figure 2.4. Model of a Regional Warehouse and its connections to the rest of the system

When assigned trucks to the ith region arrive, they enter the truck pool at that RWH and form a queue, waiting to be unloaded. Multiple servers have been assumed, so a group of trucks are unloaded at the same time. When full trucks arrive the truck pool increase is modeled by Equation 2.21.

$$TRPOL_i(t + DT) = TRPOL_i(t) + DT * TRP_i(t) \tag{2.21}$$

where:

TRPOL = total full trucks available at time t (#)

TRP = truck arrival rate at time t (#/years)

DT = length of time increment (years)

i = RWH index.

when trucks are unloaded and leave the regional silo facilities, TRPOL is reduced accordingly. This will be discussed later in Equation (2.41). Thus, the grain ready to be unloaded is equal to

$$GR_i(t) = TGRC * TRPOL_i/DT \tag{2.22}$$

where:

GR = grain in trucks ready to be unloaded at time t (tons/years)

TGRC = grain capacity of a truck (tons)

TRPOL, DT, i = as in Equation (2.21).

Now current demand is satisfied, first by using this waiting grain (GR). But before that it should be checked to see how much of this grain can be unloaded without exceeding the maximum unloading rate (RMSS) assumed for that specific RWH. A variable is used to represent the current unloading capacity (TGR). If GR is greater than RMSS then

$$TRG_i(t) = RMSS_i \tag{2.23}$$

where:

TGR = average actual unloading capacity for period (t, t + DT) (tons/year)

RMSS = max unloading capacity (tons/year)

i = RWH index.

Otherwise

$$TGR_i = GR_i(t) \tag{2.24}$$

where:

TGR = average actual offloading capacity for period (t, t + DT) (tons/years)

GR = grain in trucks ready to be unloaded at time t (tons/years)

i = RWH index.

The demand turn comes now. First, it is satisfied using Equation 2.25.

$$REST_i(t) = DEM_i(t) - TGR_i(t) \tag{2.25}$$

where:

REST = variable indicating excess demand or excess grain at time t (tons/years)

DEM = actual demand at time t (tons/years)

TGR = average actual offloading capacity for period (t, t + DT) (tons/years)

i = RWH index.

Then it is checked to see whether demand has been completely satisfied or not. This is done by checking the sign of the variable REST. If the sign is positive, there exists unsatisfied demand and if it is negative, excess grain exists. From here two separate branches appear. In the second case, the rest of the grain in unloaded into the regional silos, providing the existence of storage. Otherwise the full trucks should wait in the queue in order to be unloaded at a later time. Thus, the storage is checked against the capacity.

$$ACAP_i(t) = (RCAPWH_i - RWSTOG_i(t))/DT \tag{2.26}$$

where:

ACAP = available rate of storage capacity at time t (tons/years)

RCAPWH = regional silos capacity (tons)

RWSTOG = amount of grain in storage at time t (tons)

i = RWH index.

If ACAP is greater than zero, there is room for more grain to be stored. To decide on how much grain can be unloaded and stored, ACAP is checked against REST (or course, the absolute value of REST, since this is the extra grain after satisfying the demand from Equation 2.25). If ACAP is less than REST.

$$REST_i(t) = ACAP_i(t) \tag{2.27}$$

where:

REST = excess grain to be unloaded at time t (tons/years)

ACAP = available storage capacity at time t (tons/years)

i = RWH index.

By this equality, only as much grain will be unloaded as there is a place for it. Otherwise there is enough space to store all of the REST and empty the truck pool. In any case, the following equations will result.

$$SR1_i(t) = REST_i(t) \tag{2.28}$$

$$SR2_i(t) = 0.0 \tag{2.29}$$

$$SUP_i(t) = DEM_i(t) \tag{2.30}$$

$$TDPR_i(t) = (DEM_i(t) + SR1_i(t))/TGRC \tag{2.31}$$

where:

SR1 = average input rate to silos for period (t, t + DT) (tons/years)

REST = excess grain unloaded in period (t, t + DT) (tons/years)

SR2 = average silo output rate for period (t, t + DT) (tons/years)

DEM = actual demand at time t (tons/years)

SUP = actual supply at time t (tons/years)

TDPR = average truck unloading rate for period (t, t + DT) (#/years)

TGRC = grain capacity of a truck (tons)

i = RWH index.

Therefore, in the above case supply is equal to demand. The supply has been defined as the amount of grain used to satisfy the demand. It does not mean the amount of grain available i.e. the supply capacity.

If demand has not been completely satisfied using all of the full trucks in the pool, the rest should be compensated by the grain in silos, providing there is enough grain in there. Available grain rate is calculated by Equation 2.32.

$$ASTOG_i(t) = (RWSTOG_i(t) - TRSHOLD * RCAPWH_i)/DT \qquad (2.32)$$

where:

ASTOG = available grain for loading in storage at time t (tons/years)

RWSTOG = actual amount of grain in storage at time t (tons)

RCAPWH = regional silos capacity (tons)

TRSHOLD = threshold factor

DT = length of time increment (years)

i = RWH index .

If ASTOG is less than zero, it will be equated to zero for further computations. Now, ASTOG is checked against REST. If ASTOG is less than REST, only part of the remaining demand can be satisfied.

$$SR2_i(t) = ASTOG_i(t) \qquad (2.33)$$

where:

SR2 = average silo output rate for period (t, t + DT) (tons/years)

ASTOG, i = as in Equation 2.32.

Since the demand has not been satisfied, the stockout performance index will change

$$STKOUT_i(t + DT) = STKOUT_i(t) + DT \qquad (2.34)$$

where:

STKOUT = stockout index (years)

DT, i = as in Equation 2.32.

Thus this measure reflects the total time, when the demand has not been satisfied fully and has nothing to do with the quantity difference of demand and supply. This aspect of performance will be reflected in other indices which will be discussed later. If demand has been fully satisfied, the output rate becomes

$$SR2_i(t) = REST_i(t) \tag{2.35}$$

where:

SR2 = average silo output rate for period (t, t + DT) (tons/years)

REST = satisfied excess demand at time t (tons/years)

i = RWH index.

In any case, the following equations will be computed.

$$SR1_i(t) = 0.0 \tag{2.36}$$

$$SUP_i(t) = TGR_i(t) + SR2_i(t) \tag{2.37}$$

$$TDPR_i(t) = TGR_i(t)/TGRC \tag{2.38}$$

where:

SR1 = average silo input rate for period (t, t + DT) (tons/years)

SUP = actual supply at time t (tons/years)

TGR = average actual unloading capacity for period (t, t + DT) (tons/years)

TDPR = average truck unloading rate for period (t, t + DT) (#/years)

TGRC = grain capacity of a truck (tons)

SR2, i = as in Equation 2.35

Thus the output of the RWH and its storage, at any time, are calculated as follows.

$$RTRUPUT_i(t + DT) = RTRUPUT_i(t) + DT * SUP_i(t) \quad (2.39)$$

$$RWSTOG_i(t + DT) = RWSTOG_i(t) + DT * (SR1_i(t) - SR2_i(t) - RSTGLST_i * RWSTOG_i(t)) \quad (2.40)$$

where:

RTRUPUT = amount of grain thruput in period (0,t) (tons)

SUP = supply rate for period (t, t + DT) (tons/years)

RWSTOG = storage in regional silo at time t (tons)

SR1 = average silo input rate for period (t, t + DT) (tons/years)

SR2 = average silo output rate for period (t, t + DT) (tons/years)

RSTGLST = grain loss factor due to insects, moisture, etc.

DT = length of time increment (years)

i = RWH index.

and the full truck pool is adjusted accordingly.

$$TRPOL_i(t + DT) = TRPOL_i(t) - DT * TDPR_i(t) \quad (2.41)$$

where:

TRPOL = total full trucks available at time t (#)

TDPR = average truck unloading rate for period (t, t + DT) (#/years)

DT, i = as in Equation 2.40.

Two other important performance measures are computed in the SILOS subroutine. One is the ratio of total supply to total demand for each RWH.

$$\mathrm{TSUPPLY}_i(t + DT) = \mathrm{TSUPPLY}_i(t) + DT * \mathrm{SUP}_i(t) \qquad (2.42a)$$

$$\mathrm{TDEMAND}_i(t + DT) = \mathrm{TDEMAND}_i(t) + DT * \mathrm{DEM}_i(t) \qquad (2.42b)$$

$$\mathrm{PRODEM}_i(t + DT) = \mathrm{TSUPPLY}_i(t + DT)/\mathrm{TDEMAND}_i(t + DT) \qquad (2.42c)$$

where:

TSUPPLY = amount of grain supplied in period (0,t) (tons)

TDEMAND = total demand in period (0,t) (tons)

SUP = actual supply rate for period (t, t + DT) (tons/years)

DEM = actual demand rate for period (t, t + DT) (tons/years)

PRODEM = ratio of supply to demand in period (0,t)

DT, i = as in Equation 2.40.

Above index along with stock-out index are used to evaluate service performance at RWH's. Another performance measure represents balance distribution. This index is also calculated for each RWH, which, by adding them together, results in the balance performance measure for total logistics operation.

$$\mathrm{SDEVSD}_i(t + DT) = \mathrm{SDEVSD}_i(t) + DT * \mathrm{DEMEST}_i(t) * \mathrm{MAX}((\mathrm{TOTPRO}(t) - \mathrm{SUP}_i(t)/\mathrm{DEM}_i(t)), 0.0) \qquad (2.43)$$

where:

SDEVSD = balance distribution measure for period (0,t)

DEMEST = estimated rate of demand for period (t, t + DT) (tons/years)

TOTPRO = ratio of total regional supply rates (SUP_i) to total actual demand rates (DEM_i) for period (t, t + DT)

MAX = maximum

SUP, DEM, DT, i = as in Equation 2.42.

and the total balance performance index (BALANCE) becomes,

$$BALANCE(t) = \sum_{i=1}^{4} SDEVSD_i(t) \tag{2.44}$$

There are a few important considerations regarding the RWH operations. It has been assumed that no backlog is being kept for demand. It goes without saying that the famine situation is different from what one might see in business. In a food crisis, if, for any reason, the opportunity to feed the people is lost, it cannot be recovered. Its effect is probably a loss of lives. For example, if lunch meal is missed, there is not going to be two meals for dinner. Current demand is only accounted for and no track of past demand is kept. Even though the backlog has not been explicitly modeled, the effects of unsatisfied demand are reflected in the aforementioned performance measures.

It was said that the queuing theory cannot be used to model trucks at RWH's due to the assumptions made. But queuing delay has been implicitly modeled. All the trucks coming to a RWH enter the truck queue and will be there until unloaded. Thus the model implicitly keeps track of queuing delay. This delay is used in the capital development process which will be explained in Chapter V.

The storage capacity is a design question. In a famine situation, the trucks which carry grain to RWH's should not be kept loaded for extended periods of time. Apart from the cost consideration, there is always a shortage of trucks and drivers in an underdeveloped country. There is no need to emphasis the importance of trucks and drivers for total performance of operations. Thus when the silos are full and there is not enough demand at that time, the sacks of grain are piled in a protected area and covered with plastic for protection. This type of second class storage can also be modeled with a higher storage loss factor, than the first class silos. It should be said that the above situation is a rare event in a famine case and may be caused by a wrong control policy and imbalance distribution. In the current model, it was seen unnecessary to model this type of storage.

A minimum storage is kept at all silos, port and regional, for emergency situations and the corresponding parameter in the model is TRSHOLD. This threshold is calculated with respect to the storage capacity. The RWH model, SILOS, also handles "down" times but it is not used. Data surveillance unit and demand and supply will be discussed later. It has been assumed that the empty trucks will stay "overnight" at RWH's before they come back to the port. Regardless of their time of arrival, each truck and driver gets a specified length of time to rest and get ready to return to port. Modeling this delay and the delays between port and RWH's are discussed next.

Roads and Delays

In transporting large quantities of grain, the arrival of the cargo at its destination will be distributed in time around some mean value. This elapsed time for trucks and drivers to travel among port and RWH's and also the "over night" stay at RWH's have been modeled using a Kth order time varying distributed (continuous) delay process DELVE (74, Chapter 10). In other words, the roads in the logistics model has been represented by DELVF which is a set of K first order time varying differential equations (2.45).

$$\frac{dr_1(t)}{dt} + \frac{1}{D(t)} * \frac{dD(t)}{dt} r_1(t) = \frac{X(t) - r_1(t)}{D(t)} \tag{2.45a}$$

$$\frac{dr_2(t)}{dt} + \frac{1}{D(t)} * \frac{dD(t)}{dt} r_2(t) = \frac{r_1(t) - r_2(t)}{D(t)} \tag{2.45b}$$

$$\vdots$$

$$\frac{dr_K(t)}{dt} + \frac{1}{D(t)} * \frac{dD(t)}{dt} r_K(t) = \frac{r_{K-1}(t) - r_K(t)}{D(t)} \tag{2.45k}$$

$$D(t) = DEL(t)/K \tag{2.45l}$$

where:

X = output of the delay

r_K = input to the delay

$r_1, r_2, \ldots, r_{K-1}$ = intermediate state variables of the distributed delay

DEL = length of delay at time t

K = order of delay, parameter which is used to "tune" the model to approximate real-world behavior

d = derivative operator

t = time index.

To compute the total storage in the above delay process, the following equation is used

$$Q(t) = D(t) \sum_{i=1}^{K} r_i(t) \tag{2.46}$$

where:

Q = total storage at time t

D, K, r = as in Equations 2.45

i = intermediate state variable index.

In the current model, storage refers to the total number of trucks or drivers on each specific delay process. The DELVF subroutine represents the simulation of the above set of equations (Equations 2.45, 2.46). By assigning an array of the intermediate state variables and DEL and K parameters to each road and delay process in the model, the subroutine DELVF can be used over and over. Thus each road is identified by its delay specifications. Delays on Figure 2.4 are modeled by DELVF subroutines unless a different delay has been specified. Also, drivers time-off and truck repair shop delays in Figure 2.1 are represented by DELVF in the current model.

The distances between port and various RWH's are different and the trucks travel at different speeds. Thus, the travel delay is given by the following formula.

$$\mathrm{DELAY}(t) = \mathrm{DISTANCE}/\mathrm{SPEED}(t) \qquad (2.47)$$

where:

DELAY = elapsed time between two points (years)

DISTANCE = distance between two points (km)

SPEED = speed at time t (km/years)

t = time index.

Distances are constant most of the time unless a breakdown in one of the roads forces the trucks to use alternate roads, causing distance changes. In the current model different but constant speeds have been assumed for trucks depending on whether they are full or empty. Full trucks move slower. This makes the delay on each side of each road constant. The subroutine DELAY which takes care of travel delay computation is capable of handling different distances and speeds.

Road Breakdowns

It is quite possible that one of the main roads connecting the port to a RWH becomes unusable due to different reasons. Flood can wash away some parts of the road and make it impassable; or one of the main bridges may break down due to structural failure or natural disaster. No matter what the source of the problem, the decision makers should be ready to deal with it and the model should be equipped to handle it. Thus, the planners should consider the second shortest possible routes from the port to each RWH.

Different settings are possible for the above event and hence different ways to model it. Sometimes, the breakdown is such that a local route can be used to connect two different parts of the main road. Other times, one has to use absolutely different connections. The second case has been assumed in the current model.

The ability of a model to handle breakdowns gives an excellent opportunity to managers and potential users to test different control policies by creating different scenarios. Different routes can have breakdowns at random times. An optimal policy is one which does well on the average under different scenarios, in comparison with different policies. This is why the question of where in the road the breakdown has happened loses its importance. As a result, an arbitrary point can be chosen as the breakdown point. Even though a random breakdown point modeling is also possible, it is an unnecessary complication.

In the current study, the following assumption has been made. The breakdown point is the middle point of the road. This slightly simplifies the modeling process. In the current model, when the breakdown happens, a binary variable, XGT, changes its value and by this means, the occurrence of the event is transmitted to different parts of the model. The trucks at the port start using the second shortest route to reach the specific RWH, and the empty trucks at the RWH also use the new road to return to the port. Thus, the same SILOS subroutine can be utilized. The only difference is the use of a new distance between port and RWH instead of the old one used for delay calculations. Also, new arrays for intermediate state variables of the distributed delay are used.

Back on the old road, the trucks, full or empty, which have passed the breakdown point, continue their way to their destination. But the full trucks that have not passed the breakdown point should turn around and go back to the port. It has been assumed that these returning trucks are reassigned to the same RWH and are dispatched using the new road. The empty trucks, stuck on the other side of the road, must go back to the RWH and use the new road to return to the port. It has been assumed that these trucks would not stay again overnight at the RWH.

The structure of the delay model simplifies the modeling of the problem. To keep track of the trucks still on the old road, two new auxiliary arrays are introduced (AUXRM, AUXRF) to handle the intermediate state or rate variables of the distributed delay belonging to the old road. It was said that each road has its own arrays, one for full trucks and one for empty ones. When the breakdown happens, the values of the intermediate rates corresponding to the stuck full and empty trucks are transferred to the above auxiliary arrays and zeros fill their place in the old arrays. By knowing the breakdown point, it is easy to find out the number of intermediate rates in different sides of the road. Care should be taken in the above transfer. By looking at the Equations 2.45, one can see that the rates leave the delay process sooner if their lower subscript numbers are smaller. Thus, in tranferring the rate values into the auxiliary arrays, the value in the last intermediate rate (i.e. with the largest lower subscript) should go to the first intermediate rate (i.e., with lowest lower subscript) and so on. This is the modeling of the fact that the trucks which left their origin last, should come back to their initial place first.

Knowing two other parameters, DEL and K in Equations 2.45, completely identifies the delays for stuck trucks. The number of intermediate rates in different sides of the breakdown point is parameter K. Since the distances from the breakdown point to either destinations are known, the DELAY subroutine computes the DEL parameter. Checking the delay storages is a good way to see whether there are any trucks left on the old road. In this model, a variable, BRFLG, signals the end of the trucks on that road. The above process which is modeled in the TRNSHIP subroutine, is accomplished simultaneously with other activities and movements in the model.

Supply and Demand

Demand and supply are the forces behind all movements and flows in a logistic system. Nothing is going to move if there is no supply. If the supply exists, the demand identifies the direction of the movements and forces the supply to move. Information about supply and demand is essential for planners and decision makers. Almost all of their decisions are based on this information.

In a famine situation, the data on supply is more available than data on demand. The accuracy of the supply data is usually of a greater degree than that of demand. The fact is that, the central government of the involved country usually knows about its main silos' storage levels. Also, when a foreign country makes a donation, it sends a message to the decision makers managing the crisis. Then the donated grain is usually loaded into ships which normally takes somewhere between fifteen and forty-five days to reach their destination. This information and lead time give the managers a good basis for their policy makings.

But the situation on the demand side is not so bright. Poor data, if any at all, exists in third world countries. Problems with information gathering and availability of data were discussed in the first chapter. Famine also creates other problems. Populations start moving on the basis of any rumor that food exists in some location. This makes planning and allocation decisions very difficult. Another difference between supply and demand is the degree of accuracy of data. Information on supply is usually more certain than of demand because demand must be estimated through data which has been gathered and sent to decision makers by surveillance units in each region.

Different supply and demand patterns generate different food crisis scenarios. Here also, in comparison with other control policies, a pareto optimal control should be able to do well regardless of supply or demand patterns. And the total logistics model itself should handle any type of food arrival and movements. The current model indeed, can work with any pattern of supply and demand. More on this issue will be seen in the next sections and chapters.

Although different patterns of supply and demand could exist, some forms are most likely to happen. Bell shape curves with right or left skewness are typical. Then the area under the curve is the total amount of aid or demand. In the current model subroutine FOODAR simulates the supply. It is a table look-up function which contains the following desired features. It has been assumed that the maximum rate of food arrival is approximately equal to 1.1 percent of port capacity. It is left-skewed and its maximum is attained after the demand function's maximum point. These are the benefits of simulation. Figure 2.5 illustrates the supply function along with the total demand function which will be discussed next. Remember that subroutine EXGEN uses the subroutine FOODAR to generate stochastic exponential interarrival times for ships. That is why the non-zero initial value has been assumed. The area under the curves, representing total amountof demand and supply, can be assigned by the user.

The table look-up function is one way to approximate a function by linear interpolation. In this case the supply function is approximated by a series of straight line segments. This approach is easy to use and its accuracy depends upon the number of approximating line segments. These line segments could be of varying sizes. At a given time T, the subroutine calculates the value of the independent variable (food arrival rate) by first finding which interval (line segment) T belongs to. It then uses Equation 2.48 to get the desired linear functional approximation of the food arrival rate:

$$Y(T) = (T - XTAB(I - 1)) * (YTAB(I) - YTAB(I - 1))/(XTAB(I) - XTAB(I - 1)) + YTAB(I - 1) \tag{2.48}$$

where:

Y = desired linear functional approximation of the independent variable

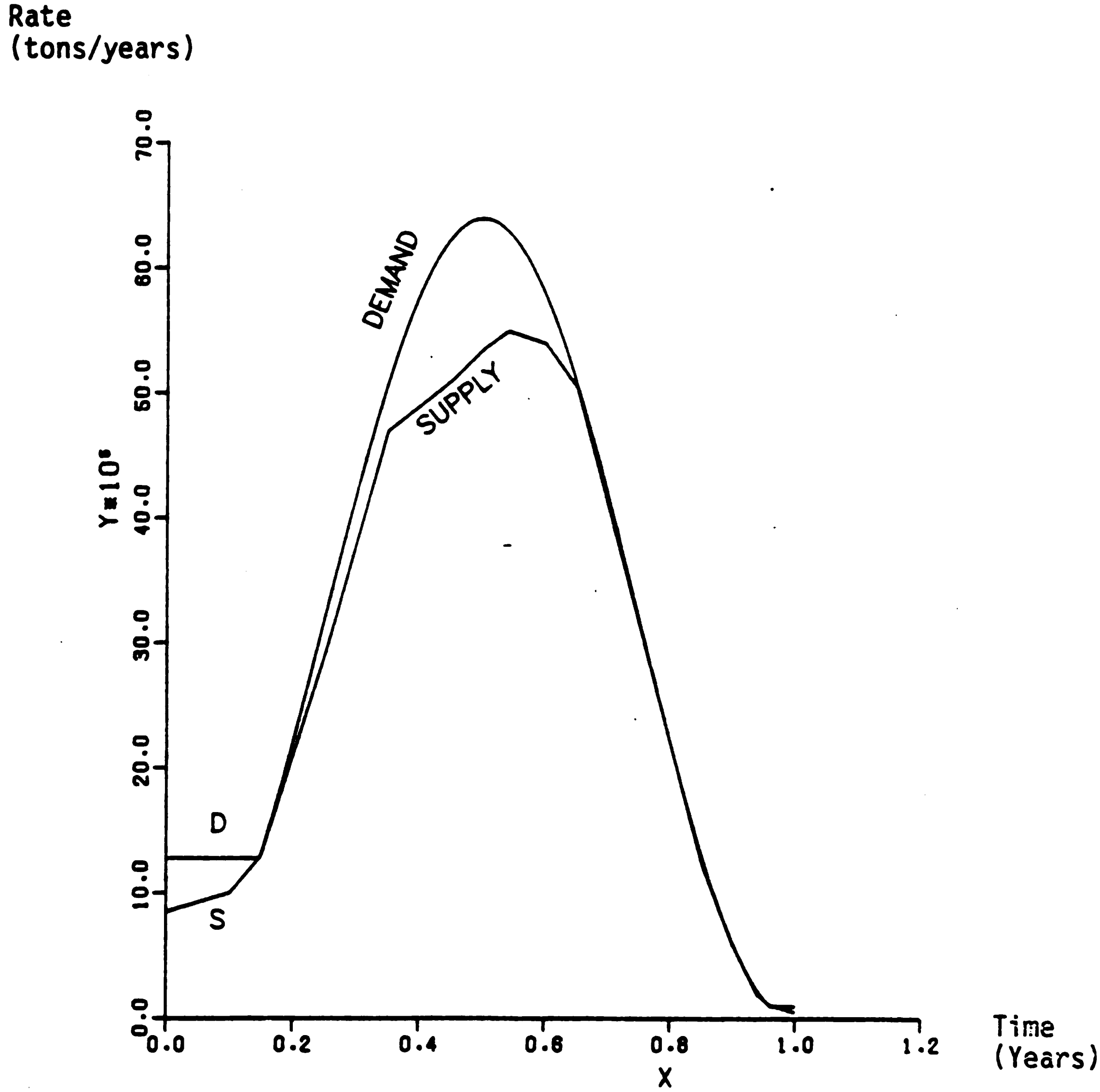

Figure 2.5. The demand and supply functions

T = dependent variable

YTAB = array of the independent variables' values

XTAB = array of the dependent variables' values

I = interval that desired value lies in.

Subroutine DEMAND simulates the following assumed function for total demand.

$$D(t) = TDEF * (1 - \cos 2\pi t) \qquad (2.49)$$

where:

D = demand rate for the country at time t (matric tons/years)

TDEF = total demand for the country for the entire operations (metric tons)

t = time index.

The area under this curve is equal to TDEF and the function attains its maximum at 2 * TDEF. It has been assumed that the demand rate is initially 20% of the maximum rate. Thus, up to some point in time, TDEM, the demand function is constant and after that it uses Equation 2.49. TDEM can be calculated using Equation 2.49 for different values of TDEF.

Total demand is the sum of four regional demands which are calculated using the following equations.

$$D_i(t) = \alpha_i(t) * D(t) \qquad (2.50)$$

$$\alpha_1(t) = .4 + \beta_1(t), \; -.2 \leq \beta_1 \leq .2$$

$$\alpha_2(t) = .4 + \beta_2(t), \; -.2 \leq \beta_2 \leq .2$$

$$\alpha_3(t) = .1 + \beta_3(t), \; -.1 \leq \beta_3 \leq .1$$

$$\alpha_4(t) = 1 - \sum_{i=1}^{3} \alpha_i(t), \quad \alpha_4(t) \geq 0$$

where:

D_i = ith region's demand rate at time t (metric tons/years)

α = partition coefficient at time t

β = population movement coefficient at time t

D, t = as in Equation 2.49.

So the demand function takes into consideration seasonality and population movements in each RWH. This allows generation of different patterns of demand. Notice that the above demand function represents the real world in the model. The decision makers do not know this function. That is why there is a need for data surveillance units. At known sampling intervals, the demand functions are sampled. This process contains errors. Then, these results are used to project the total regional demand. The second stage has its own errors. In order to get rid of these errors and provide better information for decision makers, these observations must be processed. But what kind of estimation procedure should be used and if so, does this help to increase the quality of information or not? These questions are answered in detail in Chapter III. There, different methods have been used to estimate a spectrum of different families of functions which Equation 2.50 is one member of them. After all Equation 2.50 is one of the forms the demand function can take in the real world. Next is the process of modeling the sampling procedure.

Modeling an Information System

To allow evaluation of the effects of information quality on the performance of logistics efforts, appropriate additions to the logistic model are necessary. A sampling component modeled by Dr. A. G. Knapp (64, Chapter III) has been used here. This section is an outline extracted from his work.

This model is one of many tools to be used by the system planners. Its purpose is to provide insight into the processes and structure likely to be encountered during a food crisis. Here the emphasis is on surveillance, data processing and communication. The problem becomes one of estimation, since many dynamic variables can never be known perfectly. The evaluation of an information system includes learning how precise the data must be for efficient relief work, together with the cost of obtaining the desired data quality. The evaluation is largely a sensitivity analysis. Everything else fixed, observations are made of the relationships between system performance and changes in information quality.

The quality of a given data system is modeled here with four parameters: the standard deviation and bias of measurement error (the error is assumed to be normally distributed), the sampling frequency, and the delay time between measurement and availability of information for system managers. The parameters can be varied to account for real world activities; but the activities themselves are not included in the model. As an example, a decreased delay time is possible if data are transmitted by telephone rather than messenger. To account for this change, the delay parameter is decreased; no mention is made of the cause. This approach is taken in the interests of generality because specific communication devices, sampling techniques and statistical methods will differ in cost and applicability from country to country.

The four chosen parameters provide a great deal of flexibility and generality. The delay term represents the sum of all surveillance, data processing, and communication lags. To achieve a given delay time in an actual application, adjustment can be made in one area to compensate for long lags in another. The use of a sampling frequency parameter follows the real world data acquisition process and provides a convenient base for determining the amount of data generated and the surveillance costs. Bias is included to account for regular errors in reporting observations. Possible causes would be bureaucratic disorganization, machinery errors, or corruption. This parameter is not used in studying the current model. Random measurement error is produced by the standard deviation parameter; error distributions are assumed to be normal with a mean equal to the true value. Normalcy is assumed because the variables estimated are averages derived from many samples. Although the error term of each individual sample may not be normal, the central limit theorem guarantees that the distribution of the average value approaches normalcy as the number of samples increases.

Since the information stream is being represented by data quality parameters, the surveillance and communications components are modeled as one unit. It is assumed that these are the functions most responsible for the introduction of errors and delay. The sampling component described next provides for error, delay, and the sampling frequency.

Sampling Components: SAMPL and VDTDLI

A simple method is needed to introduce data quality parameters into a simulation. Simplicity is desirable, since one of the reasons for approaching information system evaluation through the use of parameters is to avoid the detail of describing particular surveillance and communication methods. At the same time, the method must approximate the real delays, measurement error and sampling frequency in the system. The routines, SAMPL and VDTDLI, are quite easily implemented. A sampling frequency is given and, at the specified intervals, random measurement error is introduced. The actual variable, plus or minus a bias term, serves as the mean of the distribution function. The sampled value is then stored in the computer as the model advances through a given delay period, after which the sample serves as the estimated value to be used in decision rules. For the periods between sampling points, some form of filtering can be done to attempt to follow the actual variable. Chapter III is allocated for the discussion of different filtering methods and the choice of the "best" information filter for the problem under study.

The discrete model SAMPL translates the sampling interval into a specified number of simulation cycles, using Equation 2.51. A simple counter (NCNT) is set to zero each time the sampling procedure occurs. The counter NCNT is incremented by one each cycle DT and is checked against the sampling interval size NSAMP. Thus, measurement of desired variables takes place only at specified intervals. Note that SAMPT can be dynamic.

$$NSAMP_k = SAMPT_k/DT + .5 \tag{2.51}$$

where:

NSAMP = number of simulation cycles in sampling interval

SAMPT = sampling interval (years)

DT = simulation cycle increment (years)

k = index on variables.

The measurement of a desired variable, corresponding to data collection, is simulated in SAMPL with the introduction of bias and a random standard error parameter. Then, the estimation method computes an error term proportional to the true value.

$$EST_k(TS) = VAL_k(TS) * (1. + SD_k * Y) + BIAS_k \qquad (2.52)$$

where:

EST = estimated value of variable

VAL = true value of variable

BIAS = measurement bias

TS = sampling time

Y = standard normal random variable

k = index on variables.

Straightforward calculations show that the expected value of the estimate is the true value plus the bias term and the estimate variance is equal to $VAL_k^2 * SD_k^2$ (Recall E(Y) = 0.0, Var (Y) = 1.). The produced error is normally distributed. The form of Equation 2.52 is preferable for discussion purposes since the standard deviation can be described as X% of the true value. But this method becomes an inaccurate model if the true values vary considerably or approach zero. Since the size of the error in Equation 2.52 depends on the size of the variable, the implication would be that measurement techniques get better as the variable decreases. To overcome the problem, the following method should be used.

$$EST_k(TS) = VAL_k + SD_k * Y + BIAS_k \qquad (2.53)$$

where:

all as defined in Equation 2.52.

The variance of this method is equal to SD_k^2 and the standard deviation of the error is fixed. The choice of error estimators is based on examination of time series data for true variable values. In the current model Equation 2.52 has been used to estimate regional demands.

Subroutine SAMPL produces estimated values for sampled variables. These estimates are then used as inputs to a discrete, variable delay routine, VDTDLI. The form of the delay follows that of familiar discrete boxcar routines (70). VDTDLI has the added capability of handling changes in the delay rate, as might occur with a change from messenger to telephone service. The variable delay capability is not used in the current study, but is described here as an indication of the particular problems encountered with information flow.

A boxcar delay routine is so named because it operates much like a string of railroad cars on a circular track. The car at the front of the train empties its load at the designated output point. A new car with the latest supplies (or information) joins the train's tail. And each car moves forward one position. Equations 2.54 describe this process. The equations must be solved in the order presented.

$$OUT = CAR_1 \tag{2.54a}$$

$$CAR_{i-1} = CAR_i, \text{ for } i = 2, 3, \ldots, N \tag{2.54b}$$

$$CAR_N = IN \tag{2.54c}$$

where:

OUT = output of the routine

CAR_i = ith car in the array

IN = input to the routine

i = index on cars

N = number of cars.

The delay parameter of information quality is related to N, the number of array positions, by the simulation increment DT. The calculation is simply done in Equation 2.55.

$$N_k = DELAY_k/DT + .5 \qquad (2.55)$$

where:

N = size of delay array

DELAY = delay involved in the process (years)

DT = simulation increment (years)

k = index on variables.

Note that the relationships of Equations 2.54 and 2.55 require that the array, or train, be updated each simulation cycle. There must be an input and output each cycle DT.

Changes in delay time always cause addition or deletion of information from the tail of the train; and the newest data values are affected. An increased delay causes the newest data to be held for the extra period. Equations 2.54a and 2.54b are retained, but Equation 2.56 replaces Equation 2.54c.

$$CAR_j = IN, \text{ for } j = N, N + 1, N + 2, \ldots, NNEW \qquad (2.56)$$

where:

j = index on new cars in array

NNEW = new size of delay array

N = old size of delay array

CAR = array element.

A decreased delay does not cause loss of data. Rather, the newer information under the old delay scheme is superseded by new data from the new scheme. This implies that implementation of the new methods cannot force the old information through the system any faster. The only modification to Equations 2.54 is that N is recalculated to fit the new, shorter delay. Note that conservation of flow is not a criterion in modeling information transfer.

The output of VDTDLI is a lagged, randomly measured estimate to be used by decision makers. The routine needs an input and provides an output at each time interval of the discrete model. SAMPL calculates a new estimate only once each sampling interval, so additional inputs to VDTDLI are necessary. The simplest scheme is to retain a sampled value from SAMPL as a constant input in VDTDLI throughout the sampling interval, or using some filtering techniques to include the results of previous measurements of the variable in the estimation process. As was mentioned earlier, discussion on this subject will be made in detail in the next chapter. In the current study, the above information system has been used to estimate the regional demands and constant and identical transmission delay has been assumed for all regions.

Capital Acquisition Model

Availability of transportation means for carrying the grain into the country's interior is an important factor in the overall logistics picture. System planners should first decide about the type of transportation mode they are going to use. Then, comes the question of that particular mode's availability which means how much and at what rate it can be acquired. A detailed discussion on these questions was made in the first chapter. The first question has not been answered in this study because the choice of transportation mode must be answered in the context of a particular country. It is very probable that different modes are used simultaneously. Also, it has been tried to keep the model as general as possible.

The second question was felt to be the most important one to be addressed. In fact, the answer to this question will clarify many points for the first question. The second question arises in any logistical efforts, thus it does not belong to any specific case. How much "carrying" capacity and at what rate is available. How efficient are the available transportation modes in terms of speed and reliability? In the current study, modeling these aspects of the real world has been tried. Thus, trucks have been chosen to be the mode of transportation. Important concepts of capital acquisition delay and limits on the rate of acquisition have been modeled. Average capacity and equal numbers of operators for each truck have been assumed. In the current model, the truck's capacity is ten tons and one driver is operating it. Different values can be assigned if necessary.

The capital acquisition process has been shown in Figure 2.6. Managers of the system should decide about the desired amount of capital needed (YD). The word "capital" in this dissertation, has been used primarily in the context of rented trucks and hired drivers. This decision making process will be discussed in Chapter V along with other decision rules and controls. Then, the managers try to acquire the desired capital from the market. This process and the question of whether they can obtain the needed capital should be answered with regard to the case involved. Many factors influence this process. For example, the severity of the disaster; if famine is widespread the central government could announce that the country is in an emergency situation and by some legislation obtain any amount of capital possible. To keep the model as general as possible, the above

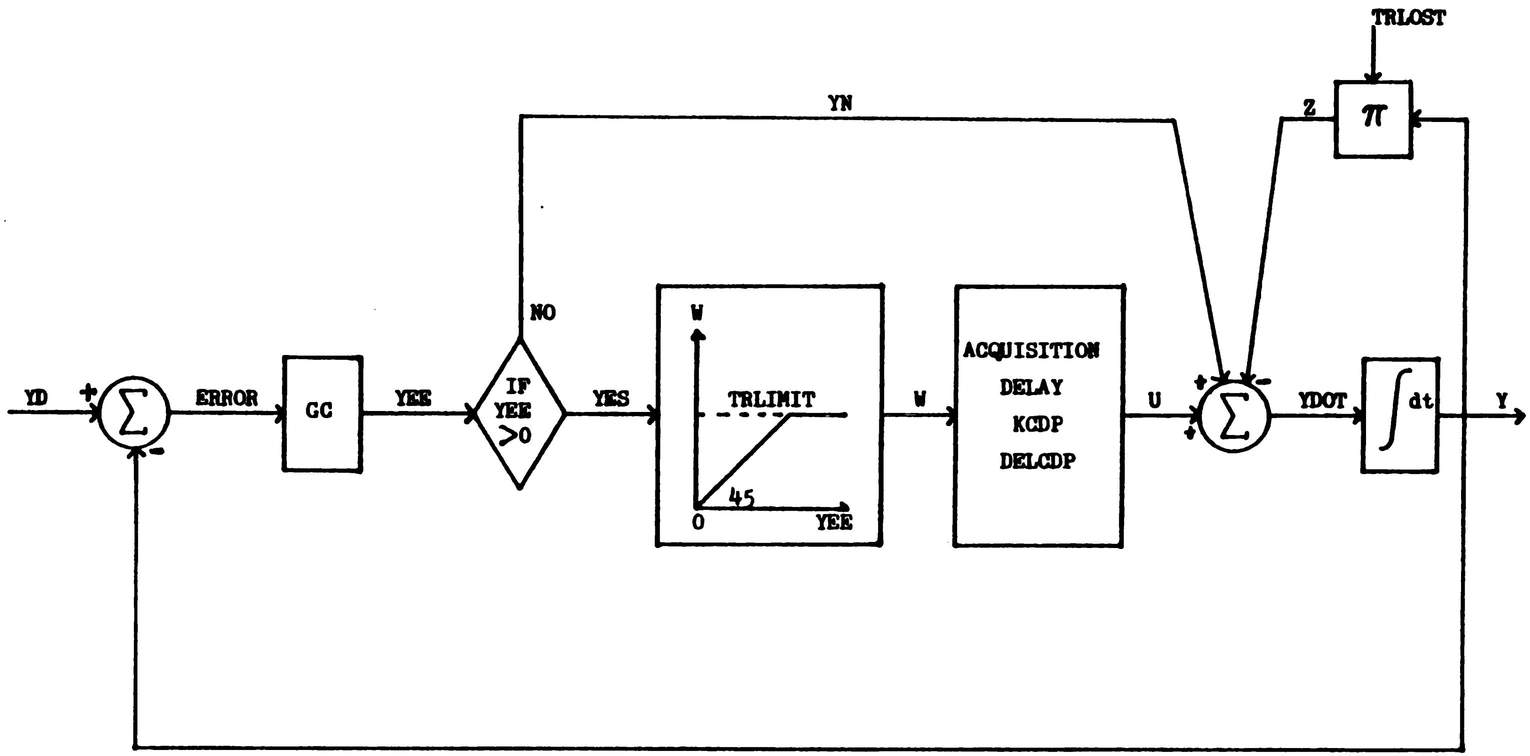

Figure 2.6. Capital Development Process

processes have not been modeled. But the delay involved has been implicitly modeled with the other delays in the acquisition process.

No matter how the managers get the desired amount of capital, there are two factors which prevent their decisions to be fully materialized. One is the rate at which they could acquire the capital. There is a maximum limit (TRLIMIT) beyond which they can not go. TRLIMIT is a design parameter. It is specified either by the managers of the system or the model can be used to see what TRLIMIT is needed in order to achieve a desired total system performance. This is one of the advantages of using models as tools in decision making. Decision makers can use the model to find out about different values of TRLIMIT for various performance levels. This can help them to plan ahead and decide whether it is needed to use extra measures in order to get the desired amount of capital.

The other important factor is the acquisition delay. Part of this delay was discussed earlier. The other part involves the time it takes for the capital to arrive at port. For example, trucks and drivers are spread all over the country. They should be brought to the port, and this process requires time. Figure 2.6 configuration goes as follows. Decision makers decide about the desired amount of capital (YD). This number is compared with the actual amount of capital existing in the system (Y). If more capital is needed, the extra amount will be ordered (YEE). After passing the test on capital acquisition rate, this amount or its modified one will be given as an input (W) to the acquisition process delay. The Kth order distributed delay (Equations 2.45) modeled by subroutine DELVF has been used to represent the above delay.

If the desired amount of capital is less than what exists in the system, the rest (YN) should be discharged. There is no delay in this process, because the trucks and drivers will leave the system at the port and their connection with the model will end. A lost factor (TRLOST) has been modeled to account for the amount of capital which after acquisition does not make it to the port due to various reasons. Thus, the actual amount of capital is obtained by the following equation.

$$Y_i(t + DT) = Y_i(t) + DT * (U_i(t) + YN_i(t) - TRLOST * Y_i(t)) \tag{2.57}$$

where:

Y = actual total amount of ith capital in the system (#)

U = rate at which new capital is added to the system (#/years)

YN = rate at which capital leaves the system (#/years)

TRLOST = capital lost coefficient

i = index on capital

DT = length of time increment (years).

As shown in Figure 2.6, the capital acquisition process contains feedback and a controller (GC). The prime purpose of this controller is to keep Y in line with YD. Other objectives of the above feedback control are: stability of the acquisition system, steady-state error performance (i.e. the difference between steady-state desired and actual capital), and the dynamic performance, meaning how fast the actual capital can adjust itself to the changes in the desired amount of capital. An off-line analysis of the capital acquisition process resulted in the conclusion that proportional control is good enough for current model purposes.

The question of TRLIMIT was also analysed in off-line fashion. The above model was operated with no limit on capital acquisition rate.

A simple variable kept track of the maximum amount of the rate (W in Figure 2.6). Different controls also were applied. The maximum rate obtained in this fashion is just an indication of capital need. It does not mean that this rate is needed throughout the logistic operations. After observations of different values for TRLIMIT, a fraction of it (80%) was used as TRLIMIT in the current model. After all, different control policies, and conclusions derived from them, are affected equally by the choice of TRLIMIT. This decision can also be reached on an on-line fashion. More on this subject will be said in Chapters IV and V.

Subroutine CAPITAL simulates the capital acquisition process. This model follows the same process of acquisition explained above. Trucks and drivers are the capitals which are modeled. Equal average delay time, TRLOST coefficient, and TRLIMIT have been assumed for both types of capital. It is assumed that the acquired capitals enter and leave the system at port. Thus, changes in capital are reflected in, TPOL and DPOL, the truck and driver pools in the port (See Figure 2.1). This follows closely the events happening in the real world. Notice that when capital is added to the system, TPOL and DPOL are increased accordingly. But there must be enough trucks and drivers in the pools allowing their discharge when there is no need for them any more. For this reason two variables, TRLACK and DRLACK, are introduced in the model which keep track of the number of trucks and drivers which should be discharged upon their return from various RWH's. Y(t) and YD(t) represent the actual number of trucks and drivers in the system at time t, respectively. It is believed that more details on this component fit better when control policies are discussed in Chapter V. Thus, the above explanation of the capital acquisition process will be completed in that chapter.

The Cost Function

The preceding sections described a mathematical formulation and modeling of the logistics system. This section describes a process for generation of the cost function. This is a crucial task because the cost function links real world system designs to the simulation of the previous sections in this chapter and control policies of Chapter V.

A detailed discussion and modeling of the cost function has not been intended here. It is mainly an accounting job. A single-valued monetary cost function is calculated which gives the total cost of logistic operations. The total cost is the sum of the costs of the major components in the system; e.g. capital, fuel, inventory, loading and unloading, ship waiting cost, and information. The above decision is based on different factors. First, there is a severe shortage of data in this area. Second, further disaggregation would not lead to significant results about the nature of famine relief resource allocation. At last, the cost coefficients are different in each case. Some resources which are more readily available in one country may not abound in another one.

In this study, only those costs which have been generated exclusively by the famine logistics effort, have been considered in total cost calculations. Thus the costs of equipment which already exists has not been included. For example, loading and unloading machinery at the port. These machines usually exist, regardless of the existence of famine in the country. The cost for such itmes acts as a fixed cost, pushing the total cost upward. For comparison of different control strategies, variable cost should be used as a criterion. Subroutines CALCULT and COSTS are used to compute the total cost and its breakdown to various categories of costs. Subroutine CALCULT is called every simulation cycle and it keeps track of variables necessary for cost calculations. Then at any desired time, the total cost can be computed by calling the subroutine COSTS. In this way, model efficiency increases and computer costs decrease by omitting many unnecessary computations.

Transportation costs are calculated by the following equations.

$$CDRWAGE(t) = CDWAGE * DT * TRDIOP(t) \tag{2.58}$$

$$CRNTR(t) = CRENT * DT * TTRIOP(t) \tag{2.59}$$

where:

CRDWAGE = drivers' wage cost in period (0,t) ($)

CDWAGE = unit wage cost per driver (#/years)

TDRIOP = incremental sum of total number of drivers in the system in period (0,t) (#)

CRNTR = truck rental cost in period (0,t) ($)

CRENT = unit truck rental cost ($/years)

TTRIOP = incremental sum of the total number of trucks in the system in period (0,t) (#)

DT = simulation cycle increment (years).

TDRIOP and TTRIOP are modeled in the subroutine CALCULT. At every simulation cycle, the total number of trucks in the system is computed by Equation 2.60.

$$TRIOP(t) = \sum_{i=1}^{4} (TRPOL_i(t) + PTSTRG_i(t) + FTSTRG_i(t) + RTSTRG_i(t) + TTSTRG_i(t) + TTSTRG_{i+4}(t) + TTSTRG_{i+8}(t) + TTSTRG_{i+12}(t)) \quad (2.60)$$

where:

TRIOP = total number of trucks in the system excluding port at time t (#)

TRPOL = number of trucks waiting to be unloaded at ith RWH at time t (#)

PTSTRG = number of trucks on the road to ith RWH at time t (#)

FTSTRG = number of trucks staying "overnight" in ith RWH at time t (#)

RTSTRG = number of trucks on the road to port from ith RWH at time t (#)

TTSTRG = number of trucks on different sides of a broken road to ith RWH at time t (#).

Notice that TTSTRG's will be zero if there are no breakdowns in the road or after the broken road has been cleared. Now TTRIOP is calculated using the following equation.

$$TTRIOP(t + DT) = TTRIOP(t) + TPOL(t) + TTIRS(t) + TRIOP(t) \quad (2.61)$$

where:

TTRIOP = incremental sum of the total number of trucks in the system in period (0, t + DT) (#)

TPOL = number of trucks in the port's pool at time t (#)

TTIRS = total truck in repair shop at time t (#)

TRIOP = number of trucks in the system excluding the port facilities at time t (#).

But TDRIOP is computed using Equation 2.62.

$$TDRIOP(t + DT) = TDRIOP(t) + DPOL(t) + TDRC * TRIOP(t) \quad (2.62)$$

where:

TDRIOP = incremental sum of total number of drivers in the system in period (0, t + DT) (#)

DPOL = number of drivers in the port's pool at time t (#)

TDRC = number of drivers required to operate a truck (#)

TRIOP = as in Equation 2.61.

Note that TDRIOP is different from TTRIOP in the sense that the drivers "on leave" are not paid but the trucks rent cost should be paid regardless of whether it is in operation or in the repair shop. It has been assumed that any changes in the number of trucks and drivers take place at the end of the DT interval.

Generally speaking, the lower limit on truck cost is its depreciation value and its upper limit is the opportunity cost. But in a famine situation, by government intervention it is very unlikely that the opportunity cost is paid for trucks or any other item. An average repair cost has been assumed for trucks.

$$CRPAIR(t) = CRPIR * TTBS(t) \quad (2.63)$$

where:

CRPAIR = total variable truck repair cost in period (0,t) ($)

CRPIR = average unit truck repair cost ($/truck)

TTBS = total trucks being serviced in period (0,t) (#).

Remember that TTBS is computed by integrating the output of truck repair delay in subroutine ARAIVAL. There is yearly fixed cost for a truck repair shop which is the only assumed transportation fixed cost.

$$CFTRNS(t) = t * CFRPIR \tag{2.64}$$

where:

CFTRNS = fixed cost of transportation in period (0, t) ($)

CFRPIR = fixed cost of truck repair shop ($/year).

The last item on the list of transportation costs in fuel cost. This cost is a function of different variables including distance, speed, and load. Here it is calculated based on the total distance travelled by each truck. Thus the cost of fuel used by trucks other than travelling is assumed to be zero. Also, equality of fuel consumption by full and empty trucks has been assumed. The logic behind this is that a truck that is empty goes faster, causing increased fuel consumption. When a truck is full it goes slower, but the heavier weight now increases fuel use. Fuel cost is calculated by the following equation.

$$CFUELS(t) = CFUEL * TROUTE(t) \tag{2.65}$$

where:

CFUELS = total fuel cost in period (0, t) ($)

CFUEL = average unit fuel cost per truck ($/KM)

TROUTE = total distance travelled by all trucks in period (0, t) (KM).

TROUTE is calculated in subroutines SILOS and TRNSHIP. It is computed by integrating the outputs of truck delays (Figure 2.4) over time and multiplying them by appropriate distances. Total variable cost of transportation is obtained by Equation 2.66.

$$CVTRNS(t) = CDRWAGE(t) + CRPAIR\ (t) + CRNTR(t) + CFUELS(t) \tag{2.66}$$

where:

CVTRNS = total variable cost of transportation in period (0, t) ($)

CDRWAGE = drivers wage cost in period (0, t) ($)

CRPAIR = total variable truck repair cost in period (0, t) ($)

CRNTR = truck rental cost in period (0, t) ($)

CFUELS = total fuel cost in period (0, t) ($).

Total cost of transportation, TCTRNS, is the sum of fixed and variable costs of transportation.

Other logistical functions have their own costs. Inventory cost is calculated as

$$CVAINV(t + DT) = CVAINV(t) + CSTRG * DT * (STOG(t) + \sum_{i=1}^{4} RWSTOG_i(t)) \tag{2.67}$$

where:

CVAINV = variable inventory cost for period (0, t + DT) ($)

CSTRG = average unit inventory cost ($/ton/year)

STOG = port storage at time t (tons)

RWSTOG = regional storage at time t (tons)

i = regional warehouse index

DT = simulation cycle increment (years).

Loading and unloading operations are highly labor intensive in most underdeveloped countries and most of the time takes place by manpower. Another important consideration is the abnormal situation of famine. This means that there is a high probability of the food-for-work program in such circumstances, covering part of the manpower cost. The above two points should be kept in mind when calculating the unit cost of loading and unloading facilities. Note that, as it was mentioned, the costs of loading and unloading equipment, at port is not included in the calculations. Loading and unloading costs are computed by the following equations.

$$\text{CVLOAD}(t + DT) = \text{CVLOAD}(t) + \text{CLOAD} * DT * \left(\sum_{i=1}^{4} \text{RLOAD}_i(t) \right) \quad (2.68)$$

$$\text{CVULOAD}(t + DT) = \text{CVULOAD}(t) + \text{CULOAD} * DT * \left(\sum_{i=1}^{4} \text{RUNLOAD}_i(t) \right) \quad (2.69)$$

where:

CVLOAD = variable cost of loading in period (0, t + DT) ($)

CLOAD = unit cost of loading ($/MT)

CVULOAD = variable cost of unloading in period (0, t + DT) ($)

CULOAD = unit cost of unloading ($/MT)

RLOAD = grain loading rate for period (t, t + DT) (tons/years)

RUNLOAD = grain unloading rate for period (t, t + DT) (tons/years)

i = regional warehouse index

DT = simulation cycle increment (years).

RLOAD and RUNLOAD are modeled in the subroutine SILOS. Information cost is based on the frequency of sampling. An average per sample cost has been assumed equal for all regions. This directly reflects the tradeoff between the quality of information and its cost. The information cost for one region is multiplied by four to get total cost.

$$CVSMPL(t) = 4. * (t/SAMPT) * CSMPL \tag{2.70}$$

where:

CVSMPL = total variable cost of information in period (0, t) ($)

CSMPL = unit cost of sampling ($/survey)

SAMPT = sampling interval (years)

Another important contributor to total cost is the cost associated with the ships waiting to be unloaded. Most of the aid is carried by commercial shipping companies and have to be paid as long as the ship has not been unloaded. The cost here includes only the time from when the ship enters the harbor until it is unloaded. Note that the total grain waiting on ships to be unloaded, QGRAP, increases discretely whenever a ship arrives but decreases continuously as the ships are unloaded. Hence QGRAP is increased by TONSH in subroutine EXGEN whenever a ship arrives and it is reduced as follows in subroutine CALCULT.

$$QGRAP(t + DT) = QGRAP(t) - DT * R1(t) \tag{2.71}$$

where:

QGRAP = total amount of grain at harbor in period (t, t + DT) (tons)

R1 = average offloading rate for period (t, t + DT) (tons/years)

DT = simulation cycle increment (years).

Then, the ship waiting time cost is obtained by Equation 2.72. This cost is proportional to the ship's load, assuming everything else to be the same.

$$TCSHIP(t + DT) = TCSHIP(t) + CSHIPW * DT * QGRAP(t) \quad (2.72)$$

where:

TCSHIP = ship waiting time cost in period (0, t + DT) ($)

CSHIPW = unit cost of ship waiting time ($/ton/year)

QGRAP, DT = as in Equation 2.71.

The above equation gives an exact amount of cost, because, in a real world situation the exact number of ships waiting and their weights are known. There are some other ways to calculate an approximate waiting cost. One way is to use IWL, number of ships in queue, and multiply it by AVTONS, the average ship capacity. This gives the amount of grain waiting to be unloaded for period DT, i.e. QGRAP. Bias in this method becomes obvious when different patterns of arrival for ships are taken into consideration. It overestimates the cost if the number of small ships is greater than large ships and vice versa.

Some fixed costs have been assumed for different logistical functions. These, together with the fixed cost of transportation, add up to the total fixed cost of logistic operations.

$$TFCOST(t) = CFTRNS(t) + t * (CFSTRG + CFLOAD + CFULOAD + 4. * CFSMPL) \quad (2.73)$$

where:

TFCOST = fixed cost of operations in period (0, t) ($)

CFTRNS = fixed cost of transportation in period (0, t) ($)

CFSTRG = fixed cost of silos ($/year)

CFLOAD = fixed cost of loading facilities ($/year)

CFULOAD = offloading facilities fixed cost ($/year)

CFSMPL = fixed cost of information gathering ($/year/RWH)

t = time index.

Total cost of operation is the sum of fixed and variable costs of operation.

$$\text{TOTCOST}(t) = \text{TFCOST}(t) + \text{CVTRNS}(t) + \text{CVAINV}(t) + \text{CVLOAD}(t) + \text{CVULOAD}(t) + \text{CVSMPL}(t) + \text{TCSHIP}(t) \tag{2.74}$$

where:

TOTCOST = total cost of operations in period (0, t) ($)

TFCOST = total fixed cost of operations in period (0, t) ($)

CVTRNS = variable cost of transportation in period (0, t) ($)

CVAINV = variable inventory cost in period (0, t) ($)

CVLOAD = variable cost of loading in period (0, t) ($)

CVULOAD = variable cost of unloading in period (0, t) ($)

CVSMPL = total variable cost of information in period (0, t) ($)

TCSHIP = ship waiting time cost in period (0, t) ($).

TOTCOST is one of the overall performance measures and it will be used for comparison of different control strategies. Appendix A represents and summarizes the numerical cost coefficients used in the current study.

Additional Model Features

Several general features and assumptions of the total model are discussed in this section. The first feature concerns computer use rather than modeling. The stochastic results of simulation runs involving random variables call for statistical evaluations, many of which are based on sample means and variance. The standard technique for obtaining the desired statistics is a Monte Carlo simulation. A parameter set is fixed and several separate model runs are made using different random values (63).

As was explained in previous sections, random variables enter the model at different points. Thus, the current model is equipped for Monte Carlo experiments. Each run of the model produces one sample from the distribution of a given variable. The desired statistics are then calculated from the samples, using well known formulas. Computer storage requirements are reduced considerably by calculating the mean and variance recursively, according to Equations 2.75. Note that only two stored values, $\overline{X}_n$ and S_n, are required for each variable. Another advantage of the recursive calculation is that current statistics are available after each run, providing a convenient structure for conducting hypothesis testing with a minimum number of computer runs.

$$\overline{X}_1 = x_1 \text{ , } S_1 = 0.0 \tag{2.75a}$$

$$\overline{X}_n = \frac{1}{n} \left((n-1)\overline{X}_{n-1} + x_n\right) \text{ ; } n \geq 2 \tag{2.75b}$$

$$S_n = \frac{n - 2}{n - 1} * S_{n - 1} + \frac{1}{n} (\overline{X}_{n - 1} - x_n)^2 \text{ ; } n \geq 2 \tag{2.75c}$$

where:

n = number of samples

x_n = nth sample

$\overline{X}_n$ = sample mean of n samples

S_n = sample variance of n samples.

Since the shape of the distribution of the desired variables and performance measures are of interest in this study, samples generated from different variables at the end of each run are stored in array TT(J, K) in the main program. "J" refers to the number of variables for which the various statistics are desired, so it changes according to the need for statistics. "K" is equal to MONRUN, the number of Monte Carlo loops. Subroutine AVERAGE keeps track of the means, and variances are calculated in subroutine MONPRNT.

In the current study, no internal food flow has been assumed, except the initial amount of grains in the silos. This feature can easily be added to the model. The decision making body has been modeled by subroutine CONTROL. There exists an initial control policy which the logistics model has been tested with. It is thought that a more appropriate place for the discussion on this subroutine is in Chapter V, where the control question is addressed.

Summary

The logistics model described here was constructed as an aid for decision makers in evaluating various strategies for famine relief logistics. The model describes and simulates different components of a logistics system. It is aggregated and does not adequately detail a specific country, but it sheds light on important issues to be faced by any relief operation.

CHAPTER III

STOCHASTIC ADAPTIVE ESTIMATION WITHIN THE FAMINE INFORMATION SYSTEM

Accurate information is needed to achieve overall system objectives. As mentioned earlier, one of the major support systems for relief operations is the information system. Management decisions on resource allocation and food distribution are based on available information and an assessment as to its accuracy.

Although different kinds of data are needed to run the total system, data on food deficit is the most important. To get existing food stocks to those who need it when it is needed and at minimum cost, estimates of food demand should be available. The information system links the real world to the model and the demand for food is the force behind movement of all flows in the system. World Health Organization's monograph on nutritional surveillance states that system managers need processed data enabling them to describe contemporary conditions, predict changes, identify trends, and elucidate underlying causes of the situation (58).

The purpose of this chapter is to examine the problem of information estimation in detail. Then different estimation methods are compared in the context of a famine relife system. A few selected filters are tested under various assumptions. At the end, one technique is chosen for use in the logistics model's information component.

To control a system, one uses available data to find out what the system is actually doing; i.e., to estimate its state. If the system's state can be estimated within some reasonable accuracy, the desired control is often obvious (101, Chapter 2). Hence estimation of the state or some function of the state from the observations is the first step in solving the control problem.

Estimation has been defined as the problem of using observed data which is contaminated by noise in order to estimate properties of the actual system (56), (85), (101). It is common to distinguish between a number of different types of state estimation problems. For example, the estimation of the system's state $X(T)$ based on observations $Y(t)$ where $t_o \leq t \leq T$, is called filtering or causal filtering and is the most commonly considered problem. The estimation of $X(T + \tau)$ from $Y(t)$ where $t_o \leq t \leq T$ and $\tau > 0$, is called prediction. The estimation of $X(\tau)$ relative to $Y(t)$, where $o \leq t \leq T$ and τ varies between t_o and T, is called smoothing or interpolation. A detailed mathematical description of the above concepts, and their breakdown into continuous, discrete, and mixed continuous-discrete estimation is in Reference (56, Chapter 5).

In our sampling component of the overall model, the "true" time series for the desired variable is estimated at specified survey times. This estimate is delayed and then used by policy makers. Between surveys the estimate remains constant; it is a sample-and-hold, or zero-order delay. A filter would affect the estimation process at the survey times, while a predictor would allow changed estimates between surveys. Before changing the sampling model, the following basic questions must be answered. Which of the existing estimation methods fits the problem stated and is "acceptable", and will such a technique perform better than the simple sample-and-hold estimator? The rest of this chapter is a step toward answering these questions.

The Demand Model

To decide on a filter which is suitable, an outline of the characteristics of the process that is going to be filtered and the type of assumptions going to be made is necessary. The overall relief system and exogenous circumstances should also be taken into consideration. A priori knowledge plays an important role here. The characteristics and assumptions of this process are as follows.

1. Discrete observations of a continuous process imply a sampled-data estimation problem. These random observations are assumed to be independent but are generated by one process.

2. Incomplete knowledge about state structure of the process. The equations of motion of the process can be narrowed to a family of functions and even this information is not certain.

3. The demand function of the process, is nonlinear (variable rate of change) and stochastic. Population movements add to this nonlinearity and randomness.

4. There is no data (observations) at the beginning. The observations are generated by surveys as we go ahead in time. There exists a relative lack of information. Sample surveys can provide data weekly, at best. Remember that there is a tradeoff between cost and more information.

5. The stochastic processes involved are assumed to be Gaussian. No

other information on error structure has been assumed. Specific descriptions about the demand model will be presented later.

Filters and Predictors

The problem of state estimation in a dynamical system, given noisy observations of the output variable, is of fundamental importance in control theory. When the models for signal and noise are completely specified, it is possible, at least theoretically, to obtain optimal solutions to the state estimation problem under various optimality criteria (56), (80). The problem is considerably more difficult when uncertainty exists regarding the system parameters, the system model, or the noise statistics; especially if the uncertain quantities are time-varying.

The derivations and applications of modern estimators and estimation algorithms are buried, so to speak, in the technical literature on communication theory, statistics, control theory, and others. Thus, it is difficult to get a comprehensive summary of useful results. In this section, first, a brief explanation of several general estimation concepts and a few comments regarding the comparison of different methods is given. Some important techniques will also be discussed to try and clarify the assumptions and limitations of them. Various estimators are also compared, keeping in mind the different characteristics of the process which was explained earlier, and a narrowing of options. The next stage is the selection of the "desired" estimator.

General Concepts

Stochastic estimation is the operation of assigning a value to an unknown system state or parameter based on noise corrupted observations involving some function of the state or the parameter. Any function which assigns an estimate to each observation is an estimator regardless of whether the resulting estimate is close to or far from the "correct" value (85). The estimation operation is termed optimal if the assignment of an estimate is in accordance with the optimization of some estimation criterion, or "cost function." This criterion is usually a function of the estimation error. An optimal estimate is a function of the received observations and chosen so as to minimize the expected value of the cost function.

One of the most important categorizations in estimation is the distinction between linear and nonlinear estimators. A linear estimator yields a linear function of observation data as the estimate (85, Chapter 4). Nonlinear estimators give a nonlinear function as the estimate of the state. The problem of estimating the parameters or states of a nonlinear system, whether the nonlinearity is introduced by the model generating the stochastic process or by the observation mechanism, is a very complicated one and by no means is solved in a usable form in the general case (56, Chapter 5), (85, Chapter 7).

The practical need for solutions to such problems has resulted in a large number of ideas and methods, but few procedures attack a specific problem and result in useful estimators. Generally, analytical solutions in closed form are not available and computational algorithms have been sought in their place. Thus, it appears that ingenuity as well as discretion is required in obtaining practical solutions to meaningful nonlinear estimation problems (86).

Another distinction is between probabilistic and deterministic models. Some techniques place the estimation problem in a probabilistic framework, meaning stochastic processes involved are modeled by stochastic differential and difference equations. In the deterministic case the problem is looked upon as a deterministic problem of minimizing errors. In this form, very little statistical assumptions are required concerning the nature of the input disturbances or of the measurement errors. The absence of these assumptions corresponds closely to the physical situation in many practical problems, as the determination of valid statistical data concerning disturbances is in itself a difficult theoretical and practical problem.

Classification and Analysis of Estimation Approaches

One may distinguish two approaches which have been employed in developing modern state estimation theory.

I. An approach in which the basic problem is taken to be optimum linear filtering and prediction (59), (61).

II. An approach in which the results are developed as elaborations of the classical method of Least Squares (95), (114), (116). In this approach, the resulting estimates may be linear or optimum under certain conditions, but in general may be neither linear nor optimum. In fact, in most practical applications they are neither, because the necessary conditions generally do not apply in practice. Most workers in the field have started from the "linear optimum filter" viewpoint, even though the papers developing the subject from the method of Least Squares viewpoint appeared earlier. The discussion now turns to first stochastic, then deterministic approaches.

Stochastic Methods

The general linear (nonstationery) filtering prediction problem is essentially completely solved in the pioneering work of Kalman (59), and (60) and Kalman and Bucy (61). The parallel work of Stratonovich (112), (113) and Kushner (67), (68) provides the bases for subsequent developments in nonlinear filtering and prediction theory. These authors adopt the probabilistic approach in modeling of their problem.

A host of papers and reports have appeared, following the fundamental work of Kalman and Bucy, formally deriving their linear filtering algorithm via "Least Squares," "Maximum Likelihood," and other classical concepts. Statistical methods have also been formally applied to the nonlinear estimation problem.

Due to a maze of problems encountered in nonlinear estimation and the relative success in linear estimation, many have attempted to apply related linear procedures to a class of nonlinear systems whose behavior is close to that of linear systems. Clearly, one can at best expect to derive an estimator which is approximately optimal. Using linearization of one sort or another, Kalman-like filtering algorithms were developed and applied to nonlinear problems. "Everyone derived his own Kalman filter, perhaps partly because of lack of understanding of Kalman's original work (56, Chapter 1)." Note that linearization of the process generating the observations is not an easy task, even if the process model is accurately known.

The Kalman-Bucy formulation of the filtering problem assumes complete a priori knowledge of the process and measurement noise statistics.

So, any kind of extended Kalman-type algorithms is based on this assumption. But in the most practical situations, as our case, these statistics are either unknown or inexactly known. The use of wrong a priori statistics in the design of a Kalman filter can lead to large estimation errors or even to a divergence of errors (81). This technique is difficult to use with respect to the problem being discussed due to incomplete knowledge of the process and measurement noise.

To reduce or bound errors and shortcomings many have tried adaptive estimation to modify the Kalman filter to actual data. Extensive literature exists on Kalman-type adaptive or extended filtering (81), (127) and is discussed later in this chapter.

There exists a large class of estimators which are based on state space structure with uncertainties modeled by white processes. This is due to the fact that the vast majority of real world problems can be expressed in the state space - white process form (101, Chapter 3). The use of this model form simplifies the mathematical manipulation and provides a good basis for implementation. The general description of a white process is that it has no time structure, meaning that knowledge of the white process's value at one instant of time provides no information of what its value will be (or was) at any other time point (101, Chapter 3).

Bayesian, Fisher, and Unknown-but-Bounded are three models which fit in the above definition. These three models are fundamentally different, both in terms of physical assumptions and interpretations and in terms of the type of mathematical concepts required. Any other estimator with a state space - white process form is a special case of the above models. Schweppe (101) bases his book on this type of classification of estimation theory. See Chapter 3 in (101) for a detailed description and definition of the above models.

The problem with the above estimators, considering the situation of discussion, is that they assume knowledge of state structure of the process and some information about different disturbances. As was mentioned earlier, there is incomplete data regarding the model of the process generating the observations and the characteristics of its disturbances. It is good to know that many common estimators fall in the above class, including Autoregressive models, Moving-average models, and Maximum likelihood estimators to name a few. Note that the basic difference equations for the Baysian model estimator are the same as the Kalman-Bucy filter (101, Chapter 6).

There exists another broad class of estimators known as tracking algorithms or recursive filters which have been used extensively in military, civilian, and aerospace industries. This filter, which utilizes the engineering concept of feedback, tracks a maneuvering target by means of estimating its position, velocity, and sometimes acceleration using observations of the target. Most of the problems addressed by this type of estimator are sampled-data estimation problems. These estimation procedures can generally be separated into two parts. One, the extrapolation (prediction), is a generation of the estimate of the state at time K + 1 based on the first K observations. The second part is the processing of the new observation to update the state estimation, i.e. to generate the estimate of the state at time K + 1 based on the first K + 1 observations. In other words, the tracker uses the model output to predict what the next observation will be and then it uses the difference between model prediction and the actual observation to "correct" the model.

Tracking problems have been looked upon from different angles, and various types of estimates have been designed. Polynomial-type filters and various kinds of extended Kalman are of this form. Kalman based tracking schemes constitute a large part of the literature (23), (107), (127). Most of the tracking techniques make different assumptions about state model for the target and rely on a statistical description of the maneuver as a random process. Considerable attention has been directed toward the synthesis of optimal target tracking filters for real-time surveillance systems (7), (87), (108).

As it was said earlier, some modifications have been necessary in most situations, in order to apply different techniques to the real world problems. This is due to the fact that many assumptions such as complete a priori knowledge of the process structure and measurement noise statistics can not be met in practical cases. These modifications are somehow particular to each situation and usually cannot be used for other cases. Different authors have designed their own estimator, based on their special interest, by modifying one basic estimation technique. These changes can come under the title of adaptive estimators, which adjust themselves to unknown or varying operating conditions. These adjustments could be caused by modifications of either external signals or the internal structure of the filter alone. Adaptation is accomplished by a variation of filter parameters (or if it is necessary, even by modifying the structure of the filter) so that a certain criterion of optimality which characterizes the operation of the filter is minimized (122, Chapter 6). See (22), (50), (79), (81), (107), (118), (120), (127) as a few examples of the vast literature on adaptive estimation theory.

An approach to tracking a maneuvering target has been developed by Bar-Shalom and Birmiwal (6) which does not rely on a statistical description of the maneuver as a random process. Instead, the state model for the target is changed by introducing extra state components when a maneuver is detected (adaptivity).

Deterministic Techniques

The need for probablistic assumptions, concerning the nature of the unknown inputs or the measurement errors, have been removed by deterministic approaches. It is important to know that many of the substantive results, including the fundamental theorems of recursive state estimation, do not require any statistical concepts or assumptions either in their formulation or in their proof. Even when the problem is formulated statistically, there is no essential difference in the treatment of problems where the state is stochastic and of problems where the state is nonstochastic or deterministic. Every problem in which the state is a stochastic process can easily be reformulated as a problem of estimating a vector of nonstochastic parameters, yielding identical solutions (115).

For the purpose of deriving optimum recursive solutions to linear filtering and prediction problems, it is unnecessary to make several assumptions regarding the state equation, which have been thought (61) to be necessary. Swerling (115), (116) shows that every problem in optimum linear filtering or prediction ofrandom processes can be formulated as an equivalent problem of estimating a vector of constant parameters by the method of least squares. The estimation procedures satisfying the above requirements are Least Squares, Maximum Likelihood (deterministic), and the method of Moments.

In dealing with the method of Least Squares, it is necessary to distinguish a terminology distinction. the "method of Least Squares" is a class of computational procedures for deriving estimates from data while "mean square error" is an accuracy measure and "minimum mean-square error" is an optimality criterion. In the ordinary least square problem, we simply choose the least square estimate such that the expected observation comes as close as possible to the actual observation while minimizing the expected sum of squares of the errors (85, Chapter 8). A minimum mean square error estimate, on the other hand, is one for which the statistical mean square error is minimum among all estimates of a given parameter within some specified class of estimates, e.g., linear estimates, regular estimates, or arbitrary estimates (115).

The usual classical approach to least square estimation leads to nonsequential (nonrecursive) estimation schemes. The basic objection to a nonrecursive scheme, when applied to a dynamical system, is that each time additional output observations are to be included, the entire least square calculation must be repeated. In general, the time required to perform this calculation increases with the number of measurements. However, for some cases, a recursive procedure has been developed which enables one to estimate the parameter value based only on the last estimate and the last additional observation (30), (85, Chapter 8). Many authors have developed optimum linear recursive estimation procedures when the observation noise is correlated (9), (10), (18). The method of Least Squares is not only the oldest method in estimation theory but it has also been used, explicitly or implicity, in many other techniques. Detchmendy and Sridhar (30) have used the classical Least

Squares method as the criterion for estimation. But they only have assumed the dynamical behavior of the process to be described by an ordinary differential equation.

A reasonable estimate of a parameter is that value which will make a given observation most likely, i.e., the parameter value which causes the conditional probability density induced on the observations to have its greatest maximum at the given observation. This estimate is called the Maximum Likelihood estimate (122, Chapter 3). It has been shown (85, Chapter 8) that the methods of Maximum Likelihood and Least Square yield the same result in the special case of additive white Gaussian noise. Nahi (85, Chapter 8) treats the Maximum Likelihood estimation as a deterministic problem. He reaches the following two conclusions. First, that the results of Least Square estimation (a purely deterministic operation) with a probabilistic interpretation (via maximum likelihood) agrees in form with the Kalman linear estimator minimizing average quadratic cost.

Second, the solution to the Kalman estimation equations requires knowledge of initial value of covariance matrix. This is the same as requiring a priori density function for the parameter to be estimated. Maximum Likelihood estimation does not require such data, and consequently the initial conditions are not given a priori. Instead we wait until n observations are received (since there are n parameters involved) in order to establish a probability density function.

The method of moments is another procedure for providing an estimate of a parameter without requiring a priori knowledge of its probability density function, although, as in the case of Maximum Likelihood estimation, a conditional probability density on the observations is required

(85, Chapter 8). This method yields an estimate which is not necessarily optimal in any sense. Yet, like Least Squares method, it is intuitively appealing due to its simplicity. In many cases, the estimate approaches the true value of the parameter as the interval of observation becomes infinite, or as the amount of observed data becomes large.

Information Characteristics

There are two other problems related to estimation theory which would be discussed here. They are the notion of observation dependency and the question of the total number of observations. Since the problem in question is a sampled data one, it is appropriate to address the above concepts within this type of estimation problem. The ideas and notions of how to handle sampled data systems are very important, as a very wide range of practical problems are of this form. Economic problems are the best examples of this type of system. Observations of some economic variable, for example demand, are taken at discrete times even though demand itself is a continuous function of time.

Some of the estimation techniques are concerned with models in which observations are assumed to vary independently. However, a great deal of data in business, economics, engineering and the natural sciences occurs in the form of time series, where observations are dependent and where the nature of this dependence is of interest in itself. The body of techniques available for the analysis of such a series of dependent observations is called time series analysis (13). A time series may be considered to be composed of several components, including trend (progressive changes over a long period of time), seasonal cycles (regular periodic variation), irregular undulating variations (for example, business cycles), and a random component whose effect may be transitory or permanent (5). Time series is a sampled data system, but since it has been assumed that random observations in question are independent, it is not necessary to explain time series analysis further.

One should be careful about the question of the total number of observations and existing data. Of course, this is a problem more closely related to discrete-time and sampled data systems than to the continuous one. How many observations are needed from the process before being able to implement a specific method is a point to consider. And after starting the estimation procedure, how frequently is a new data point needed in order for the estimator to work properly? Some techniques may sound very well in theory, but when it is time to apply them, unless there exists enough data, one will see that the technique needs a period for "take-off". The length of this transient period is different for various methods.

For Least Squares based techniques and deterministic Maximum Likelihood estimator, we need to have enough information at the beginning. Econometric methods are also in this category. For a finite number of observations, the Bayesian methods provide the optimum estimate by minimizing a certain loss function (122, Chapter 3). This is accomplished by using the complete a priori information about the probability density functions, and unfortunately, by very tedious computations. The next section discusses the model selection process and the connection of our problem with the question of the number of observations.

What Method to Choose

As it was discussed, a number of different approaches and viewpoints have been applied to the estimation problem. However, almost all of the approaches assume some a priori knowledge of the system generating the observations, ranging from complete description of the system's state equations and error structure down to incomplete knowledge of the mathematical model of the system and errors. The algorithms work well (at least theoretically) within the context of their underlying assumptions. If the observations are assumed to be random in nature, some a priori statistical description must be given to the maneuver process. This requires more knowledge about the system than is normally available (6). In addition, if the assumptions made do not correspond to the actual nature of the system, the techniques performance may be degraded.

In choosing an estimation method, a distinction should be made of the difference between theory and practice. The term practical does not really have a viable definition. Practicality of a procedure changes at each situation. Schweppe (101, Chapter 8) suggests that one approach is to define the "most practical" filter to be the "simplest" one that performs the necessary job satisfactorily. The fact is that in many cases none of the estimates can be calculated exactly and the general theory is merely a guide to the choice of "reasonable" estimation technique. Thus, the question of complexity and degrees of accuracy of a method should be decided case by case. In this situation, considering a third world country with problems such as a lack of trained personnel and high speed calculating machines which will pose to the job of information surveillance, the degree of complexity and accuracy is different from the case of, for example, a chemical experiment. Or in the case of a missile much of the control is based on the tracking method's ability, but for relief operation, the refined data on food deficit is one of the instruments in the possession of decision makers.

Another important factor in selecting an estimation procedure is the problem of nonlinearities. The development of successful estimators for nonlinear models is more of an art than a science (101, Chapter 13). Most of the work in nonlinear filtering is very theoretical, involving such hitherto obscure and difficult subjects as stochastic differential equations and the Itô calculus, which require a fair knowledge of measure theory for understanding (56, Chapter 2). The basic idea of handling nonlinear models by combining linearization with the linear model theory has been discussed in an almost uncountable number of papers. But this extension, most of the time, has been with regard to a particular problem the author has had in mind. No attempt has been made here to discuss all these possibilities.

When a good mathematical model for the real world is available, Schweppe (101, Chapter 8) gives a list of steps to consider in answering the question of the selection of an estimation method. Having considered all the characteristics of the process in current study, it was concluded that there is no single technique that can do the job by itself. Nonlinearities, incomplete information about state structure and noise model, lack of observations at the beginning and in the period that estimation takes place, are just some of the problems being faced. In addition, there are some expectations that an estimator should be able to fulfil. Even though the accuracy of a technique is a very important factor, in a famine situation, efficiency and cost play major roles. Few monetary resources exist in a third world country struggling with a wide spread food crisis. Techniques which need a considerable number of professional personnel and computers, cannot feasibly be considered, even if their performances are extraordinary. Also, due to lack of the data and costs involved in information surveillance, the method should have good transient and noise reduction capabilities.

The Selected Models

After summing up all the facts and important elements, together with the list of different methods available, it was concluded that it is better to choose a technique more suited to this problem than the others under the assumed conditions. Then, using the knowledge about the family of functions representing the process, some kind of adaptive design can be added to the basic estimation model in order to improve its performance. The technique which satisfies the previously stated conditions, is the Alpha-Beta ($\alpha - \beta$) tracker. This method is commonly used in radar applications to track positions and directions of an aircraft. Alpha and Beta refers to parameters of the filter.

In order to expand the scope of the study for the sake of comparison of different estimation models under different conditions, two other scenarios have been assumed. One is when complete information about the process model and its noise statistics is available and the other when the process model is partially known. The Kalman filter was chosen, in addition to the $\alpha - \beta$ tracker, for testing these scenarios.

Alpha - Beta Tracker

This model is a very simple but highly effective form of data processing. It is a means of estimating the value and time rate of change of an input observed by measurement errors. There are no assumptions regarding the state equations or the error structure of the model generating the observations and no constraints exist on data correlation. In actuality, in a study which was conducted on time series analysis (5), this technique proved to be the "best" in comparison with other methods considered.

The α-β tracker also has important minimum error properties. It is optimum for both the value and time rate of change tracking within the given performance measures (noise reduction and transient response), in the class of all fixed parameters, linear tracking equations, given the following relationship (7)

$$\beta = \frac{\alpha^2}{2 - \alpha} \tag{3.1}$$

The tracker gives the minimum mean square error.

The problem at hand is similar to radar tracking. There, the target can move in any direction and we have no clear idea about the model of motion or its noise. But we know other information regarding its velocity and movement capabilities. Also, no observations exist until the target comes into the domain of the radar. This tracker has also been used by Knapp (64, Chapter 6) to estimate per capita nutritional debt and consumption and grain storage levels in a famine situation.

The governing set of equations for this sampled data tracker is as follows (20, Chapter 8):

$$Y_p(t) = Y(t - SAMPT) + SAMPT * Y_d(t - SAMPT) \tag{3.2}$$

$$Y(t) = Y_p(t) + \alpha * (U(t) - Y_p(t)) \tag{3.3}$$

$$Y_d(t) = Y_d(t - SAMPT) + \beta * (U(t) - Y_p(t))/SAMPT \tag{3.4}$$

where:

Y_p = value predicted from past information

Y = smoothed value used as estimate

Y_d = function velocity estimate

U = survey result

SAMPT = sampling interval (years)

t = current time

α, β = parameters of the filter.

Implementation of this tracker is quite simple. Each new piece of information enters as an input to the above set of equations. A predicted value is computed based on past information. The new data and the predicted value are combined to form a "smoothed" estimate of the present situation. The rate of change, or velocity, of the process is also estimated, which affects the next predicted value. So, the above filter gives a new estimate at each sampling point.

A modification of Equation 3.2 can be used as a predictor between surveys. Replacing SAMPT with the differences between current time and the time of the past survey (t - T') produces the following equation, which is a common linear extrapolation equation. The function is predicted to be moving in the direction indicated by the rate of change Y_d.

$$Y_p(t) = Y(T') + (t - T') * Y_d(t) \tag{3.5}$$

where:

t = current time

T' = time of last sampling point

Y_p, Y, Y_d = as in Equations 3.2 - 3.4.

An analysis of $\alpha - \beta$ tracker characteristics is presented by Cadzow (20, Chapter 8) and Benedict and Bordner (7). Selection of α and β plays an important role in filtering design. There are three considerations with this regard. First, to satisfy the stability requirement of the model, a critically damped response will require that α and β satisfy Equations 3.6 and 3.7.

$$\alpha = 2\sqrt{\beta} - \beta \quad \text{(critical damping)} \tag{3.6}$$

$$0 \leq \beta \leq 4 \quad \text{(system stability)} \tag{3.7}$$

Two other parameter considerations stem from the necessary compromise between the conflicting requirements of good noise smoothing (heavy filtering, sluggish system) and good transient capability (light filterling, fast system) of the tracker. Values of β close to one cause fast response to new information, for when β equals one, α is also one, according to Equation 3.6. Then $Y(t)$ equals $U(t)$ by Equation 3.3, no matter what the outcomes of Equations 3.2 and 3.4 are. This is interesting from a different point of view. If either α or β is chosen equal to one, the tracker transforms into the simple sample-and-hold scheme which was discussed before. This gives a good basis for comparison of the performances of different designs.

For noise reduction, a value of β near zero is needed. Thus, the normal parameter selection process limits β to the interval between zero and one. The value of α can be obtained from Equation 3.6 when β is known. β is the free parameter which is left for construction of a tracker that gives the "best" compromise between noise reduction and transient capability or maneuver tracking characteristics of the system.

The Kalman Filter

Some of the characteristics of the Kalman filter have been mentioned and discussed earlier. As it is known, in order to use this method, state space structure and noise statistics of the process should be available. This filter has been used extensively in various fields of science, especially in aerospace industries and orbit determinations where discrete observations are received from a continuous process (56, Chapter 8). This resembles closely the problem addressed here. The Kalman filter is the "best" linear filter in the sense that it yields the minimum error covariance matrix of any linear estimator (10], Chapter 6).

Even though the filter is applicable to both continuous and discrete systems, it is more appropriate to present the continuous-discrete version of it, i.e. continuous process, discrete observations. Given the continuous-time system model and discrete observations to be

$$\frac{d}{dt}\underline{X}(t) = \underline{F}(t)\ \underline{X}(t) + \underline{G}(t)\ \underline{W}(t),\ t \geq 0 \tag{3.8}$$

$$\underline{U}(k) = \underline{M}(k)\ \underline{X}(k) + \underline{V}(k),\ k = 1, 2, \ldots \tag{3.9}$$

$$E\ [\underline{X}(0)\ \underline{X}'(0)] = \underline{\Psi} \tag{3.10}$$

$$E\ [\underline{W}(t)\ \underline{W}'(t)] = \underline{Q}(t) \tag{3.11}$$

$$E\ [\underline{V}(k)\ \underline{V}'(k)] = \underline{R}(k) \tag{3.12}$$

where:

$\underline{U}$ = observation vector

$\underline{X}$ = state vector

$\underline{V}$ = white observation noise vector

$\underline{W}$ = white system noise vector

$\underline{X}(0)$ = initial condition, which may be uncertain

t = continous time index

k = discrete time index

E = statistical expectation

d = derivative operator.

The matrices $\underline{F}$, $\underline{G}$, and $\underline{M}$ are all assumed to be known. $\underline{X}(0)$, $\underline{W}(t)$, $\underline{V}(k)$ are uncorrelated. An estimator to process the observations should be determined so as to yield an estimate of the state. The optimal (minimum variance) Kalman filter for the above system consists of the equations of evolution for the state $\underline{X}(t)$ and covariance matrix $\underline{P}(t)$. Between observations, these satisfy the differential equations (56, Chapter 7)

$$\frac{d}{dt} \underline{X}(t) = \underline{F}(t)\ \underline{X}(t)\ , \tag{3.13}$$

$$\frac{d}{dt} \underline{P}(t) = \underline{F}(t)\ \underline{P}(t) + \underline{P}(t)\ \underline{F}'(t) + \underline{G}(t)\ Q(t)\ G'(t),\ k \leq t < k + 1 \tag{3.14}$$

And at an observation at k, they satisfy the difference equations,

$$\underline{X}(k) = \underline{X}(k - T) + \underline{K}(k)\ [\underline{U}(k) - \underline{M}(k)\ \underline{X}(k-T)] \tag{3.15}$$

$$\underline{P}(k) = \underline{P}(k - T) - \underline{K}(k)\ \underline{M}(k)\ \underline{P}(k-T) \tag{3.16}$$

$$\underline{K}(k) = \underline{P}(k - T)\ \underline{M}'(k)\ [\underline{M}(k)\ \underline{P}(k - T)\ \underline{M}'(k) + \underline{R}(k)]^{-1} \qquad (3.17)$$

$$Q(k) = \int_{t_{k-T}}^{t_k} \underline{\Phi}(k, \tau)\ \underline{G}(\tau)\ \underline{Q}(\tau)\ \underline{G}'(\tau)\ \underline{\Phi}'(k, \tau)\ d\tau \qquad (3.18)$$

where:

$\underline{P}$ = state covariance matrix

$\underline{K}$ = Kalman gain

$\underline{\Phi}$ = fundamental matrix of $\underline{F}(t)$

T = step size or time interval

Everything else as in Equations 3.8 - 3.12.

Description of the Demand Model

The characteristics and assumptions regarding the demand model were discussed earlier. They were general descriptions which are appropriate to overall famine relief operations and food crisis. It was said that the process can be specified by a family of functions. Here, considering various famine scenarios, specific assumptions about the family of functions representing the demand for food are presented. In the real world, any member of this family could occur and it portrays total demand for the entire country.

Generally, in a famine, demand for food is very low at the beginning. But as time goés on and public and private food storages are depleted, the demand increases steadily until some point at which the efforts of famine relief organization give their fruits. Then the principal causes of food shortage start fading and the demand begins to decrease. This will continue until normal conditions return. This probable famine scenario represents the following functional form of demand. Demand is going to monotonically increase and after passing through a maximum, it is going to monotonically decrease. This is kept in mind in designing the family of functions that represent the set of almost all probable forms of this scenario. Note that the above description of demand is not in terms of strict mathematical terminology. For simplicity it has been assumed that the model is unimodal. The same thought applies for monotonical changes of function.

Assumptions has been made that demand functions can take the form of any member of the following class of functions.

$$D(t) = TDEF * [1. - \cos 2\pi((t - t_1)/CD)] \tag{3.19}$$

where:

D = demand rate (tons/years)

$TDEF$ = total deficit (tons)

CD = crisis duration (years)

t_1 = time index for start of the crisis (years)

t = time index. (years)

Crisis duration and total deficit are random variables because in a real situation a crisis can have any length of duration and different size requirements and no knowledge of what they are is known. For analysis purposes and from past experiences, some limits can be put on these random variables. They are:

$$.8 \leq CD \leq 2 \quad \text{(years)} \tag{3.20}$$

$$2 \leq TDEF \leq 4 \quad \text{(million ton)} \tag{3.21}$$

For any member of this family, the maximum rate of demand at time CD/2 is equal to 2 * TDEF (tons/years) and the area under the curve is equal to TDEF (tons), the total demand.

This form of the functions is for the simulation purposes only. Of course, any other form which models the food shortage situation can be applied. It should be mentioned that in the total relief system being dealt with, regional demands sum up to the total demand. The only difference is that of population movements among different regions. But from an estimation point of view the functional forms of regional demands are quite similar to the total demand function. In this way, it is not necessary to experiment and test the estimator with various regional demand functions. Although some accuracy is lost by aggregate analysis, this loss will probably be covered by the saving in cost. If regional demands are used for analysis purposes, their functional forms become uncountable and the cost skyrockets for any meaningful analysis which covers the total spectrum of possibilities. More details on the forms of regional demand functions was discussed in Chapter II.

State Space Representation

The demand function D(t) in Equation 3.19, will be represented here as a linear system. This presentation, of course, is not unique. First, the Laplace transform of Equation 3.19 is found and the transfer function of the linear system is specified. From the block diagram of this system, the state space form is derived (117, Chapter 3). From Equation 3.19, assuming TDEF, t1, and $2\pi/CD$ to be A, 0.0, and w respectively, we have,

$$D(S) = \frac{A}{S} - \frac{AS}{S^2 + w^2} = \frac{Aw^2}{S} \cdot \frac{1}{S^2 + w^2}$$

For the linear system with output D(S), let H(S) be its transfer function. Then,

$$H(S) = \frac{1}{S^2 + w^2}$$

The state space presentation of the above linear system becomes,

$$\frac{d}{dt}\underline{X}(t) = \frac{d}{dt}\begin{bmatrix} x1 \\ x2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -w^2 & 0 \end{bmatrix}\underline{X}(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} Aw^2 \quad (3.22)$$

$$D(t) = [1, 0]\,\underline{X}(t) \quad (3.23)$$

where:

$\underline{X}$ = state sector

S = Laplace complex variable

t = time index

d = derivative operator.

Observation U(k) was assumed to take the following form,

$$U(k) = D(k)[1 + n(k)] \quad (3.24)$$

where n(k) is a zero mean stochastic Gaussian process with time-varying variance R(k). This error structure is a multiplicative one in which it is necessary to have an additive error model in order to utilize the Kalman filter. But, since the mean of the errors is zero, it can be modeled as an additive one. The Kalman filter allows for time-varying variance. Then Equation 3.24 becomes,

$$U(k) = D(k) + V(k) \quad (3.25)$$

where V(k) is a zero mean stochastic Gaussian process with time-varying variance, $D^2(k)\ R(k)$. Initial state, D(o), and observation (measurement) error V(o) is assumed to be independent.

Two Probability Distribution Functions

There are two uncertain parameters in the state space model, namely A and w^2. The Kalman filter should be modified to fit the system. This modification will be discussed later. At this point, all available information on these two parameters should be obtained. Fortunately, their distribution functions can be specified. In what follows, these distributions will be derived. As will be seen later, TDEF and CD have Uniform distributions. By Equation 3.21, A's distribution is defined over the interval [2,4] with mean 3 and variance 1/3. But what is the distribution of w^2? CD is Uniform over [.8, 2] and $w = 2\pi/CD$ by definition. Let Y = w. Then

$$P[Y \leq y] = P[2\pi/CD \leq y] = P[CD \geq 2\pi/y] = 1 - P[CD < 2\pi/y]$$

$$= 1 - F_{CD}(2\pi/y) = \frac{y - \pi}{.6y}$$

where:

P = probability operator

F_{CD} = probability distribution fuction of CD.

Thus, the distribution function of Y becomes,

$$F(y) = \begin{cases} 0 & , y < \pi \\ \dfrac{y - \pi}{.6y}, & \pi \leq y < \pi/.4 \\ 1 & , \quad y \geq \pi/.4 \end{cases} \tag{3.26}$$

Now, let $Z = Y^2$. Then we have,

$$P[Z \leq z) = P[Y^2 \leq z] = P[Y \leq \sqrt{z}]$$

So, the distribution function of $Z = w^2$ becomes

$$F(z) = \begin{cases} 0 \quad , & z < \pi^2 \\ \dfrac{\sqrt{z}-\pi}{.6\sqrt{z}}, & \pi^2 \leq z < \pi^2/.16 \\ 1 \quad , & z \geq \pi^2/.16 \end{cases} \tag{3.27}$$

where the mean and variance of $w^2 = Z$ are $\pi^2/.4$ and 182.642 respectively.

Modifications of the Estimation Models

To improve the performances of the estimation models, some kind of adaptations and extensions of the methods are necessary. The performance degradation that results from improperly assigned values for uncertain parameters can be severe. To prevent such a condition, online simultaneous estimation of the state and uncertain parameters have been suggested by many authors (77, Chapter 10). This combined state estimation and system identification is called adaptive estimation (101, Chapter 2).

Sometimes, one would like to readjust the filter's internal model based upon information obtained in real time from the measurements available, so that the filter is continually "tuned" as well as is possible. Here, for both estimation models, the modifications take the form of adaptive estimation. Remember that the $\alpha - \beta$ tracker does not use any information regarding the state space structure and noise statistics of the process. Detailed discussions of the changes in the models will follow.

Extended Kalman Filter

It was stated that the state space model of the process contains two uncertain parameters and it is desirable to estimate these parameters in an online fashion in order to improve the quality of the state estimates. A number of methods have been suggested for developing such capacity. One of these methods, which has been emphasized, is to use an Extended Kalman filter to solve the nonlinear estimation problem that results from treating the parameters as additional state variables, providing the existence of a priori parameter statistical information (56), (77), (101). Maybeck (77, Chapter 10) states some techniques for the situation when complete a priori parameter statistics are not available. First, by modeling the uncertain parameters as states of the process, the problem becomes one of state estimation. Then, using the Extended Kalman filter provided by (56, Chapter 8), the problem is solved. Take $X3 = w^2$ and $X4 = A$. Then the system in Equations 3.22 and 3.23 becomes

$$\frac{d}{dt}\underline{X}(t) = \frac{d}{dt}\begin{bmatrix} x1 \\ x2 \\ x3 \\ x4 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -x3 & 0 & x4 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \underline{X}(t) = \underline{f}(x,t) \tag{3.28}$$

$$D(t) = [1, 0, 0, 0]\ \underline{X}(t) = \underline{h}(x,t) \tag{3.29}$$

Now, linearize the above state equations about a given deterministic reference (or nominal) trajectory $\underline{\bar{X}}(t)$, with known initial condition $\underline{\bar{X}}(t_0)$, satisfying Equation 3.28. Then a differential equation of states deviations from the reference trajectory is derived and linearized using a Taylor series expansion. This approximate linear equation is called the perturbation or variational equation. Then, the Jacobinans of Equations 3.28 and 3.29 evaluated along the reference trajectory are needed and they are,

$$\underline{F}(t, \underline{X}(t)) = \left[\frac{\partial f_i(\underline{X}(t), t)}{\partial x_j} \right] = \left[\begin{array}{cccc} 0 & 1 & 0 & 0 \\ -x3 & 0 & -x1 + x4 & x3 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right]_{\underline{X}(t_0)} \tag{3.30}$$

$$\underline{M}(t, \underline{\overline{X}}(t)) = \left[\frac{\partial h_i[\underline{\overline{X}}(t),t]}{\partial x_j} \right] = [1, 0, 0, 0] \tag{3.31}$$

where:

∂ = partial derivative operator.

At this point, Equations 3.30 and 3.31 should be discretized. Thus we get discrete linear perturbation equations. $\underline{M}$ does not change but discrete $\underline{F}$ is,

$$\underline{F}(k, \underline{X}(k)) = \left[\begin{array}{cccc} 1 & T & 0 & 0 \\ -Tx3 & 1 & T(-x1 + x4) & Tx3 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{array} \right] \tag{3.32}$$

where:

T = step size or time interval

k = discrete time index.

With the Kalman filter recursive structure, it is possible to go one step further by relinearizing each new estimate as they become available. The point of this is to use a better reference trajectory as soon as one is available. As a consequence of the relinearization, large initial estimation errors are not allowed to propagate through time, and therefore, our linearity assumptions are less likely to be violated. For an initial value of reference trajectory one may use the initial estimate of the states. The Extended Kalman filter is the result of combining the optimal Kalman filter, described by Equation 3.13 - 3.18, and this relinearization procedure. The following equations summarize the Extended Kalman filter for the nonlinear system (Equations 3.28 and 3.29). It consists of prediction via

$$\underline{X}(k + T|k) = \underline{X}(k|k) + \int_{t_k}^{t_{k+T}} \underline{f}(\underline{X}(t|k),t)dt \tag{3.33}$$

$$\underline{P}(k + T|k) = \underline{F}(k; \underline{X}(k|k))\underline{P}(k|k)\underline{F}'(k, \underline{X}(k|k)) \tag{3.34}$$

and at an observation

$$\begin{aligned}\underline{X}(k + T|k + T) = {} & \underline{X}(k + T|k) + \underline{K}(k + T; \underline{X}(k + T|k)) \\ & * (\underline{U}(k + SAMPT) - \underline{h}(\underline{X}(k + T|K), k + T))\end{aligned} \tag{3.35}$$

$$\begin{aligned}\underline{P}(k + T|k + T) = {} & [\underline{I} - \underline{K}(\underline{X}(k + T|k), k + T)\underline{M}(\underline{X}(k + T|k), k + T)]\underline{P}(k + T|k) \\ & * [\underline{I} - \underline{K}(\underline{X}(k + T|k), k + T)\underline{M}(\underline{X}(k + T|k), k + t)]' \\ & + \underline{K}(\underline{X}(k + T|k), k + T)\underline{R}(k + SAMPT)\underline{K}'(\underline{X}(k + T|k), k + T)\end{aligned} \tag{3.36}$$

The Kalman gain is

$$\begin{aligned}\underline{K}(\underline{X}(k + T|k), k + T) = {} & \underline{P}(k + T|k)M'(\underline{X}(k + T|k), k + T) \\ & * [\underline{M}(\underline{X}(k + T|k), k + T)\underline{P}(k + T, k) * \\ & \underline{M}'(\underline{X}(k + T|k), k + T) + \underline{R}(k + SAMPT)]^{-1}\end{aligned} \tag{3.37}$$

where:

$\underline{U}$ = observation vector

SAMPT = sampling interval

$\underline{I}$ = identity matrix with proper dimension

$\underline{X}$, $\underline{P}$, $\underline{R}$ = as in Equations 3.13 - 3.18

$\underline{f}$, $\underline{h}$ = as in Equations 3.28 and 3.29

$\underline{M}$, $\underline{F}$ = as in Equations 3.31 and 3.32

T = step size or time interval

k = discrete time index

t = continuous time index

d = derivative operator.

A Euler formula has been used to approximate the integral in Equation 3.33. In the problem under study, the following initial values have been used.

$$\underline{X}(0|0) = [0,\ 0,\ 3,\ \pi^2/.4]'$$

$$\underline{P}(0\,|\,0) = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 182.642 & 0 \\ 0 & 0 & 0 & 1/3 \end{bmatrix}$$

It should be noted that the problems of the choice of reference trajectory and the question of the validity of the linearized equations, must not be overlooked. It is expected that the linearized dynamics represent a good approximation if the system noise and the initial uncertainty about the states are sufficiently small. For then, with the choice of the prior estimate of the states as reference trajectory, the state deviations will remain small with a high probability, or in the mean square sense. Of course, it is clear from Equations 3.30 - 3.32 that the size of the state deviations is also dependent upon the stability properities of the linearized system. Detailed discussion on this issue could be found in (56, Chapter 9). Note that the obvious choice of the prior estimate of the states as the reference trajectory may turn out poor. This will be especially true if $\underline{P}(0|0)$ is large and/or if the system noise is large. In that case, the estimates of the state deviations can become large, violating the linearity assumptions.

Adaptive Tracking

In the case of $\alpha - \beta$ tracker, the adaptivity is applied to the way parameter β is determined. As in any other adaptive technique, this one has also been designed to fit the problem under study. Recall that in the tracker discussion, it was said that the choice of β is based on desired response characteristics. β close to one is desirable for quick response to new data and β close to zero helps to suppress error. This information is of great help and the bases of adaptive designs.

Looking at the assumed demand model reveals that one needs to have different β values at different points of time during the crisis. When the function has a curvature, more rapid response is necessary than when it is changing at a constant rate. There are several rate changes along the model. Trigg and Leach present an adaptive smoothing procedure in (121). By applying their technique, parameter β is set equal to the modules of a tracking signal. This signal is a measure of the degree of forecast error.

$$\text{Tracking Signal} = \frac{\text{smoothed error}}{\text{smoothed absolute error}} \tag{3.38}$$

When the error becomes large the tracking signal approaches the value of one. As the value of the signal changes, so does the corresponding value of β. The result is that the filtering procedure quickly adapts to large differences between observations and forecast. Error and smoothing equations are as follows:

$$\text{Error}\ (t) = V(t) - \overline{V}(t) \tag{3.39}$$

$$\text{New smoothed error} = (1 - \gamma) * \text{old smoothed error} + \gamma * \text{error} \tag{3.40}$$

$$\text{New smoothed absolute error} = (1 - \gamma) * \text{old smoothed absolute error} + \gamma * \text{absolute error} \tag{3.41}$$

where:

V = true value of filtered variable

$\overline{V}$ = predicted value of variable

Error = predicted error or apparent error

γ = smoothing constant

t = time index.

As each error becomes available, Equations 3.40 and 3.41 are applied and β will be set equal to the absolute value of tracking signal. The problem of determining the best value for γ has not been answered by the method. The authors have suggested the value of $\gamma = .1$ for general use and $\gamma = .05$ for those who are cautious in adapting the response rate in applications involving short-term predictions.

Another way to determine β adaptivity is to divide either the function or the length of the crisis duration into different parts and change the value of β accordingly. Various schemes can come out of this procedure. The followings are some examples which will actually be used when the tracker is applied in the next section. Designs of these schemes are based on the characteristics of the stated demand model.

1. Two-Beta. Here the parameter will have two different values depending on which part of a function the tracker is applied. One β value is for the tails and one is for the upper part of the function which

includes the maximum. There is a divider parallel to the time axes which identifies the switch points for β values.

2. Three-Beta. In this scheme three values of β are assigned depending on whether one or two dividers is desired. In the first case, each tail of the function has its own specific value of β and the top part is assigned the last value. With two dividers, the function is going to be partitioned into five sections; tails, sides, and top, with the first two being symmetric. Again, one β is for the tails, one is for the sides and one is assigned to the top portion. Note that in the first case we do not need to have symmetry, i.e., the divider does not need to be parallel to the time axes.

3. Five-Beta. In this case, the function is divided into five sections and each part is assigned a different β value.

The main question to be answered regarding these schemes is that of values of the β's and dividers. Recall that the state space of the demand model consists of an infinite number of random possibilities. One value of β which is good for a member of the family may not be good for another one. This should be noted in light of the principle that any method has to be optimum for all of the spectrum. Hence, a technique is needed in which its performance is "best" with respect to all the possibilities. The above discussion suggests some kind of optimization algorithm to be used in order to reach the optimum values for the β's and the dividers. The choice of an algorithm depends on the form of the problem involved and available possibilities.

Evaluation Tool

For the sake of comparison of the performances of the estimation models and various adaptive techniques, some kind of evaluation tool is needed. This is also a need for an optimization process. A filter is "best" when it can positively influence system outputs. In order to do so, it has to be able to improve information quality. This improvement will lead to better system outputs, if policy structure is sound. Another criterion for a filter to be the "best" is its performance in reducing measurement errors. Simulation provides a good opportunity to assess this reduction, since both true and estimated values of time series are known in a computer model. Hence, mean squared error or absolute error can be easily computed.

In this study, for evaluations, a mean squared error criterion was selected. This performance index is computed by comparing true and estimated time series for various schemes. Equation 3.42 presents the form of the index. Significant reduction in error is regarded as a sign of likely improved performance.

$$\text{MSE} = \sum_{i=1}^{n} (V_i - \overline{V}_i)^2/n \qquad (3.42)$$

where:

MSE = mean squared error

n = number of discrete intervals in simulation

i = index on simulation intervals

V, $\overline{V}$ = as in Equation 3.39.

This performance criterion has the advantage of eliminating the bias caused by different periods of the functions, i.e., the crisis durations, and makes it possible to compare different results obtained by various adaptive schemes due to changes in information quantity and quality.

Testing the Estimation Models

The main question with regard to any estimator is whether or not it can improve the total relief performances by increasing the information reliability over the basic sample-and-hold estimation process. Once the estimator has passed this test, parameters or matrix coefficient levels for fine tuning must be considered. The effect of information quality on parameter determination should also be studied. In this study, first the scenario in which complete a priori information of the process exists will be tested. Then the second scenario, in which the trajectories are partially known, will be discussed.

Before starting to test the models, groundwork must be provided. It was mentioned earlier that one is faced with an entire family of functions. The "best" estimation procedure is the one which is "best" for all of them and not just one member of the family, for no idea of what is going to happen in the real situation is known. In this class of functions, there exists an infinite number of members due to continuous state space spectrum of the parameters created by the limits on the ranges of the random variables CD and TDEF, Equations 3.20 and 3.21. Are the models tested with all the elements or just some of them? Trying to test with all of the functions involved is not only impossible but also costly. So what should be done?

In order to overcome this difficulty, a sample from the family of functions should be taken (Equation 3.19). See (24, Chapter 1) for a detailed discussion on the advantages of sampling. Two important questions must be answered here concerning the sampling method and the sample size. How to choose and how many are needed, in order to represent the total population of functions, is crucial. They affect the results of the entire experiment.

Sampling Method

Our parameter state space (sampled population) is rectangular with the sides equal to the lengths of the limits provided by Equations 3.20 and 3.21. Every point in this space represents a member of the family. Since in the real world any kind of food crisis with arbitrary duration and requirement can happen, each member has an almost equal likelihood of occurrence. Thus, CD and TDEF are independent random variables with approximately Uniform distribution. As a result, our sample should represent evenly the entire spectrum.

In the current problem, the sample elements have been chosen according to the following procedure. Each side of the state space is divided into equal segments. These segments do not need to be equal for both sides. Different step sizes can be used. The lower-left corner of the state space rectangular, where the minimums of the two limits intercepts, is the starting point. First, let CD (crisis duration) take the following values. Max and Min refer to upper and lower bounds on CD and TDEF.

$$\mathrm{Min(CD)} + i\mathrm{DTC} \text{ for } i = 1, \ldots, N \tag{3.43}$$

$$N = (\mathrm{Max(CD)} - \mathrm{Min\ (CD)})/\mathrm{DTC} + 1 \tag{3.44}$$

where:

DTC = step size (to be determined)

i = index of duration

N = number of crisis durations in sample.

Then, given CD, different requirements are chosen as:

$$\mathrm{Min(TDEF)} + j\mathrm{DTA} \text{ for } j = 1, \ldots, M \tag{3.45}$$

$$M = (\mathrm{Max(TDEF)} - \mathrm{Min(TDEF)})/\mathrm{DTA} + 1 \tag{3.46}$$

where:

DTA = step size (to be determined)

j = index for total food deficit or maximum rate of demand

M = number of different requirements in sample.

On the other hand, random measurement errors are present. This makes every point on the state space a stochastic variable. In order to truly represent the population, we have to use a Monte Carlo experiment. The above measurements refer to surveys which are taken on the field exclusively from one member of the family during the duration of a crisis and are sent to the system managers for decision makings. If the number of the Monte Carlo runs for each function is termed MRUN, the sample size, NS, will be

$$NS = N * M * MRUN$$

Now the values of N, M, and MRUN need to be determined.

Sample Size Determination

The determination of sample size is very important. A large sample is a waste of resources, and a small sample diminishes the utility of the results. The decision cannot always be made satisfactorily. Often there is not enough information to ensure that the choice of a sampling size is the best one (24, Chapter 4). Sampling theory provides a useful guide to follow in finding an answer to the problem.

The principal steps involved in the choice of a sample size have been discussed in (24, Chapter 4). The first step is to determine how accurate we want our estimate of MSE in Equation 3.42 to be. That means how close we would like it to be to the population's MSE. But this accuracy is not absolutely guaranteed. There is always a chance of a very unlucky sample that is in error by more than the desired accuracy. Thus, the second step is to decide on desired confidence limits. When the above bounds have been determined, the sample size can be calculated from common formulas for confidence limits, assuming the distribution of MSE is given.

At this point, a difficulty appears that is common to all problems in the estimation of a sample size. A formula for sample size (i.e., confidence limits) depends on some property of the population that is to be sampled. In this instance, it is the variance of MSE, for which no information on its value exists. One way to solve the problem is to use some kind of double sampling or two-phase sampling method. Here, a pre-sample with arbitrary size is taken and then the variance is estimated from it. Of course, this is a very crude way of estimating, but there is no other choice. In order to reduce the error caused by the use of this procedure, it is better to take a large sample in the first stage.

Based on this estimated variance, given the degree of accuracy, confidence limits, and the assumption that the sample MSE is normally distributed about the population MSE, and using the Central Limit theorem

(56, Chapter 6), we calculate the second phase or main sample size. Thus, the first stage can be considered as a sample size determination phase and the second stage is used for testing the estimation models and different adaptive schemes.

Three considerations must be discussed before the actual implementation of the above sample size determination procedure. These are the effect of information quality on determination of the parameter level, generalization of MSE in Equation 3.42, and the optimization algorithm which is going to be used in some of the adaptive methods. In the case of information quality, sampling frequency is going to be used. It is understood that by sampling more often, the quality of information will increase and has positive effects on total system outcomes. So, experiments and tests will be conducted with two levels of information quality, i.e., one and two week sampling periods.

The MSE as specified by Equation 3.42 is an index for one element of the sample. A criterion which is representative of the sample is needed. One has to generalize Equation 3.42 to be able to represent the sample with no bias caused by differences inside each sample (different functions) and among various samples (different measurement errors) taken from the population. The factor n in Equation 3.42 normalizes the MSE of each function in the sample (equal weight). Hence, it is sound to take an average of all MSE's in one sample and use that as the performance index. Then Equation 3.42 becomes;

$$AMSE = [\sum_{j=1}^{NS} [\sum_{i=1}^{n_j} (V_i - \overline{V}_i)^2/n_j]]/NS \qquad (3.47)$$

where:

AMSE = average mean squared error

NS = sample size

n_j = number of discrete intervals on trajectory j

j = index on trajectories

V, $\overline{V}$, i = as in Equation 3.42.

The Complex algorithm which was developed by Box (12), has been selected for optimization purpose. A discussion and FORTRAN coding of the routine are presented by Kuester and Mize (66, Chapter 10). The selection has been based on the following reasons. The algorithm has the desirable quality of quick convergence to an optimum area, although it is slower to pinpoint exact solutions. It not only is easily adopted to interfacing with the simulation model but it also allows all parameters to vary at the same time and accepts constrained parameters. Cheap but accurate, it can handle randomness and the problems of multiple responses. These characteristics fit the expected stochastic nature of the response surface in the problem (Equation 3.47).

First Phase of Sampling

Sample size determination can now be discussed. In the first stage, a quick and fairly accurate estimate needs to be determined. Thus, the tests in this stage will not be as elaborate as in the second phase. A series of tests was conducted with the model and different schemes, in order to achieve some familiarities with the total problem and especially the performance surface, before starting the sample size calculation process. These tests help not only from the cost and time points of view, but also prevent unfruitful tangents.

In addition to various adaptive schemes, two different cases have been considered in both stages. The first occurs when no filtering is done, i.e., $\beta = 1$. This is a base upon which the usefulness of all other techniques are judged. Another is when $\beta = .1$. The experience with the tracker suggests that, for nonadaptive schemes, this choice is a good compromise between noise reduction and transient capability performances of the tracker.

In this stage of sampling 150 functions were chosen from the parameter state spectrum. It consists of fifteen crisis durations (N = 15), five kinds of requirements for each crisis level (M = 5) and two Monte Carlo runs for each function (MRUN = 2). Of course, many other combinations are possible. A low MRUN allows the sample to portray more of the spectrum. Since the sample mean and standard deviations are the needed statistics for the construction of confidence intervals at the next stage, a complication arises in results comparison if different samples' variances are not equal (24, Chapter 13). Fortunately, the problem is avoided if the sample sizes are equal.

Table 3.1 summarizes the results of different methods for the first stage of sampling. As is shown, there is at least, a 50% reduction in Error mean value as a result of using the tracker. This suggests the usefulness of the $\alpha - \beta$ tracker. Better results in the case of a one week sampling interval can be attributed to a greater sampling frequency. The optimization scheme has been based on two β's. the divider was given as a known parameter. Knowledge about this method and the divider was obtained from the preliminary tests which were conducted earlier.

Poor performance of the tracking signal procedure can be caused by various factors. But the main reason may be that the scheme has originally been developed for use in time series analysis. Lack of

Table 3.1. **Expected Values of Mean Squared Error and its Variance by Various Estimation Schemes in the First Stage of Sampling.**

Procedure	SAMPT = 2 weeks (NS = 150)	SAMPT = 1 week (NS = 150)
BETA = 1 (No filtering)	.68292 (.34697)*	.68133 (.28823)
BETA = .1	.35833 (.09273)	.28537 (.05196)
2 - BETA (DEV = 2.187) OPTIMIZATION	.342 (.07778)	.26427 (.0434)
Tracking Signal	.536 (.32847)	.47018 (.16)
Extended Kalman	.12051 (.05383)	.082709 (.01323)

* Variance.

data at the beginning also contributed. This argument has been supported by the results from a separate test which was conducted by the author. As the duration of operation increases, the ability of the signal gets better and better. Using a single function with two years crisis duration, it was found that most of the tracking error occurred in the first year of the crisis. This says that it takes a while for the scheme to store enough data, upon which the tracking and smoothing is done. Also, the determination of the value of the parameter γ is experimental and this could add to the inaccuracies. Due to the Tracking Signal's performance, it was decided not to use it in the second phase of sampling.

The marked performance of the Extended Kalman filter is clear. The better results of this filter are partly the consequences of complete a priori knowledge of state space structure and noise statistics of the process and the adaptive estimation procedure which was used. Later results, when the trajectories are partially known, will clarify more the differences of the estimation models. As a result, more discussion about the Extended Kalman filter will be postponed to the second phase of sampling, when additional facts are available.

Second Phase of Sampling

Having the results of the first phase, one chooses the best answers. The minimum value for the tracker was obtained by the optimization procedure, even though the result is very close to that of $\beta = .1$. Based on these values and their variances, the sample sizes are calculated with the assumptions of a 95% confidence coefficient and that the length of the confidence interval be $\pm$ 10% of the mean (i.e. mean * $(1 \pm .1)$). Considering the underlying assumptions, sample sizes are computed by the following formula (53, Chapter 6).

$$NS = Z^2_{\alpha/2} \, S^2 \, / \, \epsilon^2 \tag{3.48}$$

where:

NS = sample size

S = estimated standard deviation

ϵ = accuracy desired

α = significance level (one minus the confidence limit percentage)

Z = abscissa of the standard Normal distribution.

Using Equation 3.48, sample sizes for different sampling frequencies are determined using various methods. First, for the two week sampling interval, the sample sizes of the tracker and the Kalman are respectively equal to,

$$NS = (1.96)^2 * (.07778)/(.0342)^2 = 266 \qquad \text{(tracker)}$$

$$NS = (1.96)^2 * (.05383)/(.012051)^2 = 1425 \qquad \text{(Kalman)}$$

which are spread over the parameters state spectrum as N = 19, M = 7, and MRUN = 2 for the tracker and N = 25, M = 19, and MRUN = 3 for the Extended Kalman. For a one week sampling period the sample size is,

$$NS = (1.96)^2 * (.0434)/(.0264)^2 = 252 \qquad \text{(tracker)}$$

$$NS = (1.96)^2 * (.01323)/(.008271)^2 = 743 \qquad \text{(Kalman)}$$

which consists of N = 18, M = 7, and MRUN = 2 for the tracker and, N = 25, M = 15, and MRUN = 2 for the Extended Kalman. Some round-offs have taken place in order to fit an integer sample size into different subdivisions.

Based on the above information, the Extended Kalman and the α - β tracker with its various adaptive schemes were tested. To improve the results for these schemes, the parameter β should be changed in the best possible way. The best, in current context, can be defined as the optimum way of designing an adaptive scheme such that the balance between Error mean reduction and rising cost is kept. The stopping criterion is the point at which no significant improvement can be obtained by a design change. The results of the Extended Kalman filter and various adaptive trackers are presented in Table 3.2. In some tracker schemes, the divider(s) also was considered in the optimization process. The predetermined values for the dividers have been shown in parenthesis. Optimum values for different parameters of the tracker, have also been given in the columns under the optimum values of the AMSE (Equations 3.47). Note that, in spite of the results of the

Table 3.2. Expected Value of Mean Squared Error with 95% Confidence Limit in the Second Stage of Sampling by Various Adaptive Schemes

Procedure	SAMPT = 2 weeks	SAMPT = 1 week
BETA = 1 (No filtering)	.31287 (VAR = .0312)	.31247 (VAR = .0266)
BETA = .1	.19134 (VAR = .0178)	.12583 (VAR = .005)
2-BETA (DEV = 2.187)*	.17248 β_1 = .9177, β_2 = .1018	.1255 β_1 = .76887, β_2 = .08187
2-BETA & 1-DEV	.16828 β_1 = .2363, β_2 = .1133, DEV = 2.25	.11213 β_1 = .2427, β_2 = .0577, DEV = 1.556
3-BETA (DEV = 2.187)*	.17173 β_1 = .6, β_2 = .1596, β_3 = .694	.12045 β_1 = .587, β_2 = .07145, β_3 = .6763
3-BETA (DEV1 = 2.5, DEV2 = 6.)*	.17625 β_1 = .485, β_2 = .1467, β_3 = .131	.11506 β_1 = .1967, β_2 = .0676, β_3 = .04675
3-BETA & 2-DEV	.2011 β_1 = .265, β_2 = .144, β_3 = .185, DEV1 = 5.835, DEV2 = 6.762	.1211** β_1 = .1068, β_2 = .5897, β_3 = .07, DEV1 = 3.1, DEV2 = 3.195
5-BETA (DEV1 = 2.5, DEV2 = 6.)*	.17147 β_1 = .6214, β_2 = .0754, β_3 = .1162, β_4 = .2283, β_5 = .7345	.123556 β_1 = .2032, β_2 = .0532, β_3 = .0793, β_4 = .1114, β_5 = .1385
Extended Kalman	.10763 (VAR = .01317)	.070551 (VAR = .00626)

* Reference to the given values in optimization.
** See comment in the text.

first phase of sampling (Table 3.1), the same sample size has been used for various adaptive tracker schemes.

Analysis of the Tracker Results

In this phase, one can again achieve considerable reduction in Error mean and its variance by using the tracker for filtering and prediction. Improvements caused by the use of adaptive schemes are relatively smaller, in comparison to the reduction seen between filtering and nonfiltering. However, a decrease in Error mean is insignificant among different adaptive procedures. In the case of 3-BETA and 2-DEV, the result is even worse than the constant β case for the two week sampling period.

These results may stem from the stochastic nature of the AMSE function. In the course of working with Equation 3.47, it was found that, as was expected, it poses a fuzzy surface which contains many local minimums. But the Complex algorithm leads one to the neighborhood of the optimum. In relation to implementation of the Complex to a stochastic function like AMSE the following point is very important. Starting with initial values for β's, the Complex tries to optimize the function iteratively. In every iteration, new values of β's are chosen by the algorithm within the given limits for parameters, until the optimum with a desired level of accuracy has been reached. In our case, the error terms in the AMSE function changes in every iteration, due to its stochastic nature. This means that in every iteration the Complex is faced with a different function. As a result it becomes hard for the algorithm to pinpoint the optimum as compared with deterministic functions.

Some reasonable consistency among the results can be seen, for example, on different β values. β_1, which most of the time represents the tail part of the functions, tends to be closer to one than β_2, which represents sides of the functions. Since the rate of change is almost constant on the sides, β_2 tends toward zero. These results are consistent with general characteristics of the α-β tracker which were explained earlier. As the number of β's increases, their values tend toward zero and generally around .1. This can be expected, as the result of the domain of each β containing less curvature.

Another factor in reducing the β value is the number of observations. As this number increases, there is less need for the tracker to adjust itself to rapid changes. In other words, the changes occur gradually. The results have been consistent with this fact. Look at the β values when 5 - BETA adaptive schemes were applied with different sampling frequencies.

Apart from the mean, we see considerable reduction in its variance when filtering is taking place. The variance of the mean has a reciprocal relationship with the sample size (53, Chapter 5). In the case of filtering, the variance belonging to a two weeks sampling interval is twice the variance of the one week case. The same result was not achieved in the case of no filtering. This might have been caused by the stochastic nature of the AMSE function.

The results of 3-BETA and 2-DEV, in the case of a one week sampling period, needs some explanation. As you see the values of dividers are very close to each other. In actual optimization tests, these two converge. If we let the limits on these parameters, which are given to the Complex, overlap, the upper divider will come down and the lower one will go up. As a result, the scheme will be transformed into the 2-BETA and 1-DEV. Letting that happen, the optimum value of AMSE became equal to .109449, with variance equal to .00488 where β_1 = .09689, β_2 = .5976, β_3 = .0528, DEV1 = 3.9356, DEV2 = 2.642, were optimum parameter values. But, it is clear that DEV1 is redundant and if the values of β_1, β_3, and DEV2 are used the same results for the mean and variance are achieved. The results in Table 3.2 for this case represent only one of many which were obtained and are not the optimum ones in the strictest sense.

Analysis of the Kalman's Results

With complete a priori knowledge of the process and its noise statistics, it is evident from the results that the Extended Kalman filter does a fine job. Later, the filter's performance will be tested when some of the above assumptions do not hold. For the time being, the discussion will focus only on the results obtained from the different phases of sampling.

Looking at Table 3.1 and 3.2, one can see that the reduction in the mean value due to an increase in sampling frequency, is not as big as the reduction in the case of the other methods. This stems partly from the fact that, since total knowledge about the process and its noise has been assumed and steady-state initial conditions are given to the filter, after a finite number of observations, the filter reaches a "saturation" state. This means that the process becomes almost deterministic for the filter and the sample mean squared error approaches that of the population (Equation 3.47). It is still evident, though, that the reciprocal relationship between the variance and the sampling frequency holds.

With regard to these results there exists an important consideration; namely the choice of T, the step size (Equations 3.30 - 3.37). This choise has important implications for the stability of the discrete linearized system. It also influences the state evolution formula (Equation 3.33) via the approximation of the integral involved. Remember that the state-space system (Equations 3.22 and 3.23) has one pole at zero and a pair of complex poles on the imaginary axis. Hence, asymptotic stability is not present to begin with. Then, this system was augmented with two uncertain parameters and was linearized. A discrete version of this linear system is actually time-varying due to the relinearization process. These sequences of approximations have made the system very "shaky".

The results in Tables 3.1 and 3.2 (for Kalman) have been obtained with T = .002 (almost 17.5 hours). The same experiments with a value of T = .003 caused the filter to show an "unstable" behavior. That means, in some cases, by increasing the number of observations, not only did the estimated mean value increase, but the variance also became bigger for one week sampling period. As an example, for the parameters values of CD = .848 and TDEF = 3.3, the values of AMSE (Equation 3.47) were .032 and .1351 for two and one week sampling periods, respectively. But for CD = .85 and TDEF = 4, these values became .1483 and .073 respectively. These fluctuations do not follow any pattern. The problem with a wrong T is that it causes errors to propagate. The T value should be reduced until the above malfunctions disappear.

General Comments and an Example

The results suggest an approximate 25 to 30 percent reduction in Error by increasing the sampling frequency. This is a significant reduction. But the cost associated with it should not be forgotten. This tradeoff of cost and quality and the question of what sampling interval to choose must be analyzed in the bigger picture, i.e., the total relief operations model. Now, given the sampling frequency which technique should be chosen? This decision is made based on the accuracy desired and the complexity of the procedure. Recall that, for simplicity, the elements of Equation 3.47 (V_i, $\bar{V}_i$) have been scaled down by one million in the calculations and tests. Hence, the numbers in Tables 3.1 and 3.2 represent this scaled down version (See Equation 3.21). Now, one should be able to see the real difference of various procedures and this fact should clarify the effect of the desired degree of accuracy on the scheme selection process. Later experiments with the two filters, by eliminating some key assumptions, will also help in the selection process. Note that the optimum results are going to be used in the model of total relief operations and the optimization is not going to be repeated in the case of the tracker selection.

There are a few major points with regard to the whole experiment and the general results that may shed more light on some existing obscurities and apparent inconsistencies. First, the influence of the stochastic nature of ASME in affecting the total experiment results should be stressed. This problem has been mentioned several times earlier in the proper place and it must not be overlooked. Second is the issue of the Complex set up. Even though elaborate discussion of the algorithm was not made, the importance of initial conditions, parameter limits and other items related to the Complex procedure, in changing the results, should be mentioned. After all, the computer has been used for simulation purposes. Depending on what type of machine is used, the result may change, even if these changes are not significant. Here, it is appropriate to mention that if one uses the results of Tables 3.1 and 3.2, one probably will not achieve the same answers. This is primarily due to different Complex set ups and the sequence of random errors generated by the machine used, given all else equal.

For a better understanding of the results, the best $\alpha - \beta$ tracker scheme, that of 2-BETA and 1-DEV, along with the Kalman filter were tested with a chosen trajectory. This trajectory is specified by CD = 1. and TDEF = 3.3. Figures 3.1 to 3.4 illustrate the performances of the two models with respect to different sampling frequencies. The size of the error (Equation 3.42) is equal to .8297 and .12 for SAMPT = 2 for the tracker and the Kalman respectively. For SAMPT = 1, they become .305 and .042.

Partially Known Trajectories

As mentioned earlier, complete knowledge about the state-space structure of the process and its noise were assumed to be known. But it is clear that this in not true in most real world situations, and at most partial information exists regarding the process. Of course, this problem primarily arises with respect to the Kalman filter where the mentioned data is needed. To evaluate the performances of the different estimation models, some experiments were conducted. In this

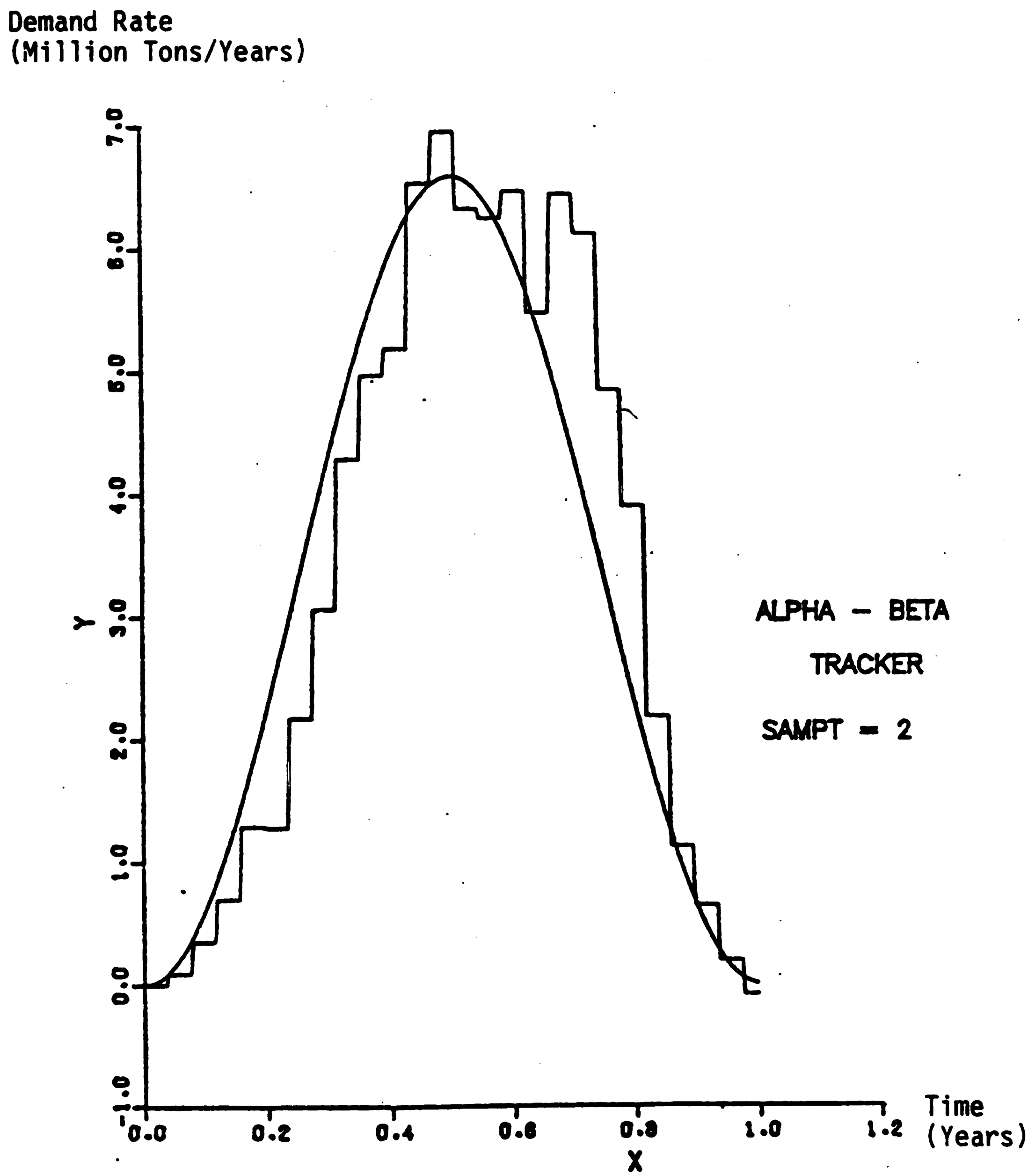

Figure 3.1. The α-β Tracker's Estimate of a Chosen Trajectory (SAMPT = 2)

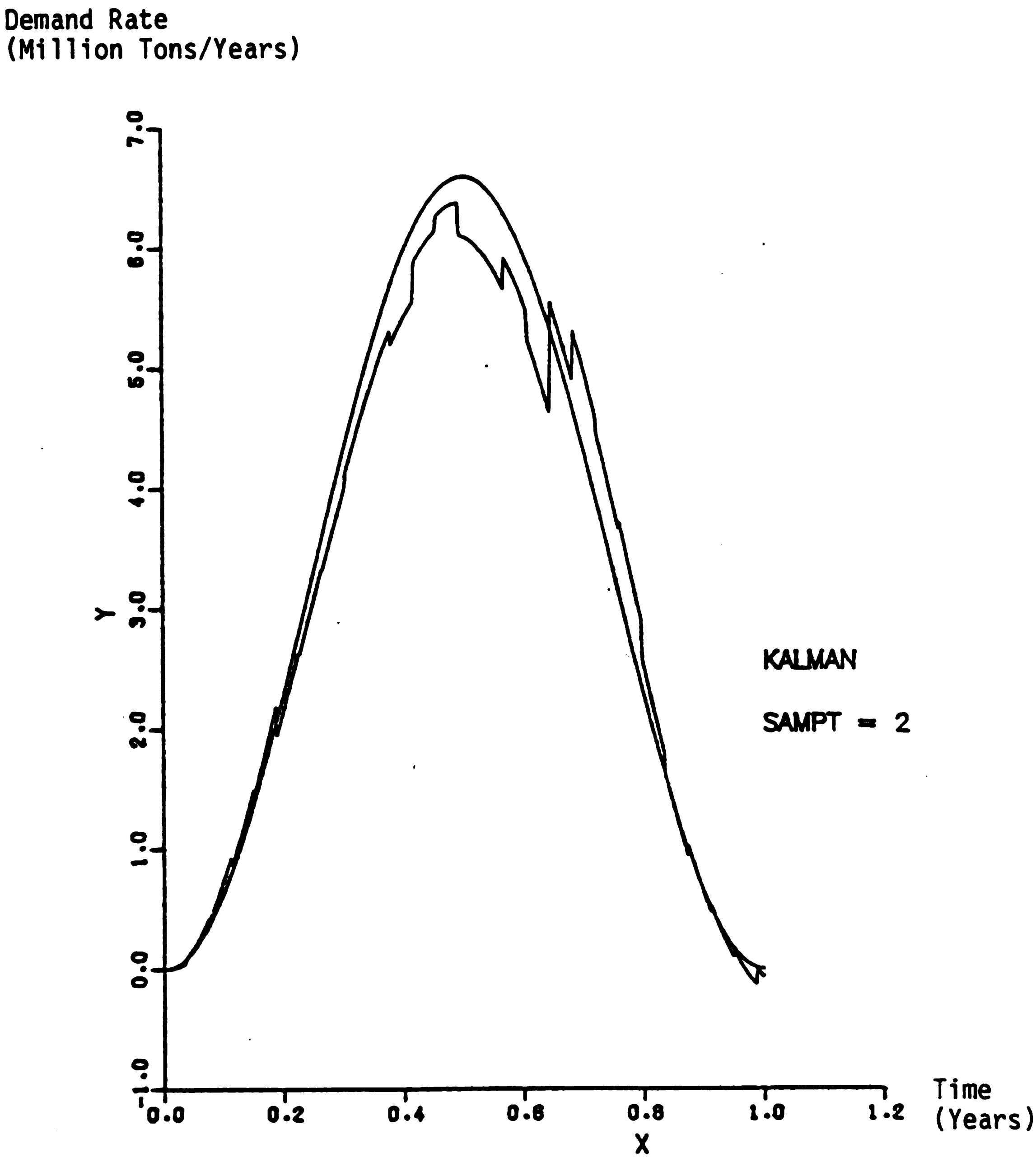

Figure 3.2. The Extended Kalman's Estimate of a Chosen Trajectory (SAMPT = 2)

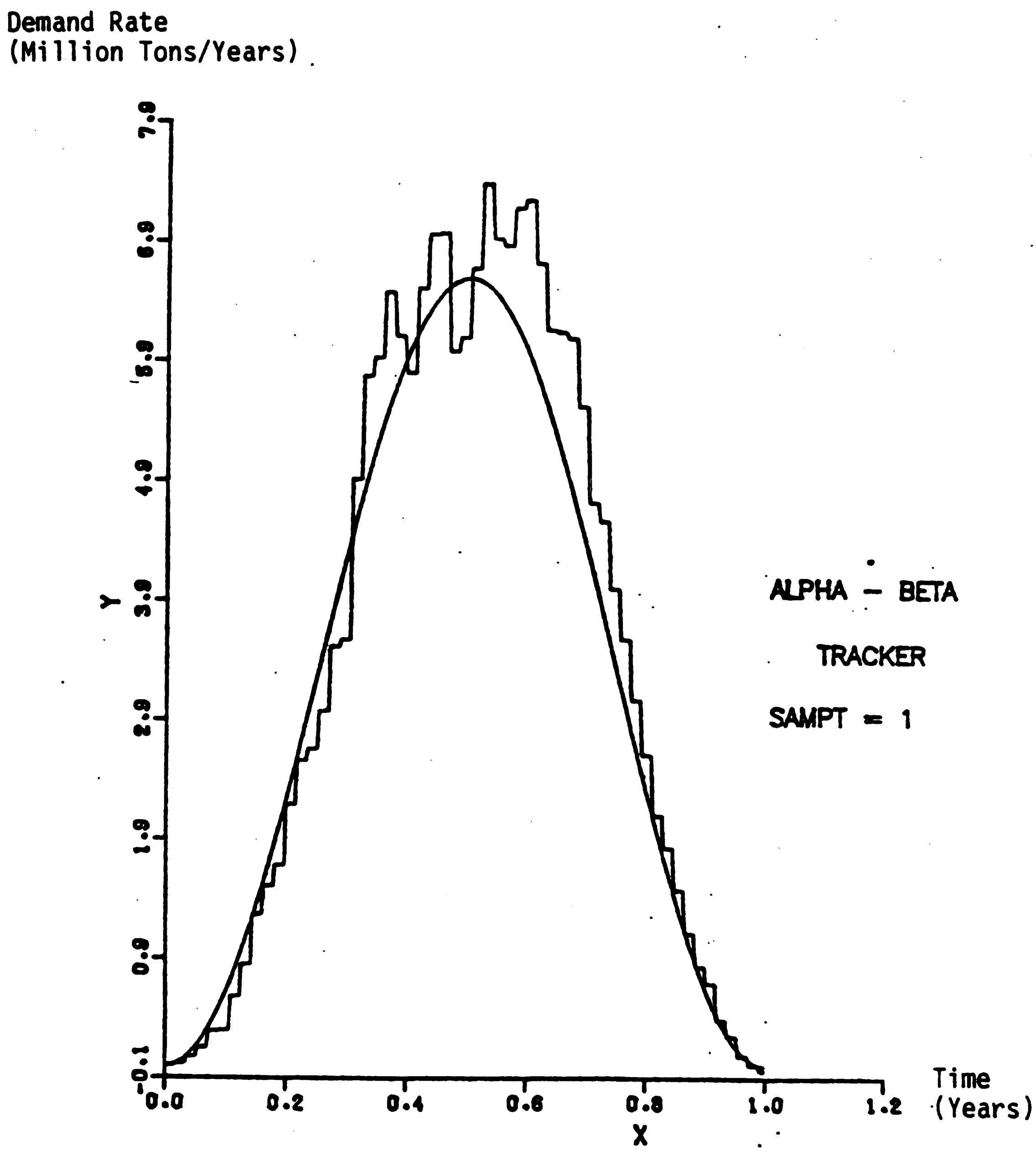

Figure 3.3. The $\alpha-\beta$ Tracker's Estimate of a Chosen Trajectory (SAMPT = 1)

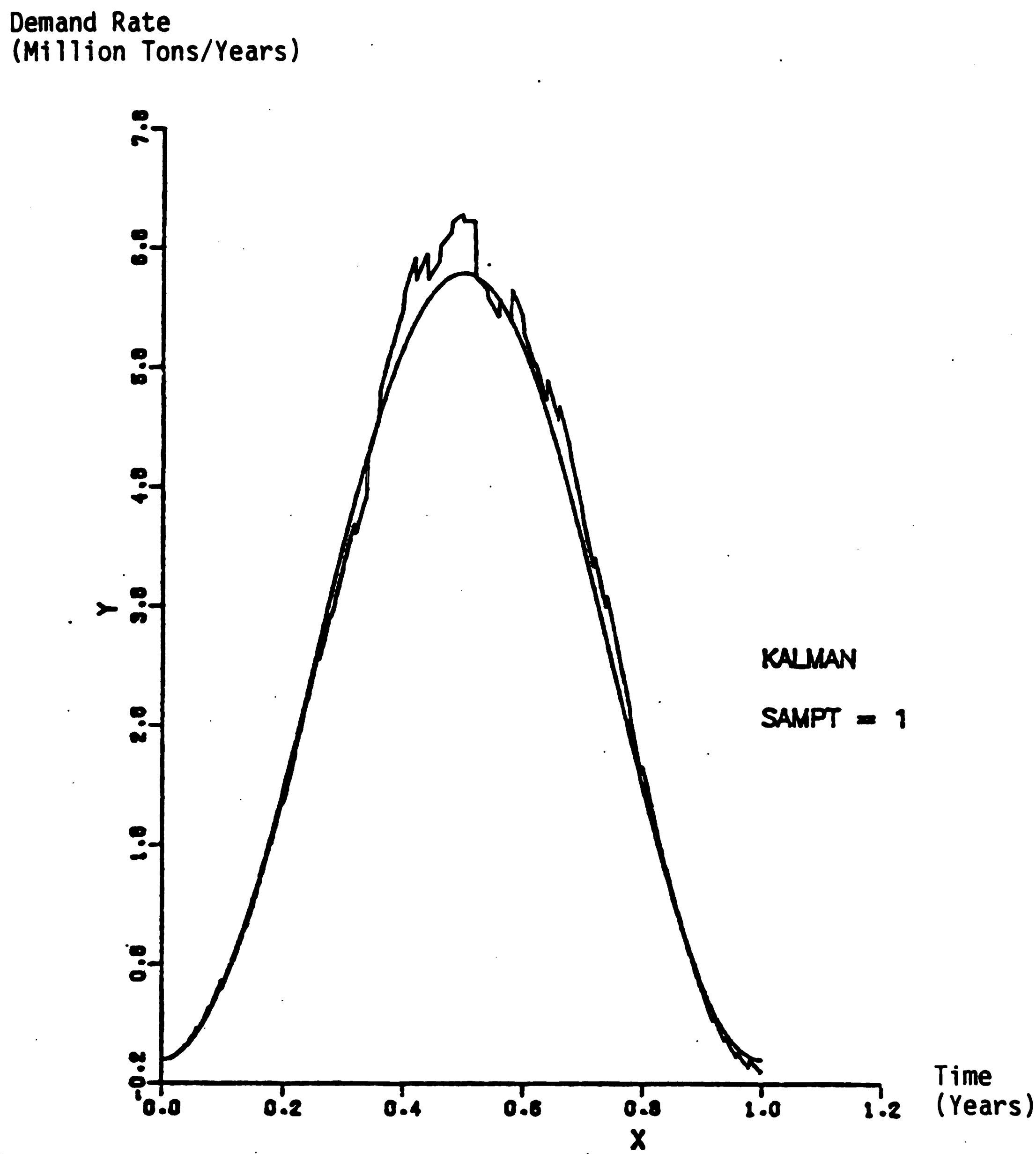

Figure 3.4. The Extended Kalman's Estimate of a Chosen Trajectory (SAMPT = 1)

section, it is assumed that the trajectories are, only, known until some point (maximum point of trajectory was picked up for current study). After this point, the filter does not have any information on the form of the trajectories. Or it is better to say that it contains incorrect information regarding the trajectories. Any other design which characterizes the incomplete information can do the job.

Currently, after the maximum point, it is assumed that the demand functions will stay constant and do not decrease (step function). To do these experiments, the same framework of the second phase of sampling was assumed. But only the Extended Kalman and the best adaptive tracker scheme, meaning 2-BETA and 1-DEV, were chosen. For better assessment of the results, the cases in which no filtering is done (Sample-and-hold) and the $\alpha - \beta$ tracker with constant $\beta = .1$, were also included. Table 3.3 summarizes the results of these experiments.

The $\alpha - \beta$ tracker shows the same performance which was seen before. The consistency remains in the reduction of the Error mean and variance. The close results of the adaptive tracker and constant β tracker, in the case of two week sampling periods, can be attributed to the fact that the adaptive scheme has been selected on the basis of its performance with a different process. The adaptive schemes were actually designed based on some a priori information about the possible structure of the process. Here, some other adaptive design may do better than this one. The result of the Kalman filter is not so great as it could have been expected. The filter deteriorates as the a priori information quality is degraded. The filter, as it has been designed, expects a different process. To get some feeling for the results, the previous example was repeated for this new form of the process and Figures 3.5 to 3.8 illustrate the performances of the two estimation models.

Table 3.3. AMSE Value by the $\alpha - \beta$ Tracker and the Kalman Filter for the Case of Partially Known Trajectories

Procedure	SAMPT = 2 Weeks	SAMPT = 1 Week
No filtering	.5549 (.08423)*	.5656 (.0683)
BETA = .1	.2488 (.02116)	.22086 (.0115)
2-BETA & 1-DEV	.2503 (.02164)	.17079 (.0075)
Extended Kalman	3.09 (4.87)	2.9 (3.577)

* Variance

As it is seen, the Kalman filter does a good job until the maximum point, but later falls apart. The size of the error (Equation 3.42) is equal to .742 and 2.88 (SAMPT = 2) for the tracker and the Kalman respectively. In the case of SAMPT = 1, MSE's values become .231 and 2.48. One can easily recognize the considerable difference between two models and how poorly the Kalman filter performs in uncertain situations.

Transient Initial Conditions

As discussed in earlier sections, it is expected that the linearized model be representative of a good approximation if system noise and the initial uncertainty about the states are sufficiently small (56, Chapter 8). Or, when the initial state covariance matrix, $\underline{P}$ (0|0), is large the estimates of the state deviations can become large, thus violating the basic linearity assumptions. For the model under study (Equations 3.28 - 3.32), system noise is zero but there exists some

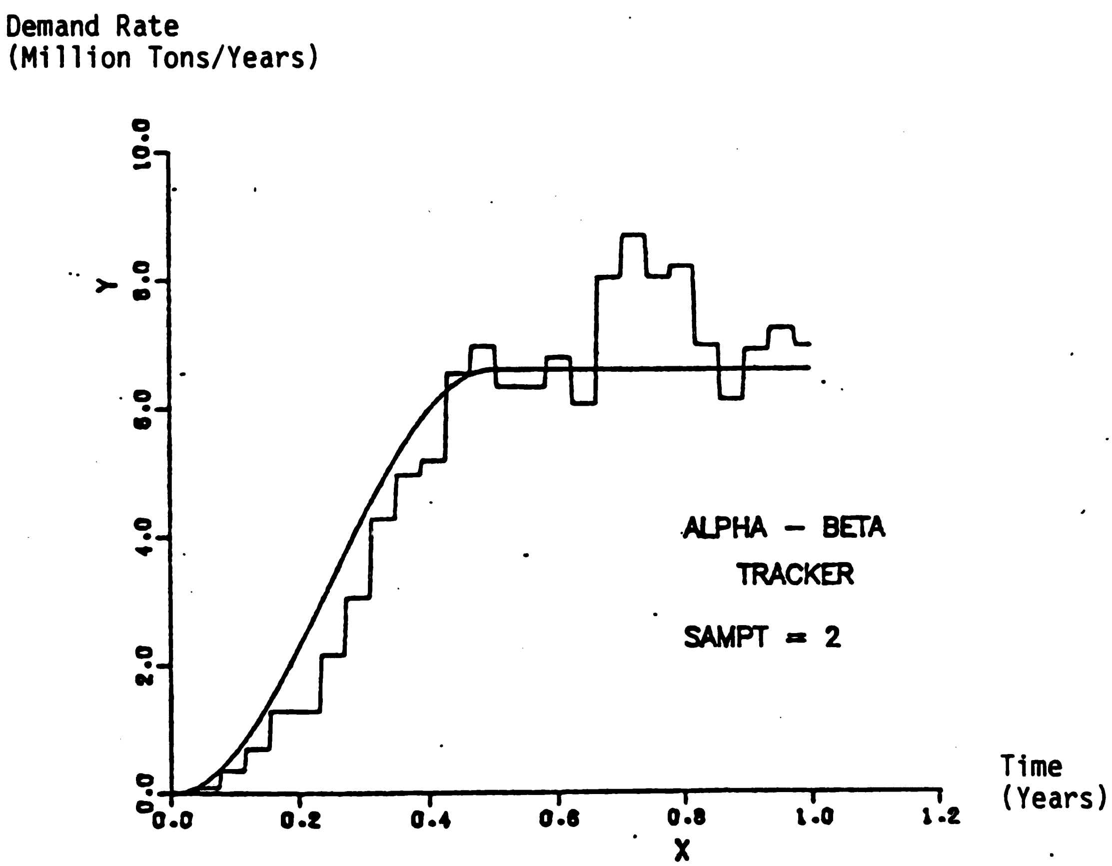

Figure 3.5. The α - β Tracker's Estimate of a Partially Known Trajectory (SAMPT = 2)

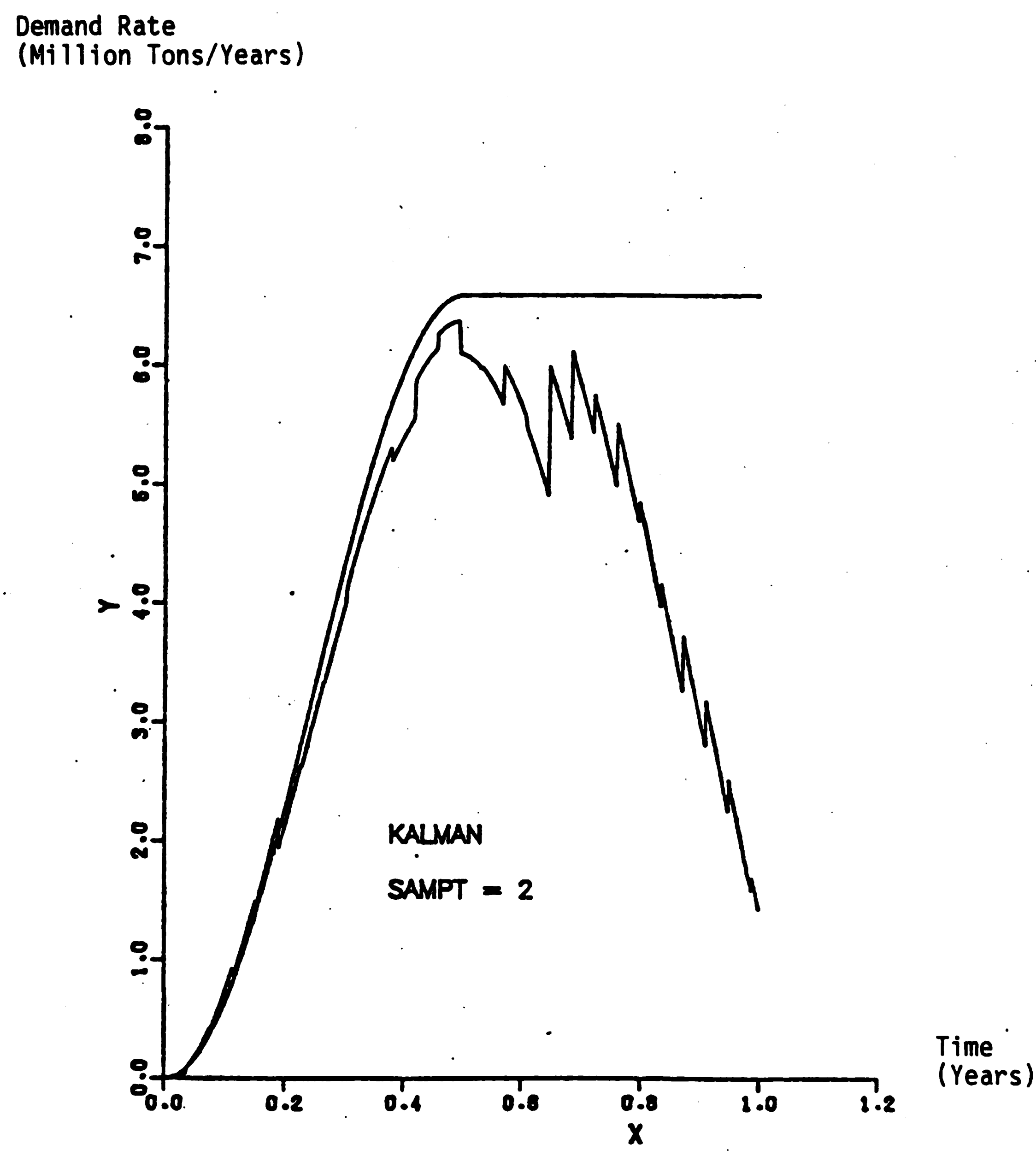

Figure 3.6. The Extended Kalman's Estimate of a Partially Known Trajectory (SAMPT = 2)

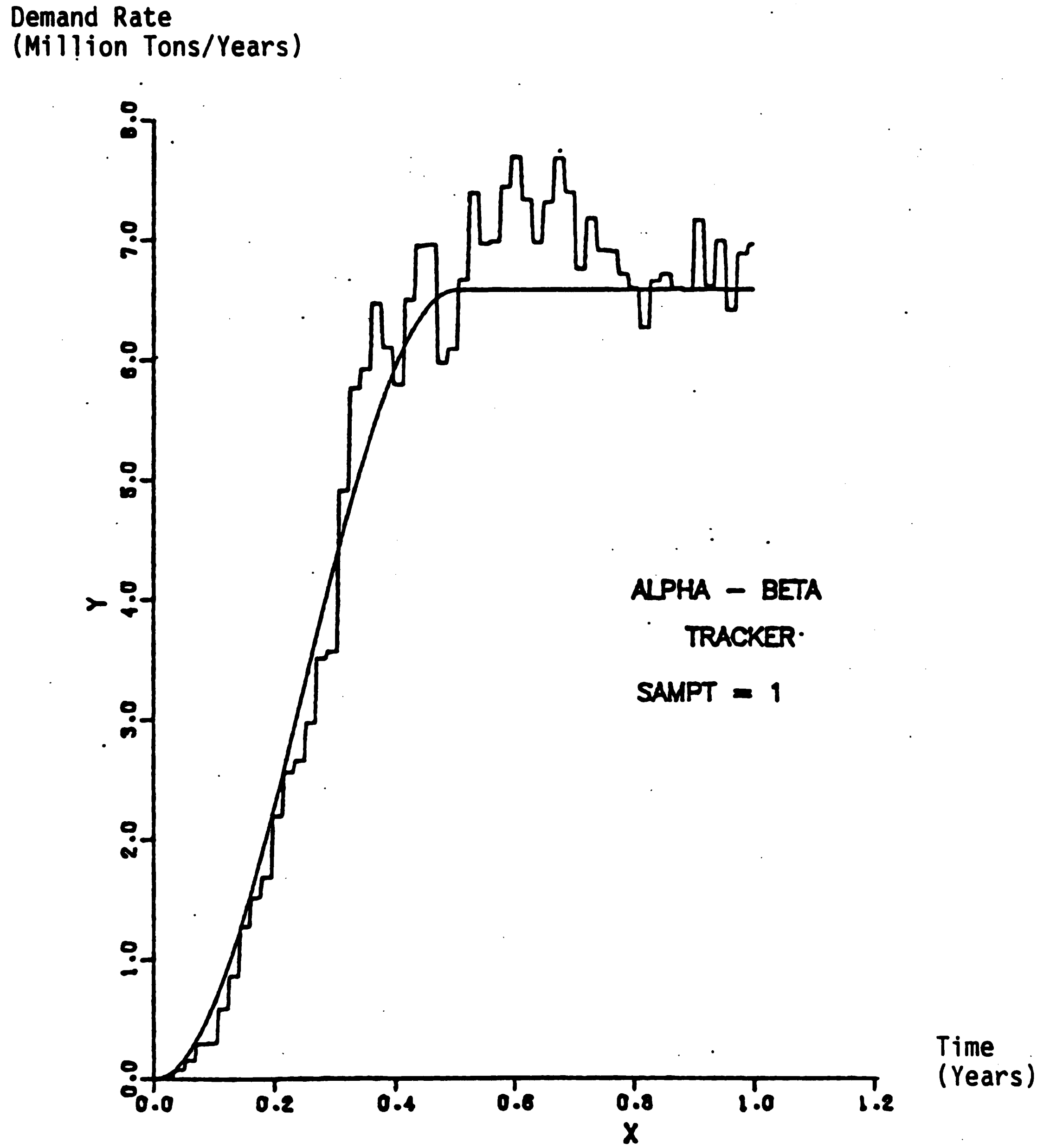

Figure 3.7. The α-β Tracker's Estimate of a Partially Known Trajectory (SAMPT = 1)

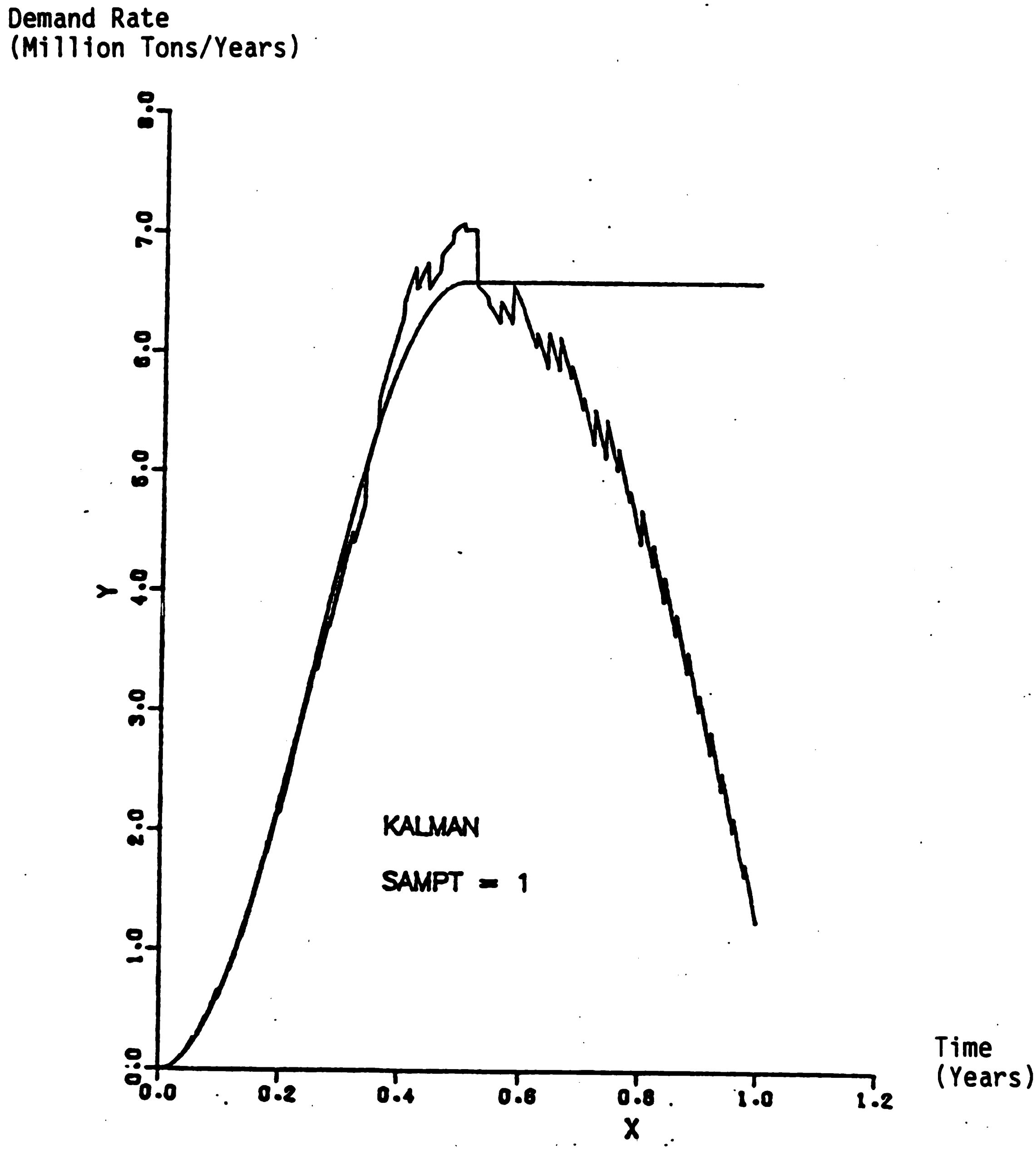

Figure 3.8. The Extended Kalman's Estimate of a Partially Known Trajectory (SAMPT = 1)

initial uncertainty, introduced by the states x3 and x4 (two uncertain parameters). The steady-state values have been assumed as the initial conditions in all the experiments up to now. Of course, the mean values, for the uncertain parameters, were assumed as their initial conditions. As for the state covariance matrix, only the initial value for x3 is large (see variance of distribution of Equation 3.27).

In continuation of the tests conducted on the two estimation models, it was decided to test the performances of these filters when initial uncertainties about the states are large. In this way, the convergence of transient initial conditions is tested. In the current study it is assumed that the initial estimate of the state x1 is equal to 25% of the maximum rate of demand for each trajectory, meaning .25* (2 TDEF). The initial estimates of other states remain the same. With this change the Extended Kalman and the best adaptive tracker were tested, assuming the conditions of the second phase of sampling prevails. Again, the results of no filtering and $\beta = .1$ were included for comparision purposes. Table 3.4 summarizes the results.

It is evident that the consistency of the $\alpha - \beta$ tracker remains unchanged. The better results of the adaptive scheme in comparison with the case of a constant β, stems from the fact that the process structure upon which the scheme has been designed does not change. Comparing Table 3.2 and 3.4, one can see that the tracker converges to steady-state conditions reasonably well. But the Kalman filter becomes unstable and diverges. It was said that in applying linear procedures to nonlinear problems, the resulting estimator is, at best, approximately optimal. What happens to the Kalman filter is that by increasing the initial uncertainty, the linear system (Equations 3.28-

Table 3.4. Expected Value of Mean Squared Error for Transient Initial Conditions

Procedure	SAMPT = 2 Weeks	SAMPT = 1 Week
No filtering	.31287 (.03123)*	.31247 (.02665)
BETA = .1	.21938 (.02038)	.1373 (.0055)
2-BETA & 1-DEV	.181058 (.014878)	.11188 (.004734)
Extended Kalman	8.5178 (1284.16)	3175.00 (224350990.00)

* Variance

3.32) is no longer a good approximation for the original system. Hence, with the choice of the a priori estimates of the states as the reference trajectory, the state deviations do not remain small and the assumptions upon which the filter functions, collapse. Decreasing the T (step size) value even to .000342 does not result in a significant difference.

The reason for the poor performance of the filter when more observations are used may in part be due to the following conclusion. At the beginning stage of sampling, each observation's contribution to the Error mean (Equation 3.42) is larger than later observations. This is caused by the high initial uncertainty. The single trajectory example was repeated for this case. The size of the error (Equation 3.42) is .867 and 2.7 where SAMPT = 2 for the α-β tracker and the Kalman filter respectively. The MSE's values, for SAMPT = 1, are .311 and 1.75. Figures 3.9 to 3.12 illustrate these results. Figures 3.9 and 3.11 show the fast convergence of the tracker as Figures 3.10 and 3.12 portray the wild fluctuations of the Kalman filter.

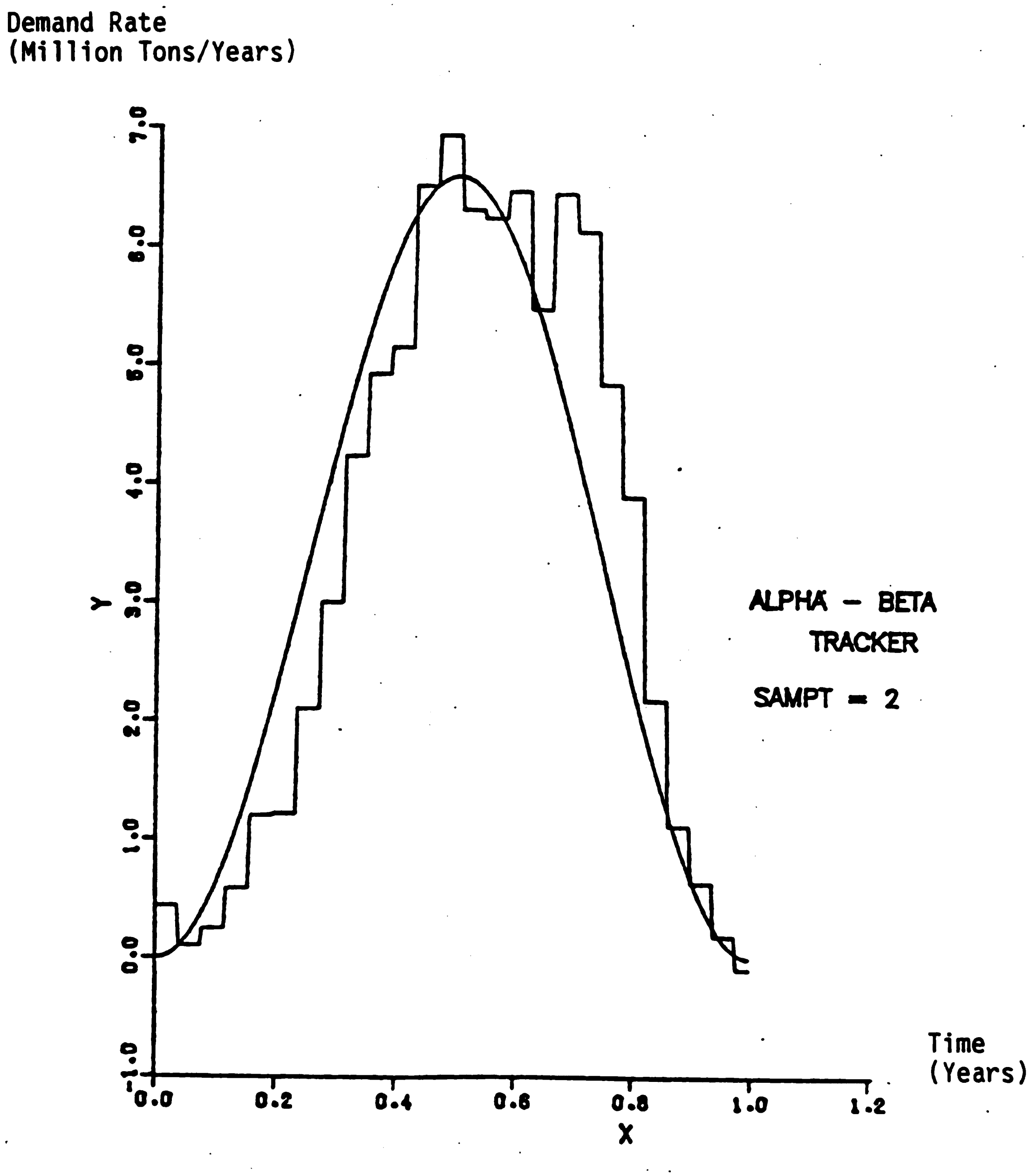

Figure 3.9. The α - β Tracker's Performance when High Initial Uncertainty Exists (SAMPT = 2)

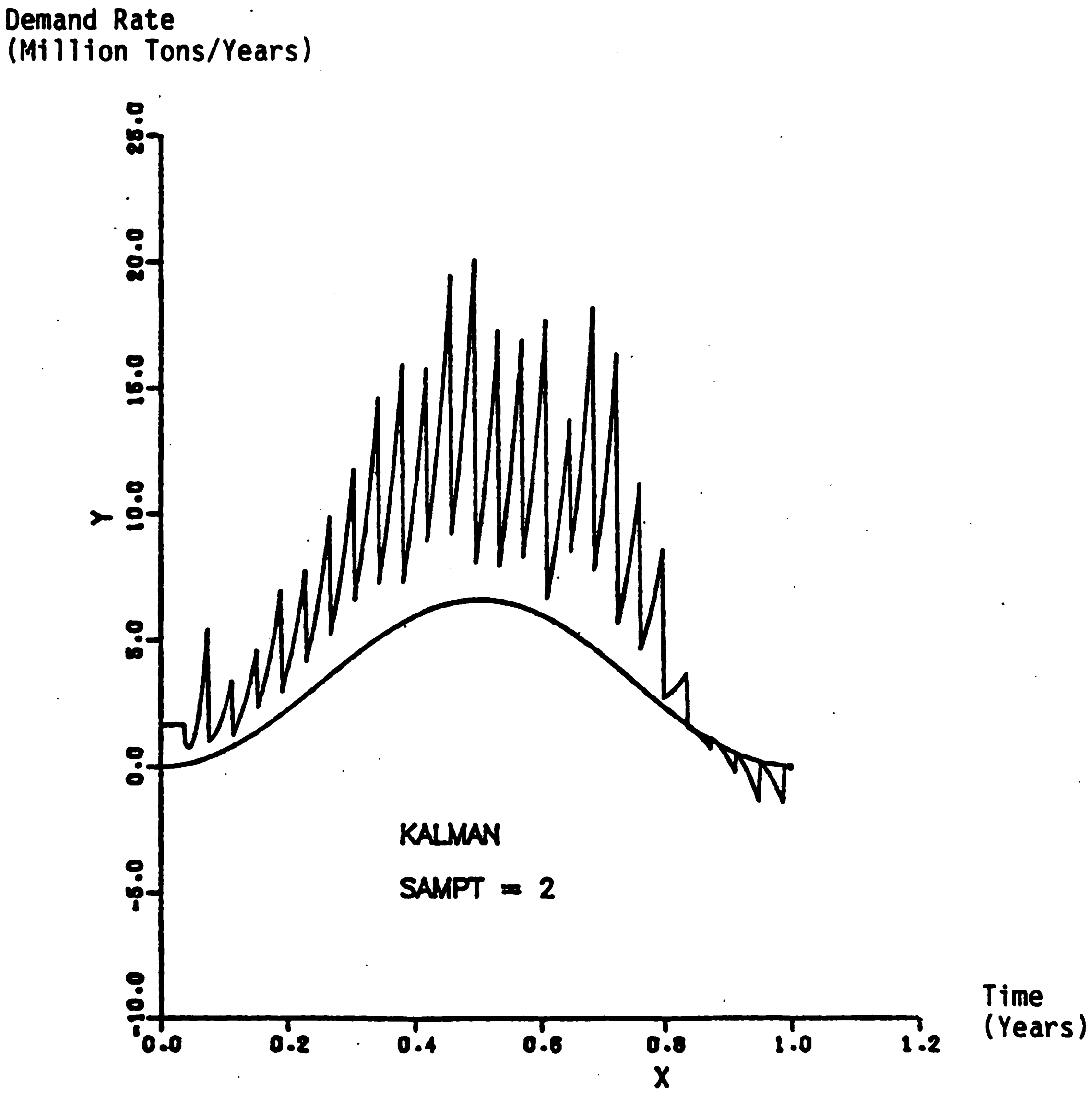

Figure 3.10. The Extended Kalman's Performance when High Initial Uncertainty Exists (SAMPT = 2)

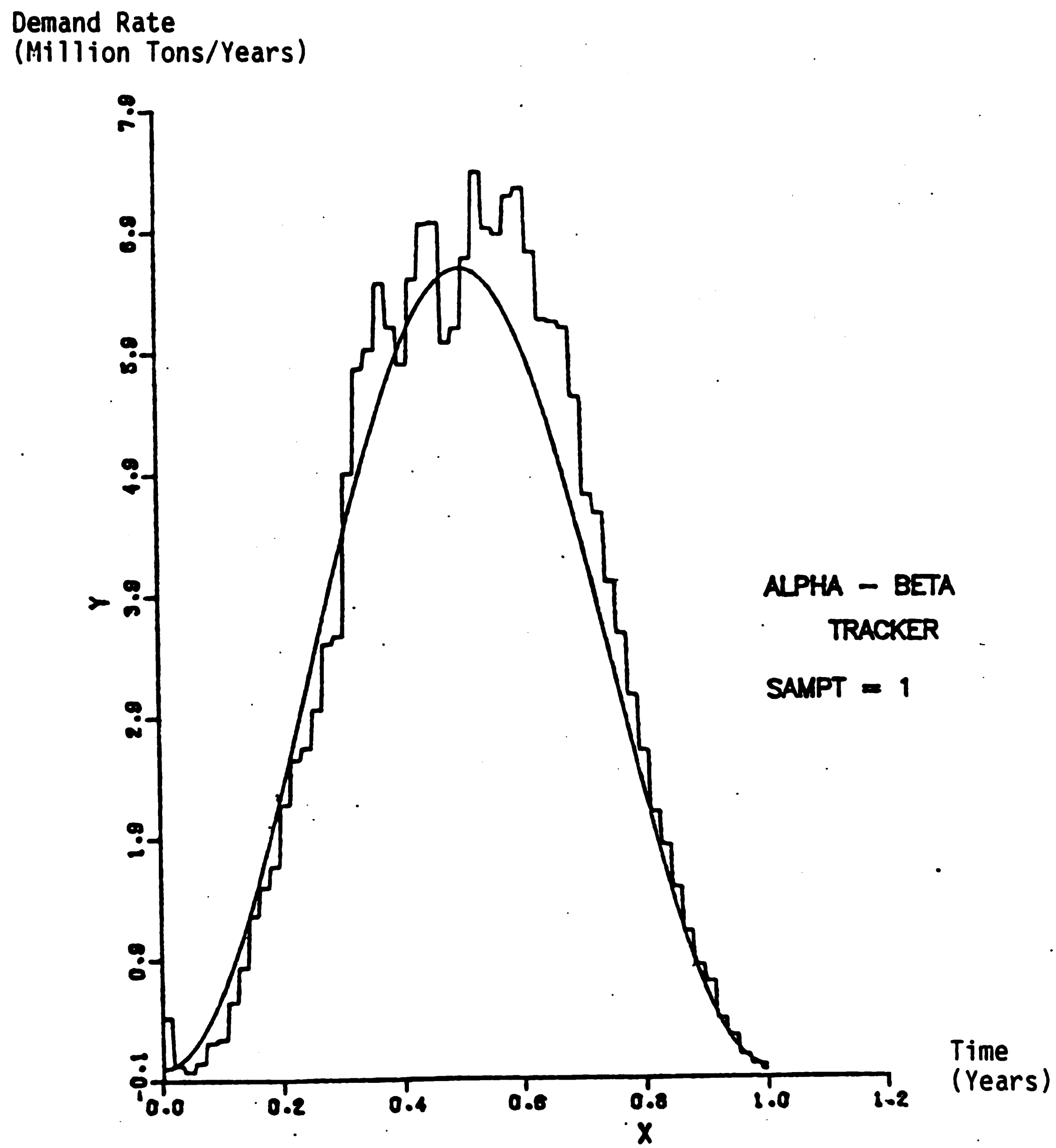

Figure 3.11. The α-β Tracker's Performance when High Initial Uncertainty Exists (SAMPT = 1)

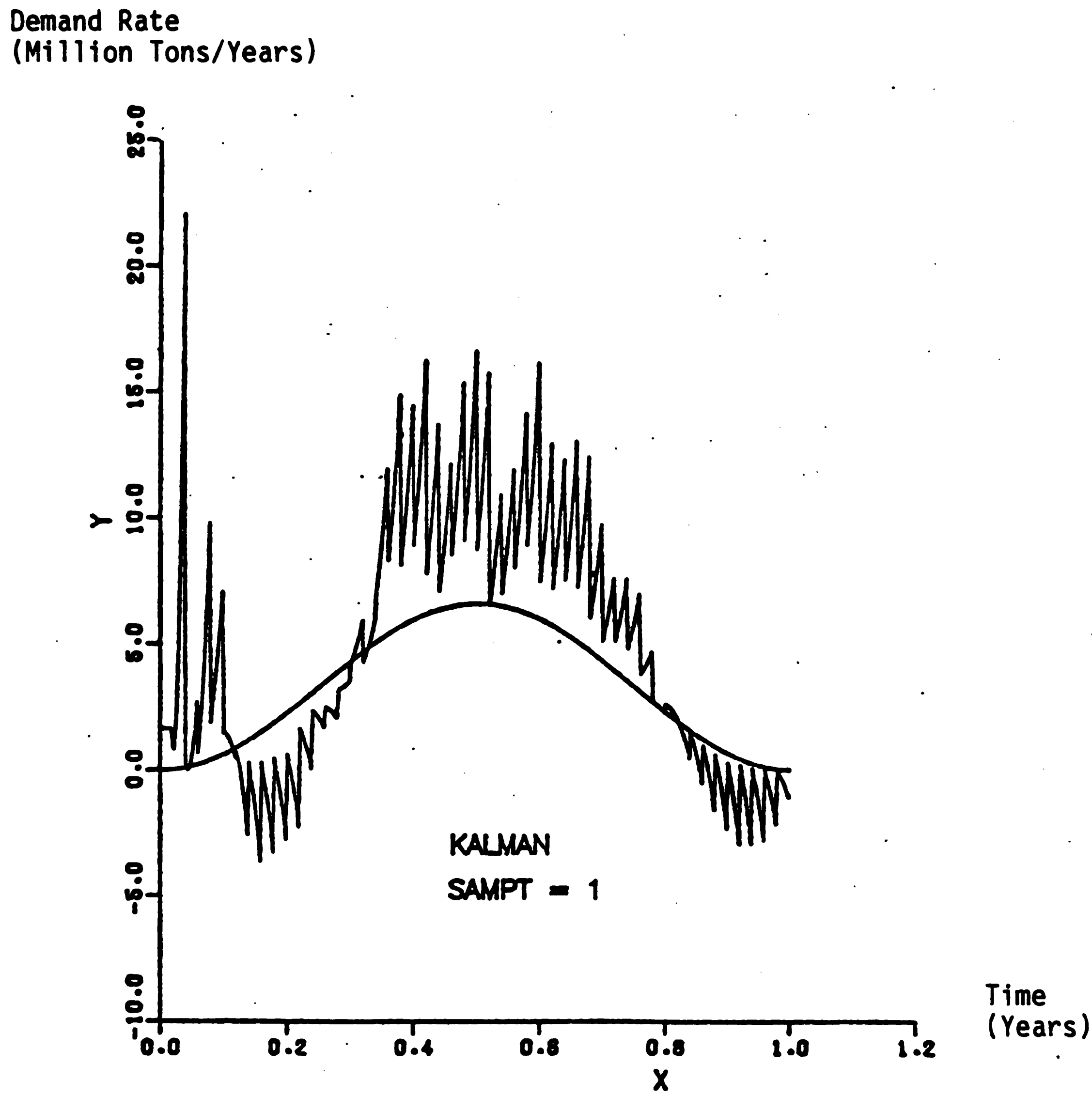

Figure 3.12. The Extended Kalman's Performance when High Initial Uncertainty Exists (SAMPT = 1)

Adding the Filter to the Model

After reexamining the results of previous sections, it was decided that under assumed circumstances, the $\alpha - \beta$ tracker will serve better than any other filter. Now, this filter should be added to the sampling component of the model described in Chapter II. This addition is an easy job.

Recall that the term EST_k in Equation 2.52 and 2.53 represents the sampled variable value before delay is introduced. EST_k is then an input to the routine VDTDLI, whose output is the estimate received by decision makers. The filter does not at all change the delay routine. An additional stage is added between sampling and delay. EST_k becomes the input to the filter (U in Equation 3.3). The filter output (Y) becomes the new input to VDTDLI. Equation 3.6 is included in the model so that β is the only parameter to be specified. The tracker is turned off by setting β equal to one, as discussed earlier.

Summary

The information filter is a tool for extracting maximum value from the captured data. It is used to give a better picture of the total problem to system managers by increasing information quality and accuracy. After a brief survey of existing literature from different viewpoints, it was seen that as knowledge of the process and its characteristics decreases the number of options (estimation models) available shrinks. Then the Extended Kalman filter (which is also known as Extended Kalman-Bucy) and the $\alpha - \beta$ tracker in conjunction with different adaptive schemes, was selected and tested.

The performances of the two main estimation models were also tested when some of the basic assumptions about the assumed process do not hold. These were the conditions of partial knowledge about the state model of the process and high initial uncertainty on the prior estimates of the states. When complete a priori information about the process and its noise statistics exists, the Kalman out performs the α-β tracker. In the case of partially known trajectories, the Kalman cannot function properly and results in large estimation errors. As the initial uncertainty gets larger, the Kalman filter falls apart. Instead, an unchanged consistency from the α-β tracker is observed throughout the above experiments; because it does not rely on any information about the process.

Additional research should be conducted in order to design better filters or to improve the ones which were used in the current study. An interesting extension of the Kalman filter is one with some kind of adaptive structure. This means that the filter is capable of adjusting itself to the change in the structure of the process. This adaptivity can be applied to the state model of the process. For example, the state model is changed by introducing extra state components when some rapid change in data is detected. Bar-Shalom and Birmiwal (6) choose this latter approach for their target tracking model.

There are some other techniques which require partial information on the noise statistics but they utilize other existing data, such as knowledge about the state model of the process, to give better results. This may be a good way to overcome the problems like high initial uncertainties. The most important class of such models comes under the name of Maximum Likelihood estimators, briefly discussed earlier. It is important to remember that regardless of which filter works better, each crisis has its own special needs which may force decision makers to choose a filter with a lower performance.

CHAPTER IV

MODEL VALIDATION

Model testing and validation is an ongoing process which should continue even after a model has been implemented and is in routine use. The purpose of the validation process is to establish that a simulation model poses internal consistency and to assure that it is an adequate representation of the complex processes of the real world.

"The concept of validation should be considered one of degree and not one of an either-or notion; it is not a binary decision variable where the model is valid or invalid (103, Chapter 6)." It is very hard, if not impossible, to establish absolute validity of a model. As the degree of validity increases, so does its development costs. Some results that can be reached by the validation process are; identification of bottlenecks, recognition of sensitive design parameters, and understanding of the model.

There are primarily two different ways in which a model could be validated. The first approach compares the model output with real world data (correspondence). This can be done either by examining past data or matching model projections to future real world figures. But the serious lack of real world data in the case of famine and especially for the third world countries, presents problems in the use of this particular validation form.

The second method attempts to assess whether the observed model outputs behave in a desired fashion, using alternative assumptions about its behavior, established by experts and from other published sources (coherence or consistency). This method is quite initutive and judgmental and the experts' view at this stage is necessary. This approach was used as a part of the validation process and it will be described in the next section.

Need for accurate data on system parameters, initial conditions, and technical coefficients becomes clear in any validation process. The last two forms of information link the model to a particular country. Once they are set, system parameters are used to "tune" the model behavior to parallel real world performance. Due to the unreliable input data, it is much more significant to analyze the model outputs relatively rather than absolute levels.

Different components of the logistic system were tested separately in previous chapters. The purpose of this chapter is to test the validity of the total system in which all of these subsystems interact. The focus has been on determining whether the model behaves in a sensible fashion. It is hoped that the usefulness of the modeling will be seen along with its validity. This model is not intended to apply in detail to any country. The results are used to correct any inconsistency in the model and deduce important conclusions for control and policy formulation.

Consistency Tests

The primary purpose of these tests is to compare model output with expected output and identifying inconsistencies. When a problem is noticed, the next step is to either explain it or eliminate it.

Different types of consistency checks are possible. These include variable magnitude; conservation of flow, the effect of a parameter change on performance of the model, and model structure change.

Variable magnitude is a common sense observation. Real world conditions and limitations should be reflected by the computer model. The following impossible situations are examples of variable magnitude inconsistencies:

- negative or astronomical cost or capital
- negative ship and/or truck queues
- negative storage and grain thruput
- negative or greater than DUR idle times

  (DUR is the duration of relief operation)

It should be noted that a large amount of cost or capital may stem from a wrong control policy. Actually, this is one of the methods which is going to be used in order to identify better control policies. These checks were conducted satisfactorily along side of other consistency tests on the model.

Conservation of Flow

In any model, conservation of flow must generally be preserved. This is done by examining related variable time series. For example, input and output of grain should be reflected on the storage levels. Decline in demand should signal an increase in storage. An increase in the capital acquisition rate must have the same effect on the capital pools at port. These conclusions can be reached by observing the outputs of the model. The following conservation of flow tests were conducted and the model handled them well.

- effects of port's thruput changes on regional storages
- different ship arrival patterns and total number of ships in and out of system including those in the queue
- effect of demand fluctuations on various storages
- port's input rate influence on port's storage level
- effect of ship arrival rate on idle time of ship service center and average per ship wait time
- supply's effect on capital acquisition rates.

One way of testing the conservation of flow in the current model is by checking the numbers of trucks and drivers in the system. As mentioned in Chapter II, the output of the capital acquisition model indicates the actual amount of capital at any time. There are two variables which keep track of the total numbers of trucks and drivers currently in the logistics system called Y and DY respectively (Equations 5.24 and 5.25). Thus at any time, if the trucks or drivers in various components of the system are added together, one should come up with Y or DY. If true, this says that the model conserves flow. This is also an indication of conservation of grain flow. Remember that the amount of grain is computed by multiplying the number of trucks with the capacity of each truck (TGRC).

The total number of trucks and drivers in different parts of the system are obtained by the following equations

$$TOTTR(t) = TRIOP(t) + TPOL(t) + TTIRS(t) \tag{4.1}$$

$$TOTDR(t) = TDRC * TRIOP(t) + DPOL(t) + TDOL(t) \tag{4.2}$$

where:

TOTTR = sum of all trucks in various parts of the system at time t (#)

TRIOP = number of trucks in the system, except port, at time t (Equation 2.60) (#)

TPOL = trucks in the port's pool at time t (#)

TTIRS = trucks in repair shop at time t (#)

TOTDR = number of drivers in various parts of the system at time t (#)

DPOL = drivers in the port's pool at time t (#)

TDOL = number of drivers on-leave at time t (#)

TDRC = number of drivers per truck coefficient.

Table 4.1 summarizes the results of comparisons between Equations 5.24 and 5.25 and the above equations. The apparent error has been caused by the choice of DT, the time increment of the model. Up to four percent error has been assumed to be "acceptable" in the current study. More on this error will be said in later sections. The results in Table 4.1 have been reached by DT = .000114.

Sensitivity Tests

One of the real advantages of simulation is the ability to perform sensitivity analysis readily. Sensitivity analysis usually consists of systematically varying the values of the parameters and/or the input variables over some range of interest and observing the effect upon the model's response (103, Chapter 6). The direction of system performance change is a good indicator of model consistency. The primary goal of these tests is to indicate those areas of the model in which changes in parameter values or formulations have a significant impact on model results. Such information is useful, not only for model tuning

Table 4.1. The Conservation of Flow Test on the Numbers of Trucks and Drivers in Various Times

	CAPITAL (#)			
Time (years)	Y	TOTTR	DY	TOTDR
.25	1725	1701	2553	2551
.5	3257	3226	4930	4938
.75	2394	2368	3508	3509
1.0	429	432	739	749

and validation, but also for policy making and as a guide to data collection priorities. Thus, the efficiencies of both research and the decision making process are improved.

A sensitivity test is conducted by running the model twice, each time with a different value for the desired parameter. Then, model outputs related to that parameter or any other specified output are measured at the end of each run. An assumed pattern should be observed. Different sensitivity tests were conducted for various components of the current model. Results and some discussions on each of these tests will follow. For a better understanding of some of these results, it is important to keep in mind the assumed shapes of supply and demand curves (Figure 2.5). In the beginning and at the end of the crisis, these specified forms impose certain restrictions on the results which will be mentioned at the right time.

First, the port system was studied. It successfully passed the validity tests. The effect of perturbing three parameters upon performance statistics and different state variables were observed. The parameters are: ship offloading rate (RMS), truck loading rate (RMT), and storage capacity (CAPWH). The port performance statistics correspond to some of the idle times mentioned in the model description in Chapter

II. The most important one is the waiting time for ships. A statistic that varies inversely with the ship waiting time is the idle time of the ship service center, when no ships are in port. Clearly, decision makers face a tradeoff between these two indices. Of course, in the case of famine and with the high cost of ship waiting time, the managers do their best to utilize the off-loading capacity at its maximum rate.

The remaining performance statistics deal with the amount of storage. If storage capacity is exceeded, no unloading can be done and service center idle time results. On the other hand, when no storage is available, trucks cannot be loaded, so there is a capital idel time. The state variables that are good indicators of performance are length of ship waiting time (IWL), current storage (STOG), and THRUPUT, the amount of grain that has passed through the port into the inland transportation system. Currently the port capacity is set at five million tons per year and the port storage capacity is 200000 tons. The ship off-loading capacity was increased several times, each time by half a million tons per year and the following results were obtained:

- length of the ship waiting line decreased considerably
- average per ship wait time decreased between 60% and 80%
- idle time of ship service center increased
- idle time of capital due to storage unavailability converged to zero
- idle times due to average storage capacity also decreased
- total cost decreased considerably.

Decreases in idle times due to shortage of grain can be expected but what about decreases in the idle times caused by overage storage capacity. A closer look at the rest of the model outputs revealed that this is caused by more efficient use of the available capital. Usually much of the trouble starts when different limitations of the model force inefficient use of the resources. For example, when there are trucks waiting to be loaded, the ship offloading rate is the bottleneck. This can be seen especially in the second and third quarters of the year. The result is longer ship waiting lines. By increasing the ship offloading rate the problem is solved. Do not forget that this is happening under assumed circumstances of supply and demand. If supply becomes greater than demand, increasing the offloading rate results in overage storage capacity. In the current model, the overall demand is ten percent higher than supply.

The improvement in the results caused by the first ten percent increase in the ship offloading rate is much more than the other increases. Actually, after the second increase, the results will not change, indicating useless offloading capacity. This important conclusion could be used by system managers for better planning of relief operations. This example shows the advantages of simulation and the importance of models as an aid for decision making. Table 4.2 summarizes the above results.

The truck loading rate was changed in the same way as the ship offloading rate. But it was found that this rate is not as effective as the ship offloading rate in changing model outputs. The limiting behavior of this rate appeared very soon, meaning that it does not pay to increase the rate any further. This can be seen by observing the loading equipment's utility factor (TIDRMT). It is much lower than the offloading one. Primarily, this is the result of a shortage of grain in storage which in turn is a product of the low ship offloading

Table 4.2. Effects of Various Ship Offloading Capacities on the System Peformance Indices

Performance (Time = 1)	RMS (Tons/Years) 5,000,000	5,600,000	6,000,000
Ship Waiting Cost ($)	94,107,057	60,068,582	44,226,158
Total Cost ($)	202,345,767	172,820,474	160,458,827
Average Per Ship Wait Time (Years)	.0681	.0417	.03
Grain Thruput (tons)	2,956,918	3,086,068	3,105,737
Total Balance	71,476	57,074	47,521
Ship Queue Length (#)	6	0	0

rate. Another source of the problem is the shortage of capital to utilize the existing capacity. The result of changes in this parameter, each of which is a reason for model validity, follows.

- average ship wait time decreased
- service center idle time increased
- capital idle time due to shortage of storage increased
- various idle times due to overage storage capacity decreased
- idle times due to shortage of capital increased.

An important conclusion of these tests, for policy formulation purposes was the limiting behavior of performances. This indicates that having extra capacity does not do too much good if other bottlenecks still exist.

The last parameter which was used to test the port's model validity is storage capacity. Again, by looking at supply and demand, one can recognize the fact that the only time storage capacity could become a bottleneck is when demand and supply are very close to each other. This is true for any type of supply and demand functions. The storage capacity was changed and the following results were obtained. Here, also, the limiting behavior caused by other bottlenecks was observed.

- increased idle time of ship service center as a result of increasing the storage capacity
- increased input as the capacity increases
- increased idle times due to overage storage capacity caused by capacity reduction.

The next components to be observed are regional warehouses. Here, the only important parameter is the maximum truck unloading rate (RMSS). It was assumed that the outgoing grain rate from a RWH is a function of demand. Also, it was assumed that storage acts as a buffer, balancing supply and demand. These assumptions make the outgoing rate and storage capacity less important than the truck offloading rate. Hence, by changing this parameter several tests were conducted on the model with the following satisfactory results.

- trucks queue at RWH's show opposite direction of movement with offloading rates
- regional grain thruput drops by decreasing the offloading rate
- stockouts decrease as offloading rates increase.

There is an interesting limiting behavior for this parameter. As the maximum truck offloading rate starts decreasing, its effects at first appear in regional warehouses. Then, the system starts backing up. Truck queue lengths start growing. Stockouts increase and ratios of supply to demand decrease. The stocked capitals at silos dry out the capital pools at port. Now, the ship queue starts growing and ship waiting time increases. This is actually a test of validity for the port and regional warehouses and their connections. On the other hand, increasing the maximum rate stops being useful after some point due to other restrictions.

The capital development process can be tested by changing the limit on the acquisition rate (TRLIMIT). A detailed discussion of this rate was given earlier. Decreasing TRLIMIT, resulted in the following satisfactory model responses;

- average per ship waiting time increased
- idle time due to shortage of capital increased
- regional stock-out times increased
- ratios of supply to demand decreased.

A decrease in TRLIMIT affects the driver acquisition rate more than the truck acquisition rate, because the first rate has a higher proportion in comparison with the truck rate. This is caused by a higher rate of drivers taking a leave (see Equations 5.22 and 5.23).

An excellent example for a sensitivity test is the change in the quality of information. It is common sense that better information should lead to a better model performance. By decreasing the sampling interval to one week and using the appropriate coefficients for an α-β tracker from Chapter III, the following results, indications of model validity, were obtained.

- regional stockout times decreased
- ratios of supply to demand increased

- regional grain thruputs increased
- better balance in distribution was obtained
- average per ship wait time decreased
- port thruput increased
- total cost of operation decreased.

The decline in total cost is the result of a lower ship waiting time. This is an important result for system decision makers. Note that this has been reached in spite of increase in information cost.

The information filters which were discussed in Chapter III were tested on the total demand function. In order to see the performance of the α-β tracker when it is used with the total logistics model and regional demands, the Figures 4.1 - 4.4 were drawn. Each figure illustrates the real world regional demand function with the estimated one for that specified region, using a sampling frequency of two weeks.

Model Structure Change

Model structure modifications will generally have a great impact on the system's performance. The first change which was considered, was the introduction of population movement into the model. Previous results were obtained by assuming zero population movement. Changing the model such that there is a steady population movement from the fourth region into the first region (β_1 = .1), was handled well by the model as can be seen by the following results.

- grain thruput of first region increased as output of fourth regional silo decreased
- stockout time of first RWH increased slightly

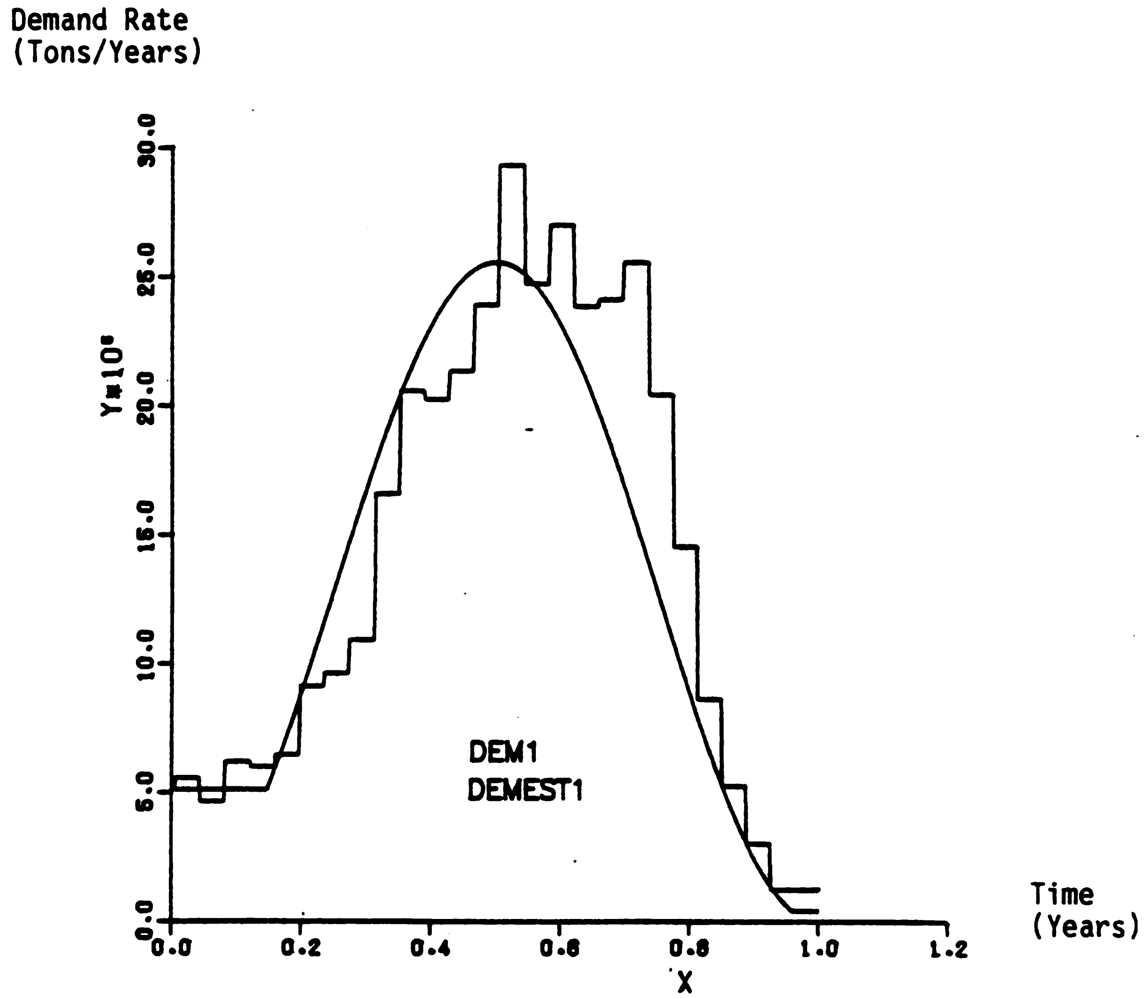

Figure 4.1. Estimate of the Demand for the First Region.

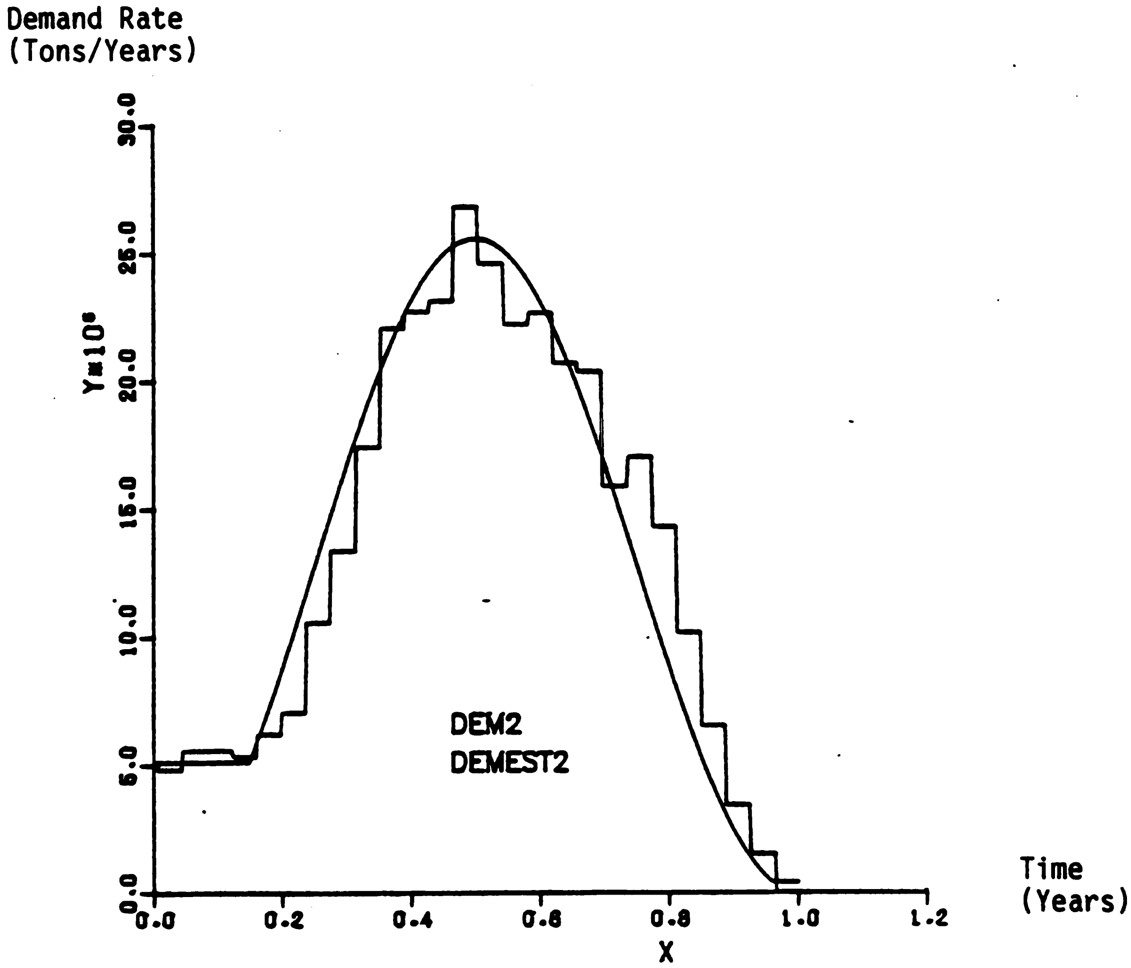

Figure 4.2. Estimate of the Second Region's Demand.

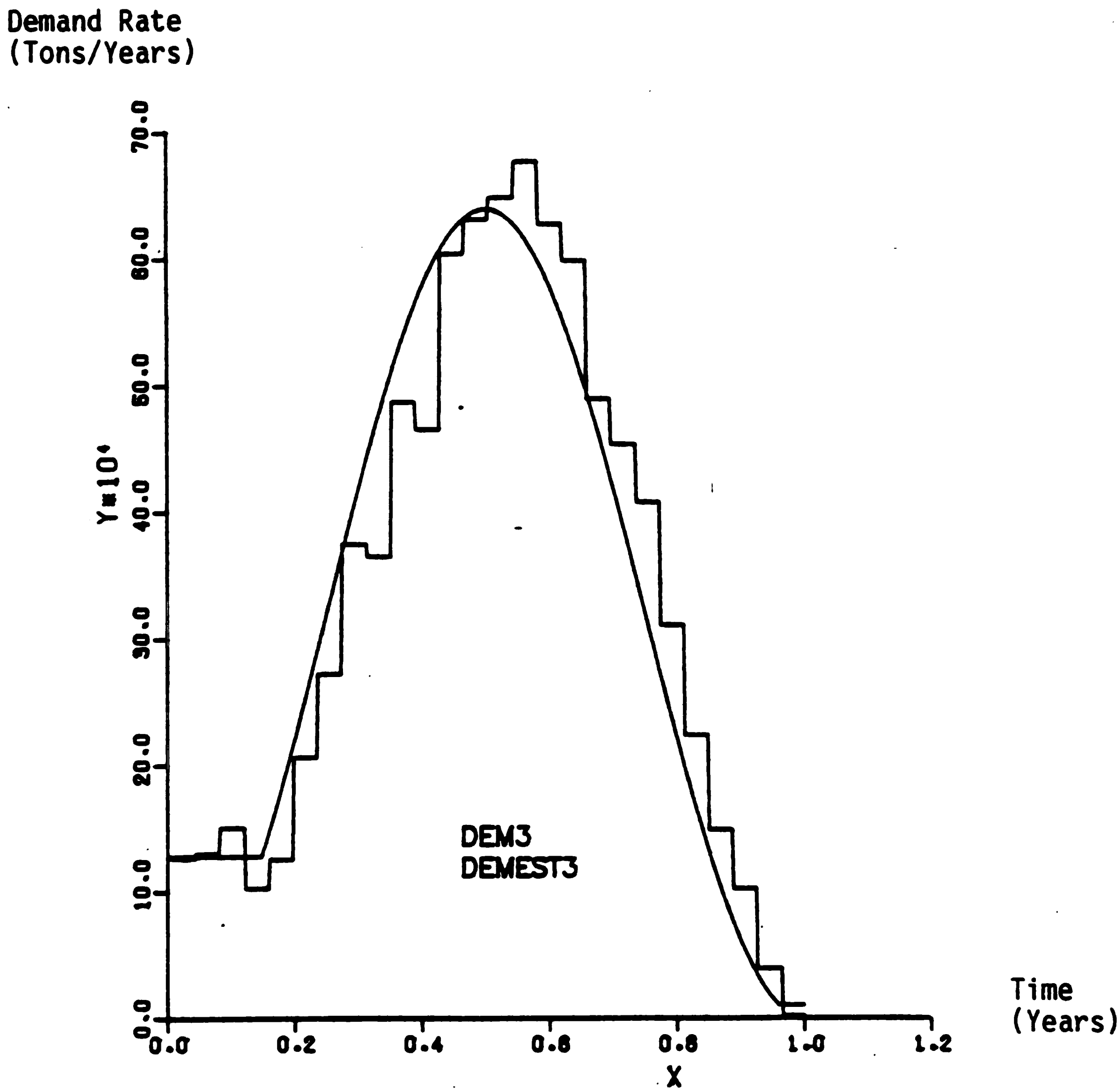

Figure 4.3. Third Region's Demand Estimate.

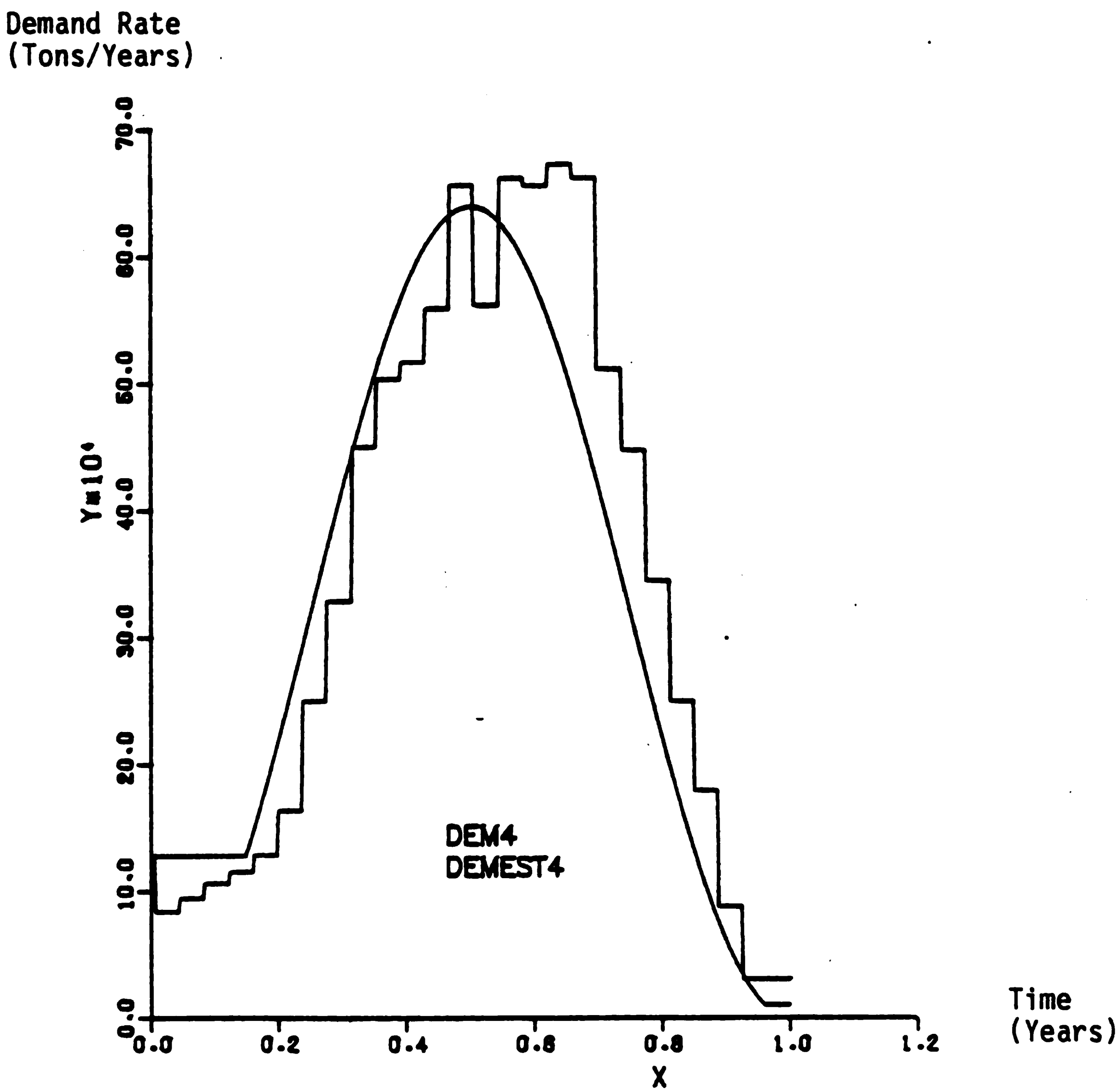

Figure 4.4. Estimate of the Demand for the Fourth Region.

- fourth RWH's stockout time decreased.

A lower stockout for the fourth region and a higher one for the first one have been caused by various factors. An important element is the existing delays in the system, meaning information and transportation delays. Between two sampling points, the demand functions of the first and fourth region, apart from their usual change, have added population movement effects. These effects are not known to system managers. They are reflected in the next estimate of demand. Thus, the managers always work with the overestimated demand for the fourth region and vice versa in the case of the first region.

The second structural change is road breakdown and transshipments. Different times and various roads were tested. Important elements influencing the outcomes are the length of the new road, which should be used after the breakdown occurs, and how early in the relief operation the incident has happened, i.e. the length of the time the new road is going to be used. The third factor is the timing of the event. If it happens at the time when the relief operation is at its peak, then the drop in performance is bound to be higher than at some other time. An early breakdown of the roads results in

- an increase of the total cost
- an increase of the corresponding RWH's stockout.

These changes are also relative to the length of the new road. Longer roads cause more damage than shorter ones. Due to the short delay between port and RWH's, in comparison with the duration of the operation, the ratios of supply to demand do not change significantly and in the case of a RWH, with the new road, it slightly increases.

This is caused by the policy of sending back the full trucks stuck on the old road to the same RWH by way of the new road. It is necessary to know that in all structural change tests the conservation of flow was preserved.

Simulation Interval DT

In any modeling and simulation process, there exist two levels of approximation; hence two types of errors. The first level is introduced when a theoretical model with some mathematical equations are used to represent a real world phenomena. Previous tests on the model are to make sure that this level of approximation is acceptable. The second type of error comes to play when the mathematical model is represented by a discrete computer model, and numerical solutions are seeked for mathematical equations, most of which involve continuous, nonlinear functions.

A common computation in the model is numerical integration using the Euler techniques. The theoretical integration form given in Equation 4.3 has been used several times in earlier chapters. The Euler numerical solution for Equation 4.3 consists of the approximation in Equation 4.4, which calculates successive values as the simulation advances through time.

$$\text{LEVEL}(t) = \int_0^t \text{RATE}(s)ds \tag{4.3}$$

$$\text{LEVEL}(t + DT) = \text{LEVEL}(T) + DT * \text{RATE}(T) \tag{4.4}$$

where:

LEVEL = variable resulting from integration

RATE = integrand variable

0, t = limits of integration

s = dummy integrand variable

T = time in computer simulation

DT = discrete time interval.

Theoretically, the error involved in this approximation approaches zero as the value of DT decreases, meaning the result of integration approaches the true value. The distributed delays which were used in the current model are another example whose error decreases with DT. Thus everything else being equal, model outputs should approach their limiting values as DT becomes smaller. This, in fact, is what happens with the current model.

The effect of the reduction of DT is hard to observe because as DT changes, a different ship arrival pattern is generated. Remember that the expected interarrival times for ships were calculated using food arrival functions. By changing DT, different points on that function are selected to calculate the ship arrival time. Also, since the supply function is a table look-up one, changes in DT give different values for the total supply due to an integration error. Thus any change in the model output can be attributed to either DT or the arrival pattern or both. But reduction in error for the conservation of flow is obvious. This error is "acceptable" for DT between .000228 and .000114.

As an example, the capital development process will be discussed here. In this model, Y is defined to be the actual number of trucks in the system at time t (Equation 5.24b). It is the output of the feedback model (Figure 2.6). As was discussed earlier, there is an error between Y and TOTTR (Equation 4.1) which is the sum of all trucks in various parts of the logistics system. This error has been used to analyze the effects of DT changes. Equation 4.5 gives the error formula.

$$ERROR(t) = (Y(t) - TOTTR(t))/Y(t) * 100 \qquad (4.5)$$

where:

ERROR = percentage error index at time t

Y = actual number of trucks in the logistics system at time t (#)

TOTTR = sum of all trucks in various parts of the logistics system at time t (#).

Table 4.3 summarizes the various values of ERROR at the end of the year as DT changes.

Table 4.3. Error Percentages in the Total Number of Trucks as a Function of the Time Increment, DT.

DT Size (Years)	ERROR
.000342 (3 hours)	5.4
.000282 (2.5 hours)	3.1
.000171 (1.5 hours)	2.95
.000114 (1 hour)	.7

When it is known that the model works properly, the actual size of error is no longer important, rather its relativeness becomes significant. The relative error is used for comparison of various control policies. A smaller DT is more desirable, but there is a cost involved with it. Thus a tradeoff must be made. An increase of DT to .000342 generated some unacceptable numerical problems. DT equal to .000228 will be used for all simulation work in this study.

Summary

In closing this chapter, some general observations and conclusions can be summarized. A set of tests for determining the validity of the model were described, showing that it behaves sensibly.

Results of the port model are in line with those of Knapp's (65). Ship offloading rate had a greater effect on model outputs than vehicle loading rate and storage capacity. For grain to be able to go through the port and for a shorter ship queue length, the ratio of offloading rate to arrival rate should be at least 1.6 - 1.8. A somewhat smaller ratio is needed for the loading rate. The fact that offloading needs to be greater than arrival would be expected from standard queuing theory, and offloading greater than loading is evident from the buffer that storage facilities provide for truck loading. Hence it was decided to increase the offloading rate by half a million metric tons to become 5,600,000 (tons/years). Storage capacity helps the performance if stocks are well below capacity at the onset of the crisis. The helpful effects are good only in the short run; so varying capacity is not a good policy to maintain long-run equilibrium.

Even though there is a cost associated with better quality information the performance of the model increases such that the total cost actually decreases. Better data causes a reduction of cost in other areas. But it is not so easy to gather information more frequently in the real world. There exists logistical constraints and other bottlenecks that were discussed in Chapter I.

An important result which was clear throughout these tests is the fact that a little more capital eases a lot of troubles and eliminates bottlenecks. It lowers the cost and generates a better performance. Of course, there is an upper limit for capital which only pushes the cost up. Notice that these results were obtained assuming the given cost structure and coefficients. The model is now ready for an application of control policies.

CHAPTER V

CONTROL AND POLICY DESIGN

The problems of planning and control of relief operations are characterized by the uncertainty that is necessarily inherent in such processes. This uncertainty arises both from the quantity and quality of available data and from the difficulties of forecasting the ways a large-scale system of complex interactive and feedback relationships will respond to policy inputs. With this in mind, the model developed in this dissertation, though not restricted to any particular country, sets up a workable and reliable alternative for dealing with these problems. The system approach used here, by modeling specific time paths of behavior, provides at least some of the flexibility necessary to deal with the complexity and uncertainty of planning.

A system simulation model can be useful to policy and decision makers in two principal ways: improving their understanding of the system they are concerned with, and formulating various policies. The model-building process and sensitivity tests, discussed in the last three chapters, can contribute substantially to an improved understanding of and sharpened intuitions regarding the relief operations, in general, as well as the particular logistics system of concern. Manetsch (73) has shown that systems analysis can be used in the development of strategies that make effective use of available food supplies during times of crisis. The objective is to minimize the adverse consequences of severe food shortages by effective control and distribution of limited food supply.

Scope and Nature of the Control Problem

One of the most significant motivations for the development of new design techniques suitable for large scale systems has been the computational impracticality of direct application of optimal control or optimization theory. This impracticality is due to many system complexities such as large dimensions, nonlinearities, coupling, time-delays and physical separation of components (55, Chapter 6). The following are some observations about the problem under study.

1. Except for ship arrival, the rest of the system is continuous time. Homogeneity of goods and services, the existence of storages and transportation delays, the scale of the system and continuous flow of grain, truck and driver through it, make the problem very similar to fluid process control (15), (16), (106). Hence, some of the techniques developed in this field might be useful in controlling the current model.

2. Decomposition of system structure has led to a number of subsystems interacting with each other in a hierarchical fashion. Although there is no uniquely or universally accepted set of properties associated with the hierarchical systems (55, Chapter 4), Singh (109) has stated some key properties which can be applied to our system. This characteristic makes the case under study a "multi-level" control problem. Each subsystem has its own state, control and output vectors and the overall system's state and control vectors can be defined as combinations of these.

The specific identifying feature of a hierarchical control system is that for most of them there are two or more local decision units acting on parts of the controlled system, and there is also a supremal control unit (coordinator) exercising influence on the local units. At higher levels the decisions are more complex and less frequent than lower levels (14), (110). Figure 5.1 illustrates the idea.

In the current system top management decides overall policy by examining demand forecasts and defining an appropriate allocation schedule to meet these demands. The next stage is to find out if, given the resources allocated by top management, it is actually possible to satisfy these changing demands. This is clearly an iterative process. Since the individual unit managers are each concerned with their own RWH only, it is the job of top management to coordinate the flow between various units.

3. This is a feedback control problem. Using initial estimates of regional deficit, managers allocate the food. Local units send back the degree of imbalance between supply and demand. This information is used to modify the allocation schedule so as to reduce successively the imbalance for each RWH. Since their decisions are based on time-lagged estimated values (Figure 2.4), an error is always present. Note that the central decision makers have a longer time horizon than local units which operate on a much more day to day basis. Unknown disturbances can affect the allocation schedules and requires further iterative exchange between them and the affected population (controlled system).

4. Multi-objectivity is another feature of the control problem under

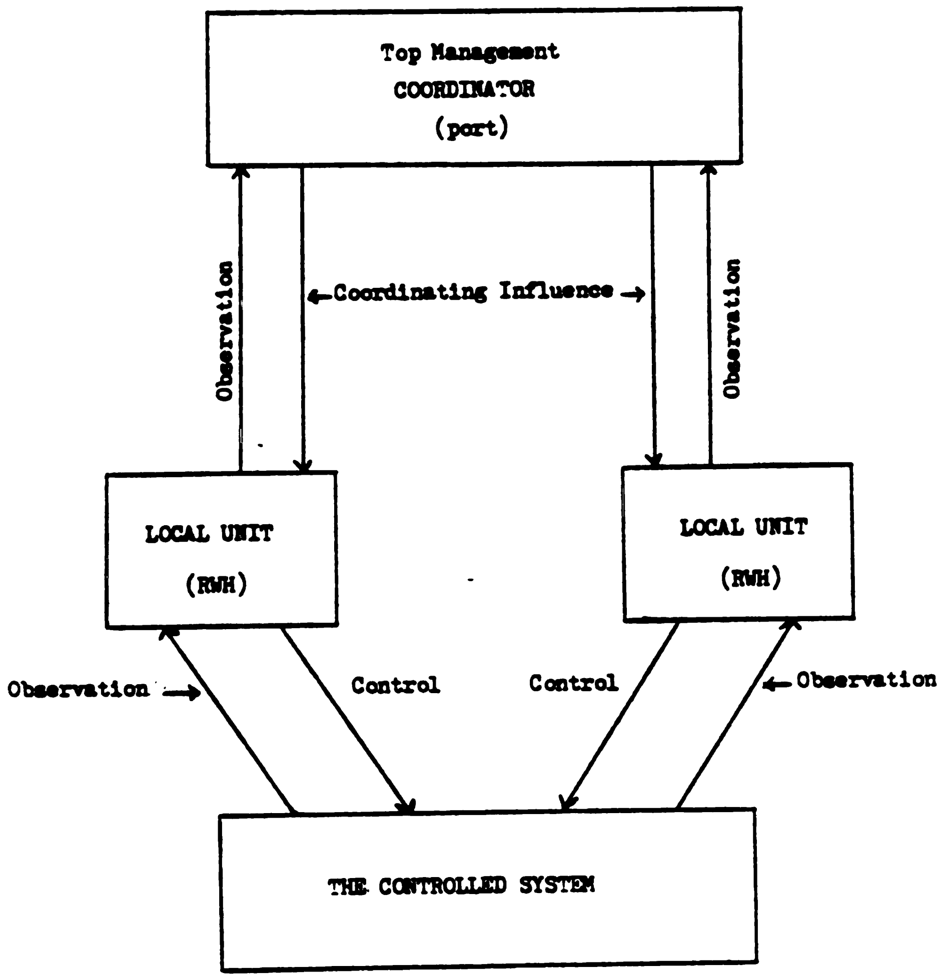

Figure 5.1.Multilevel hierarchy of control

study. There are different and contradicting objectives. This poses new problems not only for possible control strategies but also for their optimization. There is no unique solution to this type of problem. Due to characteristics of large scale systems the optimal control designs are, for the most part, necessarily near optimum in nature (55, Chapter 6). In general, there are infinitely many noninferior solutions to a multicriterion optimization problem, and one noninferior solution is as good as another (strictly speaking, one cannot be compared with another) within the framework of the problem (83), (99). Decision makers, considering the existing circumstances, select the most satisfying noninferior solution. For example, different countries have different quantities of resources needed for relief operations.

Some objectives have to be emphasized at the expense of others, but a proper balance between various objectives is also possible. Multicriterion optimization problems are also known as Pareto optimization or vector-valued optimization problems. Different approaches have been suggested for the handling of this type of problem (54), (83), (99), (102).

The goals of logistics operations are part of the overall objectives of relief operations. Once they are established, policies must be defined for their attainment. Thus, the definition of policies is an important input to the decision-making process represented by the system simulation model. The computerized simulation model allows experimentation with alternative strategies under various assumptions, and then comparison of their likely outcomes. A set of control policies are considered acceptable only if they are relatively effective in reaching the multiple goals under a wide variety of circumstances.

It is hoped that the above discussion has shed some light on the problems and bottlenecks facing the control task. The main thrust of this chapter is in considering strategies and policy guidelines for managing available food and resources such that the assumed performance criteria are optimized (in Pareto sense). The model developed in previous chapters will be used for various policy experimentations.

Performance Indices

To evaluate the results obtained from a policy experiment and in order to be able to compare different control strategy effects on the system, there is a need for performance criteria. These criteria are based on the objectives the system is designed to achieve. Since the logistics is one of the components of the relief operations, its efforts must be directed toward supporting the attainment of relief objectives. This is true of all other subsystems of the overall relief system. Every logistical mission must be guided by clearly stated objectives. The goals should be so specified as to allow continuous measurement of the degree of accomplishment of efforts toward the objective.

Logistical performance is a question of service and cost. Almost any level of service can be obtained if the price is paid. A measurement of logistics efforts to assess its efficiency in terms of economy and effectiveness must also be made. This section summarizes the performance measures in the current study. They were discussed in different parts of Chapter II.

There are two types of indices in this model: one category is for measurement of overall model performance and the other is mostly an indication of one specific component's accomplishments. The following are general performance criteria.

1. Total grain which has passed through port facilities into the country. This is the same as the total grain output of the port and is computed by Equation 5.1.

$$THRUPUT(t + DT) = THRUPUT(t) + DT * TGRWH(t) \tag{5.1}$$

where:

THRUPUT = amount of grain output of port in period (o, t) (tons)

TGRWH = average rate of total food assigned (Equation 5.17) in period (t, t + DT) (tons/years)

DT = length of time increment (years).

THRUPUT is one of the most important indications of the models ability to handle the grain shipments. If this job is not accomplished as well as it should be, the consequences are great. On one hand, the ships start queuing up, hence, increasing sharply the cost of ship waiting time and on the other hand, the food availability for RWH's decreases, causing stockouts to increase. Thus, this index could represent the effectiveness of various policies. It is modeled in subroutine CONTROL.

2. The total cost of operations which consists of all the costs incurred in all the activities as discussed in Chapter II. Equation 5.2 presents this measure.

$$TOTCOST(t) = TFCOST(t) + CVTRNS(t) + CVAINV(t) + CVLOAD(t) + CVULOAD(t) + CVSMPL(t) + TCSHIP(t) \tag{5.2}$$

where:

TOTCOST = total cost of operations in period (0, t) ($)

TFCOST = total fixed cost of operations in period (0, t) ($)

CVTRNS = variable cost of transportation in period (0, t) ($)

CVAINV = variable inventory cost in period (0, t) ($)

CVLOAD = variable cost of loading in period (0, t) ($)

CVULOAD = variable cost of unloading in period (0, t) ($)

CVSMPL = total cost of information in period (0, t) ($)

TCSHIP = ship waiting time cost in period (0, t) ($).

Under assumed cost coefficients (see Appendix A) the variable cost of transportation and ship waiting time cost constitute the two most important components of the cost function. They contribute more than any other cost items.

3. Balanced distribution, is an important goal of relief operations. Unbalanced rationing has usually been the cause of more fatality than scarcity of food. Manetsch (73) shows that more uniform food distribution across the population will, most of the time, result in substantially fewer deaths for all levels of the crisis. Thus, the model should be equipped to measure this important concept. Equation 5.3 represents the index for balanced distribution that should be minimized by a good control policy.

$$BALANCE(T) = \int_0^T \left[\sum_{i=1}^{4} \bar{D}_i(t)\left(Max\left(\left(\frac{S(t)}{D(t)} - \frac{S_i(t)}{D_i(t)}\right), 0.0\right)\right)\right] dt \tag{5.3}$$

where:

BALANCE = index for balanced distribution for period (0, T)

$\bar{D}_i$ = estimated regional demand at time t (tons/years)

S = sum of all regional supplies at time t (tons/years)

D = sum of all actual regional demands at time t (tons/years)

S_i = ith region's supply at time t (tons/years)

D_i = ith region's actual demand at time t (tons/years)

d = derivative operator

i = RWH index

T = time length of operations (years)

t = continuous time index.

As shown in the above equation, if the ratio of supply to demand for some region is greater than the country's ratio, the measure does not change. Also, the contribution of regions with greater demand to the measure of balance tends to be higher than that of regions with smaller demands. The position of the summation and the integral in Equation 5.3 can be changed. Then any term of the summation represents the total contribution of a specific region to the total balance index. These terms are also modeled in order to give a better picture of policy experiments to the decision makers.

The second category of performance measures are indicative of certain components of the logistics system. These measures, in some way, guide the policy makers toward better policy design in order to improve general performance indices. A brief discussion of each of them will follow.

One of the most important measures is the regional stockout. This index is modeled for each RWH separately. It indicates the total time that regional demand has not been fully satisfied. Equation 5.4 describes this criterion.

$$STKOUT_i(t + DT) = STKOUT_i(t) + DT \tag{5.4}$$

where:

STKOUT = total time when demand is greater than supply in period (0, t + DT) (years)

DT = simulation cycle increment (years)

i = RWH index.

The above index is a measure of "smoothness" in time, but it does not show the quantity differences of supply and demand. It does not say whether 95% of demand has been satisfied or 5%. To see their differences, another index is calculated for each regional silo, represented by Equations 5.5. Here the ratio of total supply to total demand is computed over a specified period.

$$TSUPPLY_i(t + DT) = TSUPPLY_i(t) + SUP_i(t) * DT \tag{5.5a}$$

$$TDEMAND_i(t + DT) = TDEMAND_i(t) + DEM_i(t) * DT \tag{5.5b}$$

$$PRODEM_i(t + DT) = TSUPPLY_i(t + DT)/TDEMAND_i(t + DT) \tag{5.5c}$$

where:

PRODEM = ratio of supply to demand for period (0, t + DT)

SUP = supply rate at time t (tons/years)

DEM = actual demand rate at time t (tons/years)

TSUPPLY = total supply for period (0, t) (tons/years)

TDEMAND = total demand for period (0, t) (tons/years)

DT, i = as in Equation 5.4.

This measure is always less than or equal to one.

There are several idle time indices computed for various resources which help decision makers to recognize the bottlenecks caused by limitations of these resources and capitals. They are,

- idle time of the ship service center when no ship is in the harbor
- idle time of ship offloading equipment due to overage storage capacity at the port
- idle time of trucks/drivers and loading equipment at port when a grain shortage exists
- idle time(s) of drivers (trucks) and port loading equipment when there is a shortage of trucks (drivers).

Note that if there is a shortage of more than one resource, all appropriate indices are increased. Also, the above measures are indications of time and not quantity. For example, when there is a shortage of trucks, this means that the trucks are the limiting factor in fulfillment of the manager's decision. To get a feeling of the degree of utilization of port facilities, the following two measures are also modeled.

- total times when the port's unloading and loading facilities are working at their limit capacities.

The last, but not least significant measure is the average per ship waiting time. It is modeled by the following equations.

$$TWT(t + DT) = TWT(t) + IWL(t) * DT \tag{5.6a}$$

$$AVTWT(t) = TWT(t)/INTOT(t) \tag{5.6b}$$

where:

TWT = total waiting time of all ships in period (0, t + DT) (years)

IWL = length of ship queue at port in period (t, t + DT) (#)

AVTWT = average per ship wait time at time t (years)

INTOT = number of ship arrivals to the harbor in period (0, t) (#)

DT = length of time increment (years).

In light of the fact that this dissertation is concerned with famine relief operations, THRUPUT (Equation 5.1) and AVTWT are very important in determining system stability. The most crucial condition of a successful operation is to get the grain to the famine victims, so THRUPUT must be close to the amount of grain expected (YRTONS in the model). Long ship waiting times would discourage donors from going back for further grain. Service center and port equipments idle times are factors to consider in normal conditions but become secondary in a famine. Similarly, idle times of center and loading equipment caused by storage inadequacies and the length of the ship waiting line (IWL) are important, but only in the sense that they affect THRUPUT and AVTWT.

There are some state variables which are good indicators of performance and also can be helpful in policy design. They are: length of the ship waiting line (IWL), current port storage (STOG), number of trucks (TPOL) and drivers (DPOL) in the pools at port waiting to be loaded, current storage at RWH's ($RWSTOG_i$), the amount of grain that has passed through each RWH into various regions ($RTRUPUT_i$), and number of trucks waiting to be unloaded at each RWH ($TRPOL_i$). Since capital has been modeled as continuous time and the number of trucks and drivers in the syatem are changing continuously, it is not possible to measure capital utilization in the usual sense. But there are two state variables which can be used for this purpose. They are number of trucks (TPOL) and drivers (DPOL) in pools at the port waiting to be loaded. Inputs to these pools are the capital returning from RWH's and the capital acquired by capital acquisition decision rule.

The desired situation, that means when the capital's utilization is maximum, happens when TPOL and DPOL are at their minimum. Thus the ideal situation is when the delays of trucks and drivers in the pools are minimum. Hence, behavior of TPOL and DPOL functions over time should reflect the accuracy and robustness of capital acquisition policy and the degree of capital utilization.

Control and Decision-Making Model

The purpose of this section is to describe the process of decision-making and control in logistics operations and how this process has been modeled in the current study. This component can be described as the "brain" of the model. The actions and results of other components will not accomplish anything without the existence of this part. It coordinates all the activities for better efficiency in logistics efforts. Chief functions of this component are the distribution of available food to different regions and capital acquisition planning. Its decisions are constrained by budget limitation, available food, time lags in transportation, and time lags and errors in the information.

A general description of the decision-making component and important factors influencing this process are given in Figure 5.2. As shown, the model simulates the regulation of stock levels and food releases in both the port and the RWH's. Port and RWH models and transport delay among them were discussed in Chapter II. Also mentioned in that chapter were the capital acquisition model and simulation of lags and errors in the data gathering and estimation process. Figure 5.2 puts all of these various components together from the information and decision flows point of view.

As shown in Figure 5.2, the model assumes no delay for receiving information such as regional stock levels and road conditions. Also no delay has been assumed between making a decision and its implementation. These assumptions are based on the following rationale. As was modeled in Chapter II, the storage levels at RWH's do not play an important role in the decision-making process. The demand estimates are the prime pillars of decisions. Also the length of delay for implementation of a decision is negligible in comparison with other delays such as transport, sampling and communication.

Note that the managers and decision makers are located at the port. The actual decision rules and policy parameters will be discussed in the next section. This part should have clarified and laid the grounds upon which those decisions are based.

Policy Structure

Service performance and total cost expenditure are two policy considerations in the design of logistical support systems. The challenge is the establishment of a balance between these two such that the desired

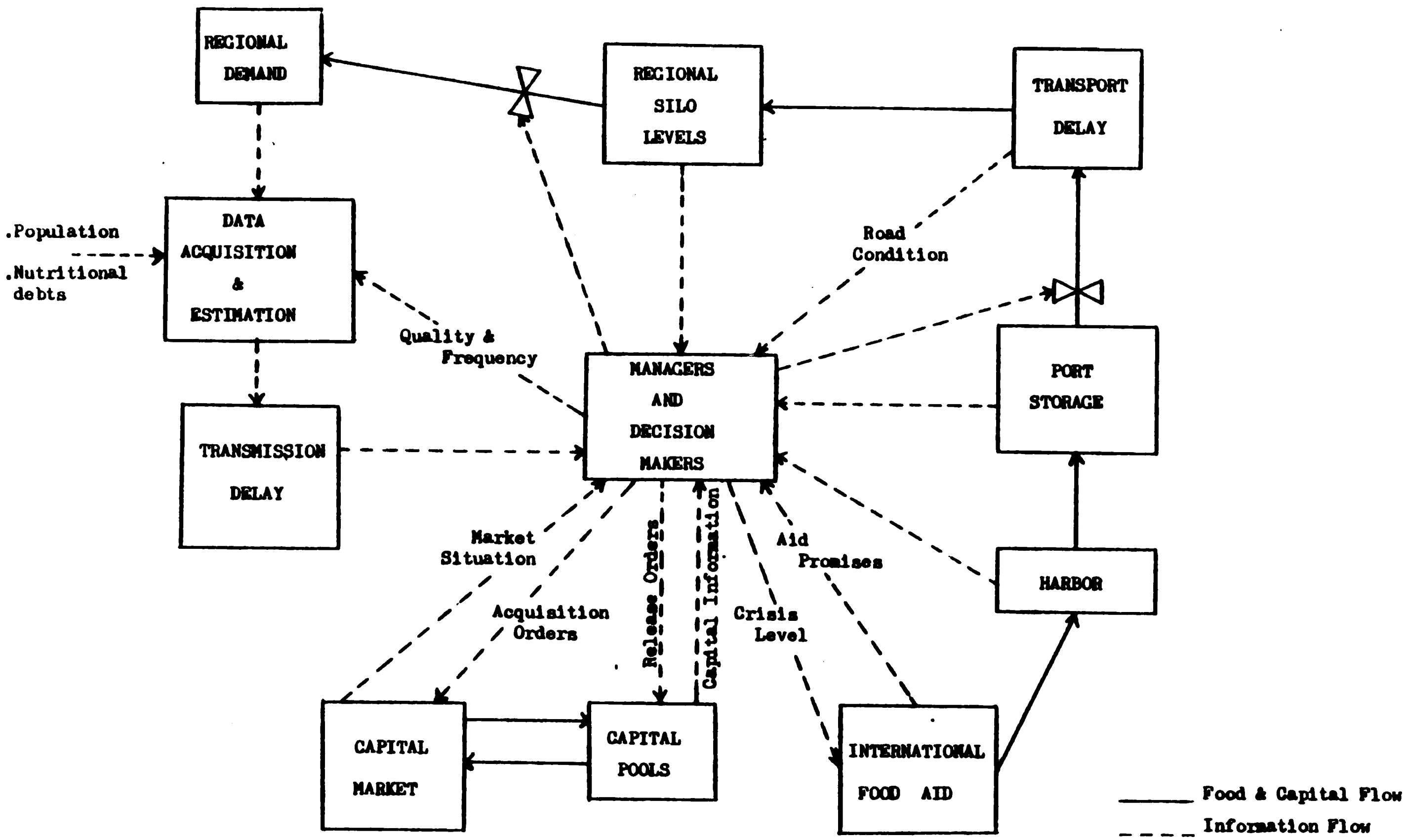

Figure 5.2. General Description of the Decision Making Component

returns on specified goals are attained. This balance is the logistical policy base which in turn provides the managerial mandate for guiding policy structure. The underlying concept for better logistics is doing more with less through continual striving for the most effective management of resources. It is clear that performance and logistical cost have a direct relationship. Reasonable balance between them is typically the best policy.

Policy structure and information acquisition are intertwined. The success of implemented policies depend on the quality and quantity of information received. Model results show that lags and errors in data gathering play important roles in determining the effectiveness of policy actions. It is important to realize in the policy formulation stage that the only data available during the crisis is the estimated values of actual dynamic variables and a priori knowledge of probable variable movements. This is especially important, because both the actual and estimated data flows are typically present in a computer simulation. The use of either "true" or estimated value of the variables follows their natural relations in the real world. Most man-made decisions require the estimated values of the variables involved in that process. Sometimes, for simplicity, the true value of information is used instead of the estimated one, if the error is small or unimportant to the problem being considered.

A desirable attribute of a policy is its simplicity. It should be noted, however, that "simple" does not necessarily mean "ineffective." As control becomes more complex, more parameters come into play, making the process of finding better control harder by expanding the domain of all combinations of policy alternatives. Another important characteristic of any decision rule is its generality. This is quite true, especially, with respect to the current study. As discussed earlier, the knowledge about demand and supply is incomplete. The decision makers and managers are facing a lot of uncertainty. These ought to be reflected in the modeling of the control component of the logistics system. Indeed, a decision rule should be able to handle a wide spectrum of scenarios, if not all.

The above discussion on policy generality should be kept in mind during analysis of the model results. Since the model has not been designed for a specific country, it might be possible to achieve a better policy rule and consequently, better results if the model is implemented for a specific case.

Two Main Decisions

The goal of the logistics effort is to achieve a desired level of performance at the lowest possible cost expenditure. In an earlier section the discussion concerned the performance measures which are going to be used to evaluate various policies. Since there are different and contradictory objectives a pareto optimum solution should be searched for this problem. Managers' decisions are based on the information they receive. These data streams have been shown in Figure 5.2. The two most important ones are the estimated regional demands and expected amount of food donated.

Two major decisions must be made by decision makers during the crisis. One is the acquisition of capital and the other is food distribution. These decisions must support the achievement of the logistical and overall relief operations goals which were formulated as performance indices in this study. A detailed description of various forms that the above decisions could take and a discussion on consequences of each policy rule are presented in the next sections. Apart from the information assumed available to decision makers, a priori knowledge and managerial intuition are the basis for these policy formulations. Various decision rules are explained first. Then the results are discussed.

Food Allocation Policies

Having current information about available grain and capitals in the port, managers have to decide about how to distribute and allocate these resources such that the desired outcomes are achieved. The regional demand estimates are the only available data assumed to consist of all the necessary information such as food demand, population, nutritional debt, etc. The storage levels at RWH's are also known. Thus the policies are primarily based on this information.

Various constraints hinder the effectiveness of allocation decisions. The error involved in the estimation process of regional demands and transmittion delay on one hand and transportation lags on the other hand block the fulfillment of the policies. Apart from the data on regional demands and storage levels, one important concept should underlie the allocation policies. Trying to avoid the high cost of ship waiting time and to reduce the effects of the errors in the demand estimates and various lags in the model, regional silos should be kept "well" stocked. This policy guideline is effective whenever there is excess supply to demand. Unexpected and unknown fluctuations in demand and population movements can be encountered to some extent, if the regional storages are used as a "buffer".

The above discussion leads to two general policies on food allocation. The first one was used in all the sensitivity and validation tests in Chapter IV.

1. In this policy, the information about the regional demand has not been used at all. A "need" index is calculated based on each RWH's capacity and storage level, which indicates how much grain should be sent to that RWH. This is a simple but very important policy alternative for two reasons. First, it can be used as a basis for evaluation of other policies and second, it shows how important the data on estimated demands is. This policy is explained by the following equations.

$$SCALE_i = CTRL_i * RCAPWH_i \tag{5.7}$$

$$RSTGMTY_i(t) = (SCALE_i - RWSTOG_i(t))/DT \tag{5.8}$$

where:

SCALE = desired level of full storage (tons)

RCAPWH = capacity of regional silos (tons)

CTRL = control parameter

RSTGMTY = regional "need" based on the desired storage level at time t (tons/years)

RWSTOG = available grain in storage at time t (tons)

DT = length of time increment (years)

i = RWH index.

Note that RSTGMTY will become equal to zero if RWSTOG is greater than SCALE. This is based on the assumption that the "need" index is always greater than or equal to zero. The period when the "need" index is less than zero is usually very short and negligible in a famine situation. Otherwise this information can be used for possible transshipment. Equation 5.9 computes this "need" index.

$$GNEED_i(t) = CCRS_i * RSTGMTY_i(t) \tag{5.9}$$

where:

GNEED = grain "need" of ith RWH at time t (tons/years)

CCRS = control parameter

RSTGMTY = regional "need" based on desired storage level at time t (tons/years)

i = RWH index.

Available food is then distributed, based on "need" indices, by the following equations.

$$TOTNEED(t) = \sum_{i=1}^{4} GNEED_i(t) \tag{5.10}$$

$$GRWH_i(t) = (GNEED_i(t)/TOTNEED(t)) * R2(t) \tag{5.11}$$

where:

TOTNEED = total regional needs at time t (tons/years)

GRWH = assigned food to the ith RWH at time t (tons/years)

R2 = port's truck loading rate at time t (tons/years)

GNEED, i = as in Equation 5.9.

2. In the second food distribution policy the regional "need" is based on both estimated demand and regional storage level. In this policy, given the amount of available food for distribution, each regional demand is satisfied first. Then, if anything is left, the rest is allocated proportional to the estimated demands given that

regional silos are below some desired level. If the available food for distribution is less than the sum of estimated demands, it is allocated proportional to each estimated demand.

Here, the "need" index consists of two parts, one part for the estimated demand and the other for possible desired regional silo level. At first, the total estimated demand (TOTDEM), which is the sum of all the estimated regional demands (DEMEST), is subtracted from the total available food for distribution, represented by the truck loading rate at port (R2). If the result is positive, then the extra food is allocated proportional to the estimated regional demand. In the following equations the same variables used in the first policy have been used for easier modeling, but care should be taken to distinguish between different definitions.

$$TOTDEM(t) = \sum_{i=1}^{4} DEMEST_i(t) \tag{5.12a}$$

$$REST(t) = R2(t) - TOTDEM(t) \tag{5.12b}$$

where:

TOTDEM = total estimated demand at time t (tons/years)

DEMEST = regional estimated demand at time t (tons/years)

R2 = truck loading rate at the port at time t (tons/years)

REST = dummy variable representing extra available food at time t (tons/years)

i = RWH index.

If REST is less than or equal to zero, the "need" index's second part, meaning the extra allocated food, becomes zero and available food is distributed based on the following equation.

$$GRWH_i(t) = (DEMEST_i(t)/TOTDEM(t)) * R2(t) \qquad (5.13)$$

where:

GRWH = allocated food to the ith RWH at time t (tons/years)

All others as in Equations 5.12.

Now, if REST is positive, each estimated regional demand is going to be satisfied. In addition, the extra available food is allocated by using the following equations.

$$GNEED_i(t) = \begin{cases} DEMEST_i(t) \\ 0.0 \text{ if } RWSTOG_i(t) \geq CCTRL_i * RCAPWH_i \end{cases} \qquad (5.14)$$

where:

GNEED = regional "need" based on the desired storage level at time t (tons/years)

RWSTOG = available grain in regional storage at time t (tons)

RCAPWH = capacity of regional silos (tons)

CCTRL = control parameter

DEMEST = regional estimated demand at time t (tons/years)

i = RWH index.

Then REST is allocated as follows.

$$TOTNEED(t) = \sum_{i=1}^{4} GNEED_i(t) \qquad (5.15a)$$

$$RGNEED_i = (GNEED_i(t)/TOTNEED(t)) * REST(t) \qquad (5.15b)$$

where:

TOTNEED = total regional "need" based on desired storage level at time t (tons/years)

RGNEED = allocated extra food based on the estimated regional demand at time t (tons/years)

REST = extra available food at time t (tons/years)

GNEED, i = as in Equation 5.14.

Hence the total allocated food for each regional warehouse is obtained by the following equation. This equation is comparable to Equation 5.13.

$$GRWH_i(t) = RGNEED_i(t) + DEMEST_i(t) \tag{5.16}$$

where:

GRWH = allocated food to the ith RWH at time t (tons/years)

RGNEED = extra allocated food based on the estimated regional demand at time t (tons/years)

DEMEST = regional estimated demand at time t (tons/years)

i = RWH index.

No matter which one of the policies has been used, the following equation calculates the total assigned grain to various RWH's.

$$TGRWH(t) = \sum_{i=1}^{4} GRWH_i(t) \tag{5.17}$$

where:

TGRWH = total food assigned to various RWH's at time t (tons/years)

GRWH, i = as in Equation 5.11 or 5.13 or 5.16.

Capital Acquisition Policies

The capital development model was described in Chapter II. The purpose of this section is to find the desired amount of capital (trucks and drivers) needed (¥D in Figure 2.6). In order to carry the available grain assigned by previous policies into the country's interior and to be able to reduce the ship waiting line thus reducing the corresponding cost, "enough" capital is needed. Results of seaport operations (65) indicate that to avoid excessive buildups, the output rate from port's silo to land transport must be considerably larger than the expected input rate of grain in ships. The implication is that adequate transportation is essential for the operation of any allocation policies.

There is an important concept underlying the logistics operations and capital acquisition policies. It is the fact that capital is needed to deliver goods, not to satisfy the demand. Thus, the data which is available and usable for managers in their decisions for capital are: expected grain arrival (YRTONS), ship waiting line in the harbor (IWL), and available grain in the port's storages (STOG), the "supply" sources.

The use of expected grain arrival rates as the base for capital development policies needs some explanation. In the real world and at the time of crisis, the managers are usually notified by the donors of the aid. Then, it takes some time for the aid to reach its destination, meaning the port in this model. This gives the managers a buffer time to make the appropriate decision about the needed capital. Thus, the expected grain arrival becomes almost an exact information (taking into consideration the probable inconsistencies and events) and does not need sampling and estimation. This lead time knowledge is a very important factor in the overall picture of famine logistical decisions as will be seen later. It depends on many factors, including ship loading time at the origin, the distance between the origin and destination of aid, ships characteristics, weather conditions, etc. For example, assuming a ship speed of 15 miles per hour, the approximate 8000 mile distance between the United States and India results in a 22 day lead time.

There are, also, various constraints on capital acquisition decisions. As discussed in Chapter II, the foremost constraint is the limiting rate of capital acquisition, TRLIMIT. The effect of capital acquisition delay (see Figure 2.6) can practically be removed by the lead time information on the food arrival rate. TRLIMIT computation varies country by country and in each case the system planners should decide how they are going to cope with capital shortages. Using this model, they can foresee the severity of the problem and design a policy for its solution, for example, trying to acquire capital with lower possible rate and stock pile it. Of course, this higher capital inventory will increase the cost, but it reduces the risk of running short of needed capital. The TRLIMIT computation, in the current model was explained in Chapter II.

It was mentioned in Chapter I that famine has some early warning indicators and by recognizing and using them, the consequences of the disaster will be far less than what they could be. Usually, a central decision-making unit is set up by the country's authorities to handle the crisis. One of the first actions taken by this unit is acquisition of capital. The data on aid lead time comes into play here. The decision makers, knowing when the first shipments of food are arriving, try to have enough capital to handle these arrivals. Thus, the capital decision-making process starts here and ends when the crisis is considered to be over. This makes capital acquisition policies different from food distribution ones. Later policies become effective after food arrival.

Capital development policies in the current study are modeled in two stages; one for the initial phase, i.e., before the food arrival and the other, for after the food arrival and up to the end of the crisis. This stems from the fact that different circumstances and information exist in the above stages. But before analyzing various policies in two stages, an important question should be answered. How will the information on the food arrival rate be transformed into the desired number of trucks and drivers? This question will be answered in the next section, followed by capital acquisition policies in different stages.

Conversion Factor

To find a conversion factor which transforms data on expected food arrival into the desired amount of capital, one should start with the fact that all of the received aid is going to be sent to various regions, thus forming the food flows on different roads. Dividing these flow rates by the capacity of each truck (TGRC) results in full truck flows. In a steady-state, the number of trucks needed to keep these flows going is obtained by the product of full truck flows by the total delay time, related to capital flows, in the logistics system.

The sum of all food flows is equal to the amount of available food for distribution which itself is equal to the expected food arrival rate (YRTONS) in a steady-state. Thus, instead of multiplying each flow rate with its delay time, the sum of all full truck flows, obtained from YRTONS is multiplied with a weighted average of all delays in four existing cycles. A cycle is defined as the route which one truck travels when it is going from the port to a RWH and back. This weighted average of the delays, called SUMDEL, is time-varying and different procedures are used for its computation depending on which stage of capital development process it is concerned with. Thus it seems more appropriate that each procedure is explained together with its corresponding capital acquisition stage. No matter which method is used, Equation 5.18 gives the conversion factor needed to obtain a desired number of trucks from the expected food arrival rate.

$$\mathrm{CONVFAC}(t) = \mathrm{SUMDEL}(t)/\mathrm{TGRC} \tag{5.18}$$

where:

CONVFAC = conversion factor at time t (years/tons)

SUMDEL = weighted average of all delays in four cycles at time t (years)

TGRC = capacity of a truck (tons).

Note that TGRC in Equation 5.18 is needed to obtain the full truck flow from grain flow. The conversion factor and SUMDEL computations are modeled in subroutine CONVDEL in Appendix B.

Initial Capital Development Stage

The purpose of this stage is to have "enough" capital ready for the start of operations when the first shipments of aid begin to arrive.

This capital accumulation process should take place such that minimum cost is attained. The duration of this stage varies case by case, but three important factors are the main determinants of it. One is the buffer time between the receiving of the food promise by a donor and actual arrival of the food at the port. The second factor is TRLIMIT, the limiting rate of capital acquisition. The third is the capital acquisition delay.

After the decision making unit is set up, the managers, based on the food buffer time and TRLIMIT will decide on an appropriate control strategy such that the needed amount of capital is ready on time and the cost is minimal. This makes the duration of this stage of capital development time-varying. Now, if TRLIMIT is low, managers start stocking the capital sooner and vise versa. In the current study, this initial stage has been modeled (in the subroutine CAPITAL) such that the desired amount of capital is available for the start of operations. Thus, the effect of changes in TRLIMIT, capital acquisition delay, and food arrival lead time, is to change the duration of this stage of capital development; hence, the cost of acquired capital.

The initial process of capital acquisition goes as follows. First the initial food arrival rate ($t = 0.0$) is computed from the supply function (subroutine FOODAR). This rate, times the appropriate conversion factor, gives the initial desired number of trucks (TYD). This desired amount of capital becomes the input to the capital acquisition model developed in Chapter II. TYD remains constant during this stage, making the control problem a regulator one, in which an attempt to make the output of the capital development model equal to its input is made (see Figure 2.6). Except for the process of determining desired amounts of capital, two stages of capital acquisition are similar, because both use the capital model of Chapter II. More on this subject will be discussed in the next section. But the question of a conversion factor for this stage still remains to be answered. The end of this stage in the current logistics model, signals the start of operations.

The conversion factor for this stage is constant. The total delay on each cycle consists of the sum of the travel delays from port to a RWH and back to port, plus the expected service time at RWH and delay due to an "overnight" stay of trucks and drivers. Travel delay is computed given the appropriate speed and distance by using the subroutine DELAY (Equation 2.47). Expected service time at a RWH is given by Equation 5.19.

$$ESTIME_i = 1./(RMSS_i/TGRC) \qquad (5.19)$$

where:

ESTIME = expected service time (years/truck)

RMSS = maximum offloading rate at RWH (tons/years)

TGRC = truck capacity

i = cycle index.

Then each cycle's total delay is computed as follows.

$$DEL_i = ESTIME_i + DISDEL_i + DELF_i \qquad (5.20)$$

where:

DEL = total delay of a cycle (years)

DISDEL = sum of the travel delays in a cycle (years)

DELF = delay due to overnight staying of trucks and drivers at RWH's (years)

ESTIME, i = as in Equation (5.19).

Since in this stage the only available information about different regions is their approximate populations, each region's population has been used as its weight in the SUMDEL computation, given by following equation.

$$SUMDEL = (1/TPOP) * \sum_{i=1}^{4} POP_i * DEL_i \tag{5.21}$$

where:

SUMDEL = weighted average of all delays in four cycles (years)

TPOP = total population of the country (#)

POP = regional population (#)

DEL, i = as in Equation (5.20).

Now using Equation 5.18, the conversion factor is obtained. Remember that the desired number of trucks and drivers are equal in this stage. The capital pools at port (TPOL and DPOL) are incremented as new capital is acquired.

Capital Development During the Crisis

In this stage different information becomes available to the decision makers. The food arrival rate and the delay on each cycle become time-varying. All of these make the desired amount of capital a function of time. This stage starts, as the initial stage ends, and it lasts to the end of the crisis. Availability of other information makes possible the generation of various policies for determining desired amounts of capital. These policies form the core of capital acquisition processes which will be combined with food allocation decisions in order to give the overall logistical policy structure. Due to their importance, they will be discussed separately. The effect of each of these general capital policies will be the same on the number of trucks and drivers. The purpose of this section is to clarify the existing differences in calculating the desired amounts of different capitals.

Assume that the desired amount of capital (YD) has been given by one of the capital acquisition policies in the second stage. This number will be given as an input to the subroutine CAPITAL, which is used as the basis for calculating the desired numbers of trucks and drivers. Various modifications become necessary at this time. A new element appears in the cycle of each truck and driver, which was not present in the first stage. As it was discussed in Chapter II, certain percentages of trucks and drivers leave the system temporarily upon arrival from different RWH's. Trucks go to repair shops and drivers take a leave. The total number of trucks currently in repair and the total number of drivers on leave should be accounted for in capital acquisition decisions.

Another important factor is truck attrition. Some percentage of the total trucks in the system goes out of work due to various reasons. No attrition for drivers has been assumed. This factor should be taken into consideration by the decision makers when they are computing the desired amount of capital. The following equations are the final form of the desired numbers of trucks and drivers, which will be used as inputs to the capital acquisition model developed in Chapter II.

$$TYD(t) = (.1 + DT * TATTC) * (YD(t) + TTIRS(t)) \tag{5.22}$$

$$DYD(t) = YD(t) + TDOL(t) \tag{5.23}$$

where:

TYD = desired number of trucks at time t (#)

YD = desired amount of capital derived from one of the capital acquisition policies at time t (#)

TTIRS = number of trucks in the repair shop at time t (#)

DYD = desired number of drivers at time t (#)

TDOL = number of drivers on leave at time t (#)

TATTC = attrition coefficient

DT = length of time increment (years).

Note that the conversion factor, which will be explained for this stage, has been used in deriving the YD. After computing the desired amount of capital, two stages of the capital development process use the same set of equations, in order to obtain the output of the capital acquisition model of Chapter II, which is the actual number of trucks in the system given by Equation 2.57. Of course, this equation is modified for trucks in order to take into account the attrition rate, as explained by the following equations.

$$\mathrm{ATTRATE}(t) = \mathrm{TATTC} * Y(t) \tag{5.24a}$$

$$Y(t + DT) = Y(t) + DT * (U(t) + YN(t) - \mathrm{ATTRATE}(t) - \mathrm{TRLOST} * Y(t)) \tag{5.24b}$$

where:

ATTRATE = attrition rate at time t (#/years)

TATTC = attrition coefficient

Y = actual number of trucks in the logistics system at specified time (#)

U = rate at which new trucks are added to the system at time t (#/years)

YN = rate at which trucks are discharged from the system at time t (#/years)

TRLOST = capital lost coefficient

DT = length of time increment (years).

The same Equation 2.57 is used for drivers

$$DY(t + DT) = DY(t) + DT * (DU(t) + DYN(t) - TRLOST * DY(t)) \quad (5.25)$$

where:

DY = actual number of drivers in the logistics system at specified time (#)

DU = rate at which new drivers enter the system at time t (#/years)

DYN = rate at which drivers are discharged from the system at time t (#/years)

TRLOST, DT = as in Equations 5.24.

Note that Y and DY are the end results of the capital acquisition model in Chapter II, with TYD and DYD (Equations 5.22 and 5.23) as its inputs.

At every simulation cycle (DT), the actual amount of capital is checked against its past value. There are two possibilities. Either the result is positive, meaning more capital should be acquired, or negative, meaning that a lower amount of capital is needed and the excess capital should be released. When capital is increased, corresponding pools at port are also increased, but there must be enough capital in the pools permitting the discharge decision to be fulfilled. As it was said in Chapter II, two variables, TRLACK and DRLACK are introduced to keep track of the numbers of trucks and drivers which should be discharged upon their return from RWH's. The following equations describe the above processes.

$$\text{CHANGE}(t + DT) = Y(t + DT) - Y(t) \tag{5.26a}$$

$$\text{TPOL}(t + DT) = \text{TPOL}(t) + \text{CHANGE}(t + DT) + \text{TRLACK}(t) \tag{5.26b}$$

$$\text{DCHANGE}(t + DT) = DY(t + DT) - DY(t) \tag{5.27a}$$

$$\text{DPOL}(t + DT) = \text{DPOL}(t) + \text{DCHANGE}(t + DT) + \text{DRLACK}(t) \tag{5.27b}$$

where:

CHANGE = difference between current and past values of actual number of trucks in the logistics system (#)

Y = actual number of trucks in the logistics system at specified time (#)

TPOL = number of trucks in the port's pool (#)

TRLACK = number of trucks whose discharge has been delayed at time t (#)

DCHANGE = number of drivers which are either acquired or will be discharged in period (t, t + DT) (#)

DY = actual number of drivers in the logistics system at specified time (#)

DPOL = number of drivers in the port's pool (#)

DRLACK = number of drivers whose discharge has been delayed at time t (#).

Now, TPOL and DPOL are checked. If they are positive, TRLACK and DRLACK will become zero. But if they are negative, that means the decision is to discharge more capital. Note that one or both of them (TPOL and DPOL) can be negative. In this case the corresponding variable (TRLACK or DRLACK) will be equated with the negative amount of capital in the pool (trucks or drivers) and TPOL or DPOL or both will become zero.

Main Acquisition Policies

The conversion factor for this stage of the capital development process is time-varying. It basically consists of the same elements of the first stage's conversion factor. The time-varying element is introduced into it by the delay of the trucks waiting to be unloaded at RWH's. Also, different and time-varying weights are used here for SUMDEL computation. In order to compute the delay of waiting trucks at RWH's, the following fundamental principle of queuing theory (steady-state condition) has been used.

$$L_q = \lambda W_q \qquad (5.28)$$

where:

L_q = expected queue length

W_q = expected waiting time in queue (excluding service time) for each individual entity

λ = mean arrival rate (expected number of arrivals per unit time).

For the delay computation, W_q is needed. Approximate L_q and λ are obtained from the model, using the following equations which have been modeled in the subroutine SILOS.

$$CIQS_i\ (t + DT) = CIQS_i(t) + TRPOL_i(t) \qquad (5.29)$$

$$TAR_i(t + DT) = TAR_i(t) + TRP_i(t) \qquad (5.30)$$

where:

CIQS = incremental sum of the number of trucks waiting to be unloaded at RWH in period (0, t + DT) (#)

TRPOL = number of full trucks waiting to be unloaded at RWH at time t (#)

TAR = incremental sum of the total truck arrivals in period (0, t + DT) (#)

TRP = number of trucks arrived at time t (#)

i = RWH index.

Then, waiting time delay is given by Equation 5.31 (modeled in subroutine CONVDEL).

$$X_i(t) = CIQS_i(t)/TAR_i(t) \qquad (5.31)$$

where:

X = expected waiting time in the queue at time t (years/truck)

CIQS, TAR, i = as in Equations 5.29 and 5.30.

Now, using Equations 5.20 and 5.31, each cycle's total delay for the second stage of the capital acquisition process is calculated as follows.

$$DEL_i(t) = X_i(t) + ESTIME_i + DISDEL_i + DELF_i \qquad (5.32)$$

where:

DEL = total delay of a cycle at time t (years)

X = expected waiting time in queue at time t per truck (years)

ESTIME = expected service time per truck (years)

DISDEL = sum of the travel delays in a cycle (years)

DELF = delay due to overnight stop of trucks and drivers at RWH's (years)

i = RWH index.

There is more information available at this stage than the first one. Hence, different weights can be used in order to compute SUMDEL. In the current model, total number of trucks in each cycle has been used as given by the following equation.

$$W_i(t) = TRPOL_i(t) + PTSTRG_i(t) + FTSTRG_i(t) + RTSTRG_i(t) \tag{5.33}$$

where:

W = ith cycle delay weight at time t

TRPOL = number of trucks in regional offloading facilities at time t (#)

PTSTRG = number of trucks on the way to a RWH at time t (#)

RTSTRG = number of trucks on the wav back to the port at time t (#)

FTSTRG = number of trucks stopping for overnight at a RWH at time t (#)

i = cycle index.

Then, Equation 5.34 gives the SUMDEL for this stage of the capital acquisition process.

$$SUMDEL(t) = (1/TW(t)) * \sum_{i=1}^{4} W_i(t) * DEL_i(t) \tag{5.34}$$

where:

SUMDEL = weighted average of all delays in four cycles at time t (years)

TW = sum of four cycle weights at time t

W = cycle delay weight at time t

DEL = total delay of a cycle at time t (years)

i = cycle index.

Again, using Equation 5.18, the conversion factor is obtained. In the case of road breakdown and transshipment the above formulas are modified. These modifications affect the total delay of each cycle by changing DISDEL, the sum of the travel delays in a cycle such that old distances are replaced by new ones. Delays on the old road are added to the corresponding cycle, as long as there are trucks left on that road. Also, the number of trucks on the broken road is added to the corresponding cycle's weight.

Other weight candidates usable in the above formulas are regional estimated demands. The model was tested using each regional estimated demand (DEMEST) as a corresponding cycle delay weight (W). Better system performances were achieved using a regional flow of trucks (Equation 5.33), but the differences were not significant. In computation of the sum of the delays in a cycle, the delays at port pools and port loading facilities were not included due to the following reasons. First, considering the port loading capacity, loading time delay for a truck is negligible. Second, in an efficient system, delay at pools should approach zero as was discussed in the performance indices section. A bigger SUMDEL means more capital. Thus, if the pool delays are included in the conversion factor, more capital is going to be acquired, adding to the inefficiency of the system. Finally, note that the repair shop delay and the delay of drivers on leave, are not part of a cycle, since just a fraction of the total flow passes through them. But the desired amount of capital is compensated for in these delays, as seen in Equations 5.22 and 5.23.

Having had the conversion factor, various capital development policies are now discussed. There are six such policies in this stage (modeled is subroutine CONTROL) which provide a good control action range for the decision makers. Each one of these policies will be an input (YD) to the CAPITAL subroutine which then is used to compute the desired amount of capital (Equations 5.22 and 5.23). These policies will now be described.

1. To begin with, one naturally chooses to continue the first stage policy. In fact this control rule is the basis of all other policies of the second stage. This policy provides the major part of the needed capital. Other policies are used to cover the shortcomings of this policy. Equation 5.35 explains it.

$$CAPNEED(t) = CPEFA * YM(t) * CONVFAC(t) \tag{5.35}$$

where:

CAPNEED = the amount of capital needed at time t (#)

YM = expected rate of food arrival at time t (tons/years)

CONVFAC = conversion factor at time t (years/tons)

CPEFA = control parameter.

The same formula excluding CPEFA was used for the first stage of the capital acquisition process with a constant CONVFAC and YM evaluated at zero (initial value).

This policy should be enough if everything goes as planned, but random events, the stochastic nature of the control problem, restrictions on different resources, and imperfect information change the picture. Even though excess capital is not desired (increase in total cost), in a famine situation the shortage of capital has a greater impact than an excess of it. If there are more trucks or drivers than needed, the extra can be discharged easily, but what should be done if there was a shortage of them? Thus there should be some information that decision makers can use in conjunction with the expected rate of food arrival in order to achieve a policy on capital acquisition. There are three pieces of data which will be used in the current study to construct the other policies. They are: ship waiting queue length (IWL), quantity of grain in the port storage (STOG), and quantity of grain waiting to be unloaded in the harbor (QGRAP). These state variables are chosen on the basis of the fact that the capital is needed to deliver goods, not to satisfy demand. Note that the above information was not available in the first stage of the capital acquisition process.

2. This policy, like others which will be discussed later, is a combination of the first policy with one of the above pieces of information. Here, the ship waiting line, IWL, is going to be used as the following equation explains,

$$QUE(t) = IWL(t) - QUEFLAG \tag{5.36}$$

where:

QUE = ship queue length which is going to be used in decision-making at time t (#)

IWL = actual ship queue length at time t (#)

QUEFLAG = desired ship queue length. (#)

If QUE is greater than zero, there is indication of a probable need for extra capital in order to clear the harbor. In that case

QUE becomes active, and is added to Equation 5.35 to give the following equation.

$$CAPNEED(t) = CPEFA * YM(t) * CONVFAC(t) + CPQUE * QUE(t) * AVTONS/TGRC \tag{5.37}$$

where:

CAPNEED = the amount of capital needed at time t (#)

CPQUE = control parameter

AVTONS = average tons per ship (tons/ship)

TGRC = capacity of a truck (tons/truck)

QUE = as in Equation 5.36

CPEFA, YM = as in Equation 5.35

CONVFAC = conversion factor at time t (years/tons).

3. This policy is simply the previous one with the exception that the exact amount of waiting grain is used in the policy formulation. The use of AVTONS makes the above decision rule biased toward smaller ships. The exact amount of waiting grain is calculated from equation 2.71 and modeled in subroutine CALCULT. There, it is used for cost calculation purposes. With this option, the basic capital acquisition policy (Equation 5.35) becomes,

$$CAPNEED(t) = CPEFA * CONVFAC(t) * YM(t) + CPQUE * QGRAP(t) \tag{5.38}$$

where:

CAPNEED = the needed capital at time t (#)

QGRAP = total quantity of waiting grain at harbor at time t (tons)

CPEFA, CPQUE = control parameters

CONVFAC = conversion factor at time t (years/tons)

YM = expected rate of food arrival at time t (tons/years).

4. The storage at port is an important indicator of the smoothness of the port's operations. High storage levels show that the grain is not leaving the port fast enough, forcing the offloading equipment to be underused and the ship queue to grow. This can happen either from a low demand or a shortage of capital. In any case this information should be utilized in policy construction. The fourth policy uses the port's storage along with Equation 5.35 as follows. First the threshold amount of grain is reduced from the current level, and then the remainder is used,

$$ASTOG(t) = (STOG(t) - TRSHOLD * CAPWH) / TGRC \qquad (5.39)$$

$$CAPNEED(t) = CPEFA * CONVFAC(t) * YM(t) + CPTND * ASTOG(t) \qquad (5.40)$$

where:

ASTOG = available storage at time t (tons)

STOG = total storage at time t (tons)

TRSHOLD = threshold parameter of the port's storage

CAPWH = port's silos capacity (tons)

TGRC = grain capacity of a truck (tons)

CAPNEED = needed capital at time t (#)

CPEFA, CPTND = control parameters

YM = expected rate of grain arrival at time t (tons/years)

CONVFAC = conversion factor at time t (years/tons).

5. The last two policies are combinations of the previous four ones. Combining the basic capital acquisition policy given by Equation 5.35 with the second and fourth policies results in the fifth decision rule given by Equation 5.41.

$$CAPNEED(t) = CPEFA * CONVFAC(t) * YM(t) + CPQUE * QUE(t) * AVTONS/TGRC + CPTND * ASTOG(t) \tag{5.41}$$

where:

CAPNEED = needed capital at time t (#)

YM, CONVFAC = as in Equation 5.35

QUE, AVTONS, TGRC = as in Equation 5.36

ASTOG = as in Equation 5.39

CPEFA, CPQUE, CPTND = control parameters.

This policy was used in all the sensitivity and validity tests in Chapter IV.

6. The sixth policy is the combination of the first, third, and fourth policies which is given by the following equation.

$$CAPNEED(t) = CPEFA * CONVFAC(t) * YM(t) + CPQUE * QGRAP(t) + CPTND * ASTOG(t) \tag{5.42}$$

where:

CAPNEED = needed capital by sixth policy at time t (#)

YM, CONVFAC = as in Equation 5.35

QGRAP = as in Equation 5.38

ASTOG = as in Equation 5.39

CPEFA, CPQUE, CPTND = control parameters.

Note that the last two policies blend the second, third and fourth together and give new options to decision makers.

General Logistical Policies

The combination of various food allocation (FAP) and capital acquisition (CAP) policies form the general logistical control structure. Twelve different combinations are possible from two FAP and six CAP rules. Of course, the possibilities become infinite if the values of the control parameters are taken into consideration. The purpose of this section is to discuss various results obtained from different general logistical policies in order to choose the "best" policy among them. The "pareto" optimum principle is the underlying criterion of selection.

A very important point with respect to this selection process is the fact that no optimization method has been used in this study. But the discussions and results of this chapter form the basis for optimization work. The variables which have significant influence on model results and the important range of values of each control parameter are identified in this study. Because of the multiobjectivity feature of the current control problem, any optimization work is significant by itself. But having the results of this section, the only remaining important task is the search for an optimization technique. Note that the Complex algorithm explained in Chapter III can only be used when a single objective function exists.

As the number of control parameters and their ranges increase so do the complexities of the control and optimization problems. This has been kept in mind in designing previously mentioned policies. There are twelve control parameters in this study and their descriptions are summarized in Table 5.1. From these, the first eight are the most important ones. The regional silo level parameters do not influence the model outputs significantly in the second food allocation policy. They become active whenever supply is higher than demand at the RWH level. But the story is different for the first food policy. Here, there are two parameters (CTRL and CCRS) which can influence the allocated food for each RWH and each of them alone or both together can be used.

Table 5.1. Policy Parameter List

NAME	DESCRIPTION	EQUATION	LOWER LIMIT	UPPER LIMIT
CPEFA	Capital acquisition, expected food arrival	5.35	0.0	none
CPTND	Port's storage effect	5.40	0.0	none
CPQUE	ship queue length, quantity of grain waiting to be unloaded	5.37, 5.38	0.0	none
QUEFLAG	acceptable number of ships in queue	5.36	0.0	none
$CCRS_i$	regional food allocation coefficient i=1, 2, 3, 4	5.9	0.0	none
$CCTRL_i$ $CTRL_i$	ith region's storage level control, i = 1, 2, 3, 4	5.14, 5.17	0.0	1.0

In the face of different possible policy combinations and the ranges of policy parameters as given in Table 5.1, the tasks of finding a "pareto better" control policy will be easier if policies with higher and better influence on the model are distinguished and separated from the rest. In this way the search domain becomes smaller and the computer cost decreases substantially. Otherwise, due to continuity of the ranges of control parameters, the number of policy possibilities is infinite.

In the current study, various policies were tested with different values of related parameters. Some of the better results obtained and the corresponding policies are summarized in Tables 5.2 and 5.3. Alphabetic abbreviations stand for the policy category and the numbers identify the control rule in that class. For example FAP2 stands for the second policy in the food allocation category. The parameter values these results have been achieved at are reported below each policy name. In all policy experiments with the first food distribution policy, CCRS's were equal to one and CTRL's have been equal to .9. After some initial experiments it was found that the determination of numerical values for these parameters are quite impossible without any knowledge of the demand functions. Any arbitrary choice which works and results in better performance for one case does not give the same results when the scenario changes. For example, it is better to keep low the coefficients of the third and fourth regions because their demand is half of the first two regions under the assumed demand functions. But this policy does not work when the population moves.

Thus it was concluded that with the above parameter values, on the average, this policy should result in better performance than any other choice of parameter values. But if a priori information exists on the demand function, certainly other choices are preferable. The storage level control parameters for the second food policy, CCTRL's, were kept equal to .95 in all policy experiments. Even though the experiment results are not too sensitive to these parameters, higher

Table 5.2. Averages and Standard Deviations of Overall Performance Measures for Selected General Policies (ten Monte Carlo replications)

POLICY	TOTAL COST ($)	BALANCE	SHIP COST ($)	AVE. PER-SHIP WAITING TIME (years)	THRUPUT (tons)
FAP1 & CAP1	190147475	132072	86699401	.0587	2691502
	(36365026)	(16530)	(34989284)	(.02317)	(92352)
FAP1 & CAP4	184238268	117418	74604860	.0495	2882622
(CPTND = .06)	(33452465)	(20160)	(31159149)	(.0198)	(118570)
FAP1 & CAP5	184163963	115612	75055019	.05	2869955
(CPQUE = .01, CPTND = .01, QUEFLAG = 5)	(34098110)	(20924)	(31003187)	(.01962)	(120833)
FAP2 & CAP1	184368828	85435	86627160	.0587	2694589
	(37089807)	(7556)	(35082032)	(.02336)	(86394)
FAP2 & CAP2	181428921	73101	77904218	.0522	2820276
(CPQUE = .01, QUEFLAG = 4)	(35827411)	(10809)	(31120641)	(.01998)	(107788)
FAP2 & CAP3	189339626	71389	72314137	.0483	2918394
(CPQUE = .0085)	(38048860)	(11638)	(29172926)	(.0185)	(116103)
FAP2 & CAP4	178306164	72055	73460279	.0488	2906493
(CPTND = .06)	(33184545)	(10235)	(30361543)	(.0192)	(118238)
FAP2 & CAP5	178547072	70787	73914953	.0492	2895614
(CPQUE = .01, CPTND = .04, QUEFLAG = 4)	(33564497)	(11051)	(30686857)	(.01946)	(113232)
FAP2 & CAP6	188800762	70852	71784188	.0477	2932647
(CPQUE = .0085, CPTND = .03)	(37846927)	(10959)	(29187199)	(.01852)	(117434)

* Numbers in parenthesis represent standard deviation.

Table 5.3. Averages and Standard Deviations of Regional Performance Indices for Selected General Policies (ten Monte Carlo replications)

	STOCK-OUT TIME (years)				RATIO OF SUPPLY TO DEMAND			
POLICY	RWH 1	RWH 2	RWH 3	RWH 4	RWH 1	RWH 2	RWH 3	RWH 4
FAP1 & CAP1	.9599	.9615	0.0	0.0	.7511	.7512	1.0	1.0
	(.0038)	(.003)	(0.0)	(0.0)	(.0347)	(.0346)	(0.0)	(0.0)
FAP1 & CAP4	.5426	.5459	0.0	0.0	.7761	.7757	1.0	1.0
(CPTND = .06)	(.0992)	(.0997)	(0.0)	(0.0)	(.0436)	(.0438)	(0.0)	(0.0)
FAP1 & CAP5	.6449	.6492	0.0	0.0	.7783	.7776	1.0	1.0
(CPQUE = .01, CPTND = .01, QUEFLAG = 5)	(.0375)	(.0369)	(0.0)	(0.0)	(.0438)	(.0438)	(0.0)	(0.0)
FAP2 & CAP1	.7866	.7742	.5552	.5689	.8118	.8219	.8454	.8323
	(.13)	(.1)	(.098)	(.1307)	(.0277)	(.0337)	(.0349)	(.0384)
FAP2 & CAP2	.6251	.6043	.3762	.4471	.8214	.8329	.8591	.8446
(CPQUE = .01 QUEFLAG = 4)	(.118)	(.074)	(.083)	(.0665)	(.0273)	(.0339)	(.0358)	(.0362)
FAP2 & CAP3	.5023	.4897	.3408	.3405	.83	.842	.866	.854
(CPQUE = .0085)	(.0569)	(.0524)	(.0829)	(.0573)	(.0329)	(.0398)	(.0407)	(.0388)
FAP2 & CAP4	.4508	.4084	.3459	.36096	.8298	.8412	.867	.8525
(CPTND = .06)	(.0928)	(.0853)	(.0968)	(.0982)	(.036)	(.0414)	(.0418)	(.0405)
FAP2 & CAP5	.4431	.4078	.33415	.3523	.8315	.8429	.8664	.8521
(CPQUE = .01, CPTND = .04 QUEFLAG = 4)	(.0939)	(.0936)	(.0853)	(.0794)	(.0364)	(.0422)	(.0413)	(.0395)
FAP2 & CAP6	.4207	.386	.3246	.3281	.8317	.8442	.8661	.8533
(CPQUE = .0085, CPTND = .03)	(.0905)	(.0871)	(.0859)	(.0731)	(.0363)	(.0426)	(.0416)	(.0388)

*Numbers in parenthesis represent standard deviations.

values are better because this helps the task of clearing the port much easier in periods of high supply. On the other hand, these parameters become inactive in periods during which the demand is large.

The expected food arrival control parameter CPEFA has also been kept equal to one in all policy tests. One of the underlying ideas of these experiments was to identify the important state variables which have significant impact on model results and can be used by policy makers. From different CAP policy structures, it is obvious that the desired amount of capital can be obtained by just increasing one of the coefficients. For example, CPEFA can be used alone. But in this case, these parameters should be time-varying or the result is either excess capital or a shortage of it. Also, since the magnitude of the expected food arrival is large, a small perturbation in CPEFA will result in a proportionally higher amount of capital. This is not the case when dealing with other state variables. CPEFA's equality to one also stems from the fact that, at least theoretically, if everything goes well the acquired capital based on the expected food arrival should be enough. Finally, since this coefficient was equal to one in the pre-crisis stage of capital development, it seems better, for the sake of comparison, to keep it the same in the second stage of the process too. The first food allocation policy (FAP1) was tested with few capital policies due to its poor performance. As is shown in Tables 5.2 and 5.3, there is a sharp improvement in various performance criteria as FAP1 is replaced by FAP2. It is important to remember that the above search is just a screening process, and is in no way an exhaustive one. The discussion and analysis of the results will be presented in the next section.

Policy Results Analysis

This section has two emphases. One is on the analysis of the numerical results of various policy experiments shown in Tables 5.2 and 5.3 leading to the choice of one of the policies. The other is drawing some conclusions which are useful for further extensions of this work, especially in the optimization part.

For a better understanding of the results it is good to remember the underlying basis of all designed policies. As was stated in the policy design sections, the concept of "well" stocked regional warehouses should be employed in order to achieve a better system performance. Doing so has two important implications. First, it covers for errors inherent in the estimation process of regional demand in the case of a sudden increase in actual demands, meaning better service from the logistical point of view. Second, it causes the port to clear faster, resulting in a shorter ship waiting line and, hence, reducing the cost.

Looking at the results presented in Tables 5.2 and 5.3, the poor performance of FAP1 is obvious. Unbalanced food distribution is the result of the fact that no information on demand has been used. In spite of this, since the concept of "well" stocked regional warehouse has been utilized, there does not exist a large gap between the results of the two food policies. The imbalance in food policy has been reflected in regional performances. Part of the better-than-expected performance of FAP1 should be credited to the fact that no delay has been assumed for the availability of information on regional silo levels for the decision makers. Note that the impact of this data is minimum in FAP2 and effective only for the short period when supply is high.

An interesting point is the effect of regional silo capacity on FAP1 policy results. Since the capacity of all RWH's are assumed to be equal, this substantially improves the service level at the regions with lower demands, as can be seen from Table 5.3. This can be modified by changing the values of corresponding control parameters (CTRL) which again brings up the problem of a lack of data needed as a basis for the above alterations. It is clear that the initial capital acquisition policy (CAP1) cannot be continued during the crisis without modifications. Better performances of FAP1 with other CAP policies are due to the existence of more needed capital generated by the use of these policies. These results point to an important conclusion which is observed throughout other policy experiments, and that is the impact of a little more capital on policy results. An item of the total logistical cost, one as significant as the ship waiting cost is the cost of fuel. This cost was found to be the main reason behind the increase in transportation cost, and which offsets some of the cost saved by the shorter ship waiting time (the result of the use of other CAP policies with FAP1). The increase in THRUPUT (last column of Table 5.2) also increases the cost of capital acquisition and fuel.

By minimizing the effect of regional silo level data (RWSTOG) in the design of the second food allocation policy, two undesired features of this information have been removed. One is the use of unlagged actual RWSTOG figures, which is a departure from a real world situation. Second is the problem caused by the capacity of RWH's. These make FAP2 to be nearly based on estimated regional demands. Of course, if more information is available for the decision makers, this policy (FAP2) might not be a desirable one. But in the face of the model's underlying assumptions on the available data of supply and demand it proves to be sound. Hence, FAP1 is discarded and this reduces the number of important policy parameters to the first four of Table 5.1.

The difference between the other general logistical policies, is the question of which capital development policy has been used. Again, it is seen that relying only on the expected food arrival rate is not enough for capital acquisition. A higher balance and ship waiting cost and lower thruput are caused by the shortage of capital. A lower than expected total cost for CAP1 is the result of lower capital cost. These problems are solved by going from CAP1 to CAP2 as the performances improve, but still there is insufficient capital. These conclusions were reached in the process of working with various policies and trying to obtain a "pareto better" policy by changing the control coefficients.

Generally, the comparison of idle time due to the shortage of trucks (TIDTR) and the idle time caused by the shortage of grain (TIDGR) is a good indication of the need for extra capital. If the idle time attributable to trucks increases faster than grain shortage, more capital can be utilized. This excess capital need is satisfied by increasing the appropriate capital control parameter. This fact was used in the process of arriving at the final results of various policies.

The last four general policies' performances are quite close to each other with some exceptions. The use of the quantity of grain waiting to be unloaded (QGRAP) causes the acquisition of useless capital. This is the main reason for an increase in the total costs of CAP3 and CAP6 policies. Of course, this extra capital provides better service as seen from the reduction in balance index. It was said in previous sections that by looking at two state variables over time, capital acquisition decisions can be adjusted in order to optimize capital efficiency. These are capital pools at the port, meaning TPOL (truck pool) and DPOL (driver pool). For policies with QGRAP option, TPOL and DPOL were higher than the other policies. This needs further explanation, since important elements are at work behind these results.

It was concluded in Chapter IV that the port offloading capacity is a significant factor in the overall performance of the logistics model. This fact was reiterated by the policy experiments. During the model operation there is a stage at which the port offloading equipment is working at its limit capacity. In that case, the cost of ship waiting time is not going to change by changing the policy. Then the extra capital acquired by the ship queue information is going to be useless after the port storage has been depleted. This causes an increase in total transportation cost which in turn increases the total cost of logistics. Under the assumed supply and demand functions, this phenomena takes place in the second and third quarter of the year. The better performance of CAP5 policy, where ship queue length has been used, is probably due to the use of average ship tonnage, AVTONS, and the use of port storage in the policy structure.

An important result obtained from the extra capital discussion is the tradeoff between cost and balance indices. It was observed that as more capital becomes available, along with the increase in cost, the balance performance improves until some peak is reached, after which no significant change happens and only the cost increases.

The better performance of the fourth capital acquisition policy, CAP4, is primarily caused by the following fact. When the port's storage, STOG, increases, extra capital can be utilized. Exactly at the same time, the appropriate coefficient, CPTND becomes active resulting in the desired decision and vice versa. But this does not happen when ship queue data is used. Actually, when the queue is long and STOG is low, it means that the port is working at its limit offloading capacity; hence extra acquired capital due to the queue is not usable. This shows that the port's storage level is an important state variable which should be used in the decision-making process.

The above policy conclusions are also reached with respect to the regional performance indices (Table 5.3). The policies with better overall performance, have lower stockouts and higher ratios of supply to demand. The equality of these indices for different regions signals a good overall balance, which is also desired. This, in fact, shows whether the overall relief operation's goal, which is balanced distribution, has been achieved or not. Of course, optimal policy will result in such a balance. In what follows, an attempt is made to answer the apparent inequalities of these measures in the current study.

The differences in the regional performances of two different policies are reflected in their overall performance and thus, does not need further discussion. The two better policies, CAP4 and CAP5 have very similar regional performances. The question is the inequalities between various regions for a given policy. The most important factor is the difference between regional demands. It is clear from the results that the regions with similar demands have similar performances. In Chapter II, the error of estimation was modeled proportional to the true value (Equation 2.52). Thus the regions with the greater demands have generally poorer performances. (See Figure 4.1 - 4.4 for a better understanding of the above issue). In spite of all of these, the "pareto better" solutions, i.e. CAP4 and CAP5, have very close inner equality of regional performances.

Other elements couple with the demand factor to give the results shown in Table 5.3. For example, the stockouts were defined to be the total time that supply is less than demand. In the case of rapid fluctuations in demand, this index becomes biased toward the regions with higher demand rates. This follows from the time it takes to raise the supply level to match demand, resulting in an increase of the stockout time. An important element which should be recognized in analyzing all of the results obtained from policy experiments is the number of Monte Carlo replications (MONRUN). In the current study, MONRUN was set equal to ten, but in a large scale project, it would be wise to increase this number considerably.

There are some final comments to be made before closing this section. It is necessary to emphasis the importance of an amount of capital sufficient "enough" in arriving at a better solution. Increasing the cost by acquiring more capital helps to offload the ships faster, thus reducing the total cost by lowering the tremendous cost of ship waiting time. But this should be continued only as long as the tradeoff is of benefit to decreasing the total cost. The sign indicator that this limit has been reached is the ship offloading rate, RMS. Zero idle time due to overage storage capacity (TIDCAP) and low storage levels at port explain approaching to that limit. So, if the offloading equipment is working at the maximum rate, any increase in capital most probably increases the total cost. Only the policies which reduce the ship queue at port are "cost cutters".

The capital pools, TPOL and DPOL, at the port are good indicators of a sound acquisition decision. Everything else being almost "acceptable", low TPOL and DPOL and their numerical equality or closeness show not only the soundness of policy but also the efficient use of capitals. Finally, in comparing different results, the random error should not be overlooked.

The "Pareto Better" Policy

The multi-objectivity feature of the control problem under study causes the existence of infinitely many noninferior solutions to the optimization problem. One noninferior solution is as good as the other and strictly speaking, one cannot be compared with another (99). The analysis of the results in the previous section suggests the general logistical policy FAP2 and CAP4 as a candidate for the "Pareto better" policy. The following are some explanations for this choice. One of the conclusions drawn from the experiments was the fact that the port storage level (STOG) contains enough, if not all, information regarding the port's activity. It was seen that the use of ship waiting line data will result in complication when the port reaches its offloading limit.

Another characteristic of this policy is its simplicity. The number of control parameters is minimum, and one parameter (CPTND), actually should be perturbed for policy experiments. Note that this choice is by no means the "last" word. It is the result of the assumed framework of this study. The purpose of this section is to study the above policy in more detail. First, various values of the parameter CPTND are examined in order to present different tradeoffs for various performance measures. Then the robustness of the policy is tested in several ways.

Providing data on different opportunities possible by a policy is good information for decision makers. For better management of the logistics system, the managers should know about the consequences of change in policy parameters. For this reason the corresponding control parameter, CPTND was changed and the results are presented in Tables 5.4 and 5.5. The case of CPTND equal to zero has been included for comparison purposes.

The total cost reaches its minimum at CPTND equal to .04 and its general shape (U form) can be seen from the results. As the value of the control parameter, CPTND, increases, so does the available capital, resulting in the increase of the transportation cost and reduction of ship waiting time cost. This tradeoff is good until the total cost passes through its minimum and starts to increase. As the quantity of capital increases, the port thruput also increases and the balance measure's best value is obtained at CPTND equal to .06. Actually the results for the CPTND values around .06, are very close to each other, but still show the tradeoff between cost and service.

Looking at the overall balance index and regional measures for the control parameter values greater than .05, it is seen that as the value of CPTND increases, the balance measure slightly increases as the stockouts start decreasing and ratios of supply to demand stay the same more or less. At first glance, this seems a contradiction, but a closer analysis of the results reveals an interesting policy design fact. As the policy parameter increases, more capital is available in the first quarter of the year. This causes the port storage to deplete faster. When the "crunch" comes, meaning the suden sharp increase in the demand, the well stocked regional silos sustain themselves for a while. This is the reason for the reduction in the

Table 5.4. Means and Standard Deviations of the Overall Performance Criteria for the "Pareto Better" Policy (ten Monte Carlo replications)

CPTND	TOTAL COST ($)	BALANCE	SHIP COST ($)	AVE./SHIP WAITING TIME (YRS.)	PORT INPUT (tons)	PORT THRUPUT (tons)
0.00	184368828	85435	86627160	.0587	2863985	2694589
	(37089807)	(7556)	(35082032)	(.02336)	(88915)	(86394)
.02	178934640	73416	75862475	.0507	3031605	2885178
	(33857896)	(10434)	(31722716)	(.02038)	(140739)	(112184)
.04	178065088	73230	74029477	.0492	3038164	2896264
	(33249528)	(10573)	(30823798)	(.01953)	(143178)	(114516)
.05	178171745	72535	73751196	.0490	3043079	2901017
	(33214855)	(10860)	(30538240)	(.01933)	(143429)	(118077)
.06	178306164	72055	73460279	.0488	3045552	2906493
	(33184545)	(10235)	(30361543)	(.01921)	(143920)	(118238)
.07	178501349	72131	73383839	.0488	3045552	2908228
	(33201831)	(9691)	(30359080)	(.01920)	(143920)	(115755)
.08	178691017	72460	73237665	.0487	3047636	2911545
	(33214199)	(9188)	(30311930)	(.01918)	(144834)	(115168)
.09	178886008	72844	73070678	.0486	3046226	2915040
	(33227797)	(8579)	(30226593)	(.01914)	(143886)	(115541)

* Numbers in the parenthesis represent the standard deviations.

Table 5.5. Means and Standard Deviations of the Regional Performance Measures for the "Pareto Better" Policy (ten Monte Carlo replications)

	STOCK-OUT TIMES (years)				RATIOS OF SUPPLY TO DEMAND			
CPTND	RWH 1	RWH 2	RWH 3	RWH 4	RWH 1	RWH 2	RWH 3	RWH 4
0.0	.7866	.7742	.5552	.5689	.8118	.8219	.8454	.8323
	(.1303)	(.0999)	(.0981)	(.1307)	(.0277)	(.0337)	(.0349)	(.0384)
.02	.4904	.4653	.3895	.4071	.8279	.8391	.8636	.8474
	(.0979)	(.1019)	(.0880)	(.0982)	(.0343)	(.0419)	(.0409)	(.0406)
.04	.4649	.4289	.3632	.3789	.8298	.8410	.8652	.8494
	(.0992)	(.0982)	(.0861)	(.0959)	(.0364)	(.0423)	(.0413)	(.0407)
.05	.4578	.4149	.3531	.3695	.8298	.8412	.8661	.8508
	(.0972)	(.0911)	(.0903)	(.0970)	(.0364)	(.0419)	(.0413)	(.0402)
.06	.4508	.4084	.3459	.3610	.8298	.8412	.8670	.8525
	(.0928)	(.0853)	(.0968)	(.0982)	(.0360)	(.0414)	(.0418)	(.0405)
.07	.4483	.4041	.3413	.3542	.8297	.8412	.8682	.8542
	(.0925)	(.0841)	(.0979)	(.0985)	(.0356)	(.0411)	(.0423)	(.0411)
.08	.4447	.4010	.3362	.3483	.8295	.8412	.8691	.8556
	(.0913)	(.0817)	(.0979)	(.0976)	(.0353)	(.0409)	(.0426)	(.0416)
.09	.4407	.3992	.3312	.3413	.8292	.8412	.8702	.8570
	(.0894)	(.0808)	(.0972)	(.0973)	(.0349)	(.0407)	(.0429)	(.0421)

* Numbers in parenthesis represent the standard deviations.

stockouts. But, later, the effect of the "crunch" appears in the balance measure, as the low port storage can not supply enough grain. The regions with higher demands contribute more to the balance criterion.

Note that the above scenario has been the direct consequence of the shapes of supply and demand curves. It was said that this information is not usually available for the decision makers.

Testing the Policy Robustness

The purpose of these tests is to examine the robustness of the selected policy under different circumstances. It was said that one of the desired characteristics of a good policy is its generality, meaning that it can handle various scenarios. This was based on the fact that very little information is available about the famine situation and any famine logistics model should be able to operate in different conditions. This point has been stressed several times in previous chapters, especially in the policy design section. Several robustness tests have been conducted and will be discussed here.

The first robustness test has been done by changing the supply and demand functions. This is the most important test because all the movements, flows and decisions are based on these two functions. This is also a test for other components of the logistics model, espcially the information subsystem and the estimation technique ($\alpha - \beta$ tracker). Figure 5.3 illustrates the new form of the supply and demand curves. There are several differences between these curves and the original supply and demand functions (Figure 2.5). The initial values of both supply and demand are higher in this new version. The implications of this change will be discussed when the results of this test are

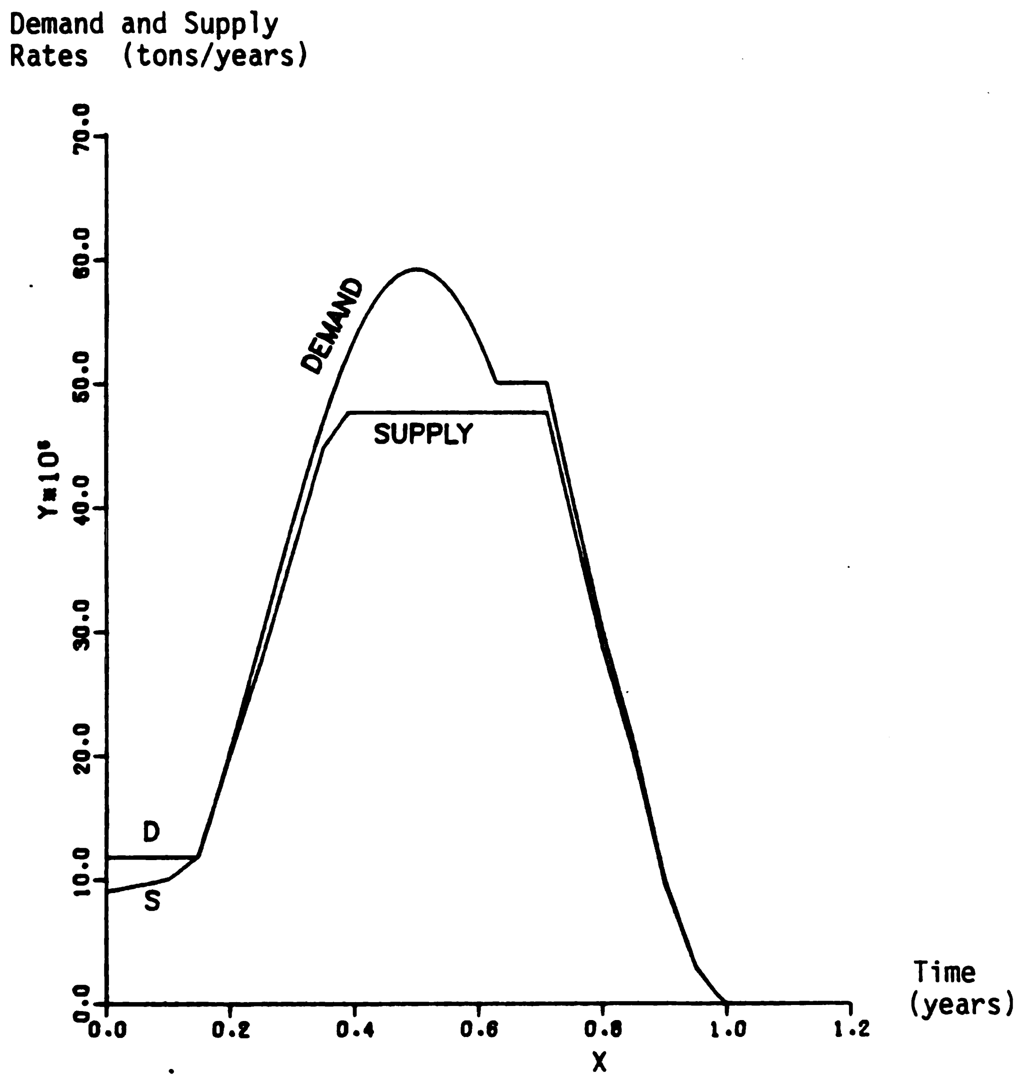

Figure 5.3. New Supply and Demand Functions for the Robustness Test of the "Pareto Better" Policy

analyzed.

The supply is flat at the top, meaning a more uniform arrival of ships and after some point, when the demand becomes equal to the maximum supply, the demand values are computed by multiplying the value of supply by some known constant. In the current study this constant is equal to 1.05. These changes in the supply and demand functions will increase the area under both curves. But it is desirable to have the crisis level remain as before. This causes the reduction in the maximum rates of demand and supply. Of course, the total quantities of demand and supply are slightly larger in this new version. The results of this robustness test is summarized in Table 5.6. The number of Monte Carlo replications (MONRUN) is equal to ten.

By looking at the results, one can observe a big reduction in the ship waiting cost, but this decrease has not been fully reflected in the total cost. To find out where this extra cost is coming from, a detailed cost analysis was conducted in order to itemize the cost function. First, it is helpful to know that two factors are responsible for the reduction in the ship waiting cost. These are the more uniform arrival of ships and the lower maximum rate of food arrival in comparison with the limit offloading capacity at port (RMS). This new form of the supply function is equivalent to the increase of the offloading capacity, the importance of which has been discussed in previous chapters.

Again the fuel cost was found to be the prime cause of the increase in the transportation cost, which offsets some of the cost saved by the shorter ship waiting time. More than eighty thousand tons of extra grain are shipped through the port under the new functions. This causes

Table 5.6. Results of the Robustness Test Due to New Demand and Supply Functions

SCENARIO	TOTAL COST ($)	BALANCE	SHIP COST	TRANSPORTATION COST ($)	PORT INPUT (tons)	PORT THRUPUT (tons)
Original Functions	178306164	72055	73460279	88979645	3045552	2906493
	(33184543)	(10235)	(30361543)	(3523859)	(143920)	(118238)
New Functions	161232975	69061	56814650	90160379	3103107	2981750
	(25539016)	(11002)	(22161571)	(3365487)	(153415)	(118886)

	STOCK-OUT TIMES (years)				RATIOS OF SUPPLY TO DEMAND			
	RWH 1	RWH 2	RWH 3	RWH 4	RWH 1	RWH 2	RWH 3	RWH 4
Original Functions	.4508	.4084	.3459	.3610	.8298	.8412	.8670	.8525
	(.0928)	(.0853)	(.0968)	(.0982)	(.0360)	(.0414)	(.0418)	(.0405)
New Functions	.4465	.4881	.3747	.3929	.8772	.8482	.8815	.8736
	(.0502)	(.0640)	(.0785)	(.0646)	(.0386)	(.0358)	(.0465)	(.0268)

* Numbers inside parenthesis are the standard deviations.

not only an increase in fuel consumption, but also increases the cost of capital needed for carrying the extra grain. Another factor is the cost of capital in the initial stage of the capital development process. It was mentioned that the initial value of the supply curve is higher in the new version. This says that more capital is needed for the start of operations, or that more capital should be acquired and probably kept for longer periods (because of TRLIMIT) in the pre-crisis stage, thus increasing the total transportation cost.

The increase in the regional stockout measures is the direct consequnce of the new form of supply and demand curves. In the period of peak demand the supply is much lower than the original supply function. This causes stockouts to increase. But the more uniform arrival of the grain creates the some kind of stability in the operation. It causes the reduction in the balance measure and the rise in the ratios of supply to demand. Of course, part of this good performance should be credited to the higher amounts of supply available in the new scenario. The uniform ship arrival also causes the reduction in most of the standard deviations of performance measures.

An important conclusion of the above test is with regard to the reduction of ship waiting time cost and total cost due to more uniform arrival of the ships. This suggests that in the time of crisis in a country, it is better that an international agency be selected as a main contact of all possible donors. This organization in cooperation with the decision makers in the involved country should arrange a more uniform arrival of the food.

The second robustness test is based on population movements. It was stated in Chapter II, that the demand model can simulate the probable population movement during famine crisis. By this model feature different scenarios can be generated in order to test the policy robustness. The "Pareto better" policy was tested by letting the population move from the first and the second regions into the third and fourth ones, with more people moving into the fourth region than the third one. This was done by letting the population movement parameters have the following values: $\beta_1 = -.15$, $\beta_2 = -.15$, and $\beta_3 = .1$. The test results are presented in Table 5.7 with MONRUN equal to ten.

When the population moves, its effect will appear in the policy result after the new demand estimates are transmitted to the decision makers. This adds a great deal of error to already inherent estimation errors, resulting in a worsening of the balance criterion. The new error causes the excess shipment of grain to the first and second regions and the lack of enough supply in the third and fourth regions. This can be observed by looking at the regional performance indices. The first two regions' stockout times and ratios of supply to demand improve as the ones of the second two regions' decline. The fourth region is hit harder because more people move into that region. The reduction in the total cost and the ship waiting cost is due to the shorter distances the trucks should travel. As more and more people move, larger quantities are shipped to the third and fourth regions. But these regions are closer to the port than the other two, less fuel consumption and faster capital turnover. The result is a high availability of capital at the port which allows the ships to be offloaded faster.

Road breakdowns are used as the third robustness test for the selected policy. Different times and different routes were selected in order to test a variety of scenarios. Again MONRUN was set equal

Table 5.7. Results of Policy Robustness Test with Population Movement Scenario

SCENARIO	TOTAL COST $	BALANCE	SHIP COST (4)	AVE PER SHIP WAITING TIME (years)	PORT INPUT (tons)	PORT THRUPUT (tons)
No. Pop. Movement	178306164	72055	73460279	.0488	3045552	2906493
	(33184545)	(10235)	(30361543)	(.01921)	(143920)	(118238)
Population Movement	176848253	78732	71886902	.0478	3066386	2940004
	(33052067)	(4316)	(29768132)	(.01887)	(149827)	(117323)

	STOCK-OUT TIMES (years)				RATIOS OF SUPPLY TO DEMAND			
	RWH 1	RWH 2	RWH 3	RWH 4	RWH 1	RWH 2	RWH 3	RWH 4
No. Pop. Movement	.4508	.4084	.3459	.3610	.8298	.8412	.8670	.8525
	(.0928)	(.0853)	(.0968)	(.0982)	(.0360)	(.0414)	(.0418)	(.0405)
Population Movement	.4364	.3772	.4135	.4620	.8387	.8529	.8354	.8072
	(.0948)	(.0937)	(.0773)	(.0761)	(.0401)	(.0460)	(.0353)	(.0304)

* Numbers in the parenthesis represent the standard deviations.

to ten and the effects of road breakdown on various performance criteria was observed. These results are tabulated in Tables 5.8. Routes number two and four are selected for breakdowns which occur either at times equal to .26 or .56. Since the average ship waiting time and its cost, and the port input were the same for all of the cases, they are not reported. Instead, the total cost of transportation is given in the Table 5.8a.

The excellent performance of the policy and the model is obvious. For better understanding of the result it is necessary to remember that the distances of new roads are 590 KM for the second route and 680 KM for the fourth one. Thus, the distance does not change for the second route, but it increases fifty percent for the fourth road. Another factor is the length of time the auxiliary road is used, i.e. the time when the incident happens. Looking at the results of route number two, one can see that the total cost and balance are better for time equal to .56 than .26. This trend can also be seen for the other route. Small perturbations of the regional performance measures are in part due to the assumed policy of dispatching the full returning trucks from the broken road to the same regional warehouse.

Before closing this section, it would be well to note that the Monte Carlo analysis by itself is a weak robustness test. All the results presented in this chapter are obtained as the model had been operating in the Monte Carlo mode. In this way, at every iteration a different sequence of random numbers is used, hence slightly different scenarios are generated.

Table 5.8a. Mean and Standard Deviation of Overall Performance Indices Resulted from the Road Breakdown Robustness Test

SCENARIO	TOTAL COST ($)	BALANCE	TRANSPORTATION COST ($)	PORT THRUPUT (tons)
No Breakdowns	178306164	72055	88979645	2906493
	(33184545)	(10235)	(3523859)	(118238)
Breakdown (T = .26)				
Route #2	178420594	72378	89101607	2906501
	(33167400)	(9798)	(3704836)	(118251)
Route #4	180506992	72541	91191194	2906473
	(33476270)	(9607)	(8816501)	(118209)
Breakdown (T = .56)				
Route #2	178381512	72069	89058221	2906660
	(33172857)	(10213)	(3637272)	(118493)
Route #4	179436276	72225	90101296	2906350
	(33170913)	(9995)	(5877131)	(118022)

* Numbers in parenthesis represent the standard deviations.

Table 5.8b. Regional Performance Measures Resulted from the Road Breakdown Robustness Test

	STOCK-OUT TIMES (years)				RATIOS OF SUPPLY TO DEMAND			
SCENARIO	RWH 1	RWH 2	RWH 3	RWH 4	RWH 1	RWH 2	RWH 3	RWH 4
No Breakdowns	.4508	.4084	.3459	.3610	.8298	.8412	.8670	.8525
	(.0928)	(.0853)	(.0968)	(.0982)	(.0360)	(.0414)	(.0418)	(.0405)
Breakdowns								
T = .26, Route #2	.4502	.4073	.3454	.3601	.8298	.8412	.8670	.8525
	(.0944)	(.0869)	(.0971)	(.0996)	(.0360)	(.0414)	(.0417)	(.0405)
T = .26, Route #4	.4505	.4072	.3452	.3596	.8296	.8412	.8670	.8525
	(.0937)	(.0871)	(.0972)	(.1005)	(.0356)	(.0414)	(.0417)	(.0406)
T = .56, Route #2	.4508	.4083	.3462	.3609	.8298	.8413	.8670	.8525
	(.0928)	(.0855)	(.0965)	(.0982)	(.0360)	(.0415)	(.0418)	(.0405)
T = .56, Route #4	.4512	.4085	.3465	.3609	.8296	.8412	.8670	.8525
	(.0920)	(.0852)	(.0964)	(.0982)	(.0357)	(.0414)	(.0417)	(.0405)

* Numbers in parenthesis represent the standard deviations.

Summary

The model seems to perform well based on the reliability and expectedness of outputs. The control issue of the logistics system was discussed in some detail in this chapter. After probing in the scope and the nature of the control problem, two important decisions were identified which should be answered by the system decision makers. These were the questions of food allocation and capital acquisition. Some policies were designed for the solution of these problems such that a set of performance indices are optimized in pareto sense.

The decision rules to implement a relief plan must stipulate what is to be done, when to do it, and at what rate. Generality and simplicity are also two desired features of any control policy. It was seen that all decisions are based on supply and demand information. Food distribution policies were based on estimated demands and regional silo levels where capital development decisions were derived primarily from the expected rate of food arrival. Based on the fact that in a famine situation trucks and drivers are only needed to deliver foods and not to satisfy demand, it was concluded that other information can be used in designing capital acquisition policies. These were the port storage level and ship queue in the harbor.

After many experiments with different overall policies as the related control parameters were perturbed, one policy was chosen as the "Pareto better" policy. The robustness of this policy was tested in different ways. An important conclusion of these tests was the sharp reduction in the ship waiting time cost due to a more uniform arrival of the grain. A significant valid research project which was only touched in passing is the optimization task of the current control problem.

CHAPTER VI

SUMMARY AND CONCLUSIONS

Summary

Famine relief logistics is viewed as a complex process involving the dynamic interactions of many subsystems. Necessarily simplified analytical models have been found which are of significant use for either explanation or prediction of system behavior. The purpose of this chapter is, first, to summarize the foregoing chapters as one entity. Then, the major results of the study are presented, followed by observations concerning the practical utility of the model. Finally, the areas for further research are discussed.

A sketch of various sub-systems involved in a famine relief and their interconnections was discussed in Chapter I. In that introduction, an attempt was made to shed some light over the wide spectrum of issues and problems which are associated with the overall relief operations. The economic, socio-political, and cultural bottlenecks were also explained. Since the emphasis of this dissertation is on famine logistics, the tendency was more toward discussing the problems most likely to be encountered in that area of relief systems. To stress the importance of logistics in a food crisis, Dando (28) identifies "transportation famine" as one of the basic types of this kind of disaster.

In order to be able to define the problem under study, major famine logistics sub-systems and linkages (Figure 1.1) were discussed in some detail. Exploring this structure, many points become clear which were used in the modeling process. Figure 1.2 clarifies the relationship between logistical goals and the obstacles which must be passed for achievement of them. Logistical system design could be based on either spatial or temporal economics. Here the design is more on temporal structure and economics.

A hypothetical country with approximately a sixty million population was assumed, divided among four regions. This assumption is for modeling purposes and has no effect on general conclusions drawn from the study. The entire modeled logistics system and its various components along with the explanation of the assumptions made, are described in Chapter II. This model consists of six major parts. The port, four regional warehouses and roads, supply and demand, information and data acquisition component, capital development model, and the cost function. All policy experiments are based on this model. Due to the fact that capital development decisions are part of overall logistical policies, a further complementary description of this part of the model was discussed in Chapter V.

Available information and its communication play a vital role in the successful implementation of the designed policies. There is no need to stress the importance of accurate data, since the subject has been discussed in various chapters in detail. Due to the imortance of the quality and quantity of information on one hand and the general shortage of data on famine, specially in the case of a third world country on the other hand, there is an immense need to extract maximum benefit from the gathered information. In an attempt to come to grips with the error involved in the available data, the use of some kind of filtering method was seen necessary. To achieve this aim, a detailed discussion and analysis of various existing estimation approaches was made, and has been reported in Chapter III.

Two estimation models resulted from the above search. These were the Extended Kalman filter (parameter identification via state augmentation) and the $\alpha - \beta$ tracker with adaptive tracking feature (time-varying β parameter). Since little is known about the demand function, encountered in a famine, it is obvious that its details are hardly known. From past experiences and some common sense knowledge, various related characteristics can be identified. In order for an estimation procedure to be chosen for the famine information system, it should perform well, on the average, for all different demand functions possible. To do this test, a demand model was designed (Equation 3.19) which can represent a wide spectrum of demand functions. The demand function described in Chapter II (Equation 2.49) is one member of that family. The selected filters were then tested on sample functions of the demand model (Equation 3.19). The result was the selection of the adaptive α-β tracker for use in the logistics model. This choice resulted from extensive tests based on different conditions which are common in the case of famine relief efforts. When high uncertainty exists regarding the initial values of the demand model's state variables and the model trajectories are partially known the adaptive $\alpha - \beta$ tracker performs far better than the Extended Kalman filter. (Figures 3.5 - 3.12).

The validity of the logistics model developed in chapters II and III, was tested and proved in Chapter IV. Various consistency tests were performed. Apart from the validation goal, these tests may serve other purposes. They provide an indirect way to test policy options. One or more parameters could be changed to reflect a particular policy goal and the consequences thus simulated. Logical or theoretical inconsistencies of the model are revealed through sensitivity analysis. The results of the above tests can also suggest data collection priorities by indicating those parameters which are of greatest consequence to the performance of the model. In short, the above tests and their results may add to one's understanding of and insights into both the model and the corresponding real system.

One of the main objectives of this thesis is the design and experimentation of different control policies. This subject was discussed in Chapter V. Service performance and total cost expenditure were used as the basis for the development of different performance measures which were used in the process of policy evaluation, leading to the selection of the "Pareto-better" policy. The model's applicability to policy formulation was demonstrated in Chapter V, where the results of a series of computer runs examining various combinations of policy options were analyzed. These policies are composed of two different but highly interconnected decision rules, meaning the food allocation and capital acquisition decisions.

The existence of several conflicting objectives in the model makes the control problem more complex. Since no optimization procedure was used in arriving at the best policy alternative, the selected policy is just a preference based on the model's assumptions. But by systematically investigating policy alternatives, the range of choice and the relationship between alternatives and the relative values of the objectives were identified. Note that the process of finding the better filtering technique (Chapter III) is part of the control process, since decision on the quality and quantity of the information is one of the policy entry points of the model. Chapter V concludes with the results of several robustness tests conducted on the "Pareto-better" policy.

Major Results and Conclusions

By knowing that any result obtained is a natural consequence of the goals set forth for this study, they are repeated here. There are two main objectives in this dissertation: modelling and control. In light of these aims various inferences and results are reported following the same arrangement of the chapters, i.e., modeling, estimation and control.

The most important design parameter of the port subsystem is the ship offloading rate. This parameter has a significant influence on policy implications. These are based on the sensitivity tests of Chapter IV and policy runs of Chapter V. A ten percent increase in the ship offloading rate (RMS) resulted in a sixty percent reduction in average per ship waiting time. Another rough calculation showed that the ratio of offloading rate to arrival rate should be at least 1.6 to 1.8. The vehicle loading rate of the equipment does not influence the model output, primarily due to other existing bottlenecks in the system. Even so, this rate should be at least as great as the expected grain arrival rate.

The port's storage capacity is effective in the short run and it is not a good policy option for long-run objectives. At the regional warehouse level, the storage role is to equalize supply and demand, and their capacities have minimum effect. This makes the maximum truck unloading rate (RMSS) the only important parameter at the RWH's. The effect of this parameter on system performance is two-fold. On the one hand it limits the regional supply rate, and on the other hand it influences capital turnover. The second effect is the most important one, because a higher unloading rate makes the delay of trucks shorter and capital availability at port higher. But there is a limit beyond which the extra unloading capacity is useless.

It is usually given that better information shouTd lead to a better performance of the system. This assumption can be used to study and test model validity and policy structure. The experiments of Chapter IV show that the above statement is true regarding the current model. In fact, given the assumed cost coefficients, it is quite advantageous to have better quality with higher frequency. Increasing the quality and guantity of available information will lead to lower cost, better performance, and service. But, there exists a range of problems, such as cultural, political and logistical ones, that complicate the task of information gathering in a third world country framework, thus making the availability of more data harder.

The results of analysis of various estimation and filtering techniques in Chapter III suggest important insights into the question of what filtering method should be used in order to capture most of a given data set. Given the complete knowledge of the structure of the model generating the information, the Extended Kalman filter outperforms any other filter (Table 3.2). But this performance degrades, as less and less is known about the original demand model. On the contrary, the adaptive $\alpha - \beta$ tracker shows a consistent performance under different circumstances. The two methods were tested for robustness under two conditions. The first condition was when the trajectories of the model generating the stochastic process are partially known. The second was a test on transient initial conditions in which high uncertainty existed regarding the initial values of the demand model's state variables.

The above conditions are quite common with any disaster relief operation. Under these conditions the adaptive $\alpha - \beta$ tracker performed well and the Extended Kalman filter did a very poor job. Tables 3.3 and 3.4 summarize the above results.

Several inferences can be made regarding the results and implications of various policy designs. It was mentioned in Chapter V that the findings of the policy experiments are the basis for further optimization work. By formulating different control policies and testing them, the most important policy design variables were identified. These were estimated regional demands, port storage level, expected food arrival rate, number of ships in the harbor waiting to be unloaded and the amount of grain on these ships. It was concluded that the port's storage level has enough information needed for capital acquisition policies. This variable along with the expected food arrival were successfully used to estimate the desired number of trucks and drivers.

The concept of well stocked regional storages proved to be a good underlying assumption for the design of food distribution policies. Even in the FAP1 policy, which did not use any information on demand, above concept leads to good clearance of port from grain. This fact is illustrated with a low ship waiting time and cost associated with this policy (Table 5.2). The comparison of the two food distribution policies shows the importance of the data on regional demand not only for overall performance of the logistics system but also on the balanced distribution of the food. The badly balanced allocation of food under the first policy (FAP1) gives witness to this fact. Even under the various scenarios tested for policy robustness, the error caused by the use of regional estimated demand as the only basis for food allocation decisions was very low. In fact, the general logistical policies' overall performances were satisfactory considering the quality and quantity of different data available for decision making (Tables 5.2 and 5.3)

The importance of the port's offloading capacity was demonstrated again. It was seen that whenever port storage is very low and there are ships waiting to be unloaded, the port's offloading capacity limit has been reached. The policy implication of this state is that acquisition of any extra capital is useless. Another important result was obtained by changing the supply function. This was one of the robustness tests conducted on the "Pareto better" policy. In this new supply function (Figure 5.3) the grain arrival rate was more uniform than the previous one (Figure 2.5). Although the change was only for the peak of the crisis, the results were significant. The ship waiting cost, and consequently the total cost were reduced substantially. This result suggests the importance of the formation of an international body in the time of crisis in order to manage more uniform delivery of aid to the stricken country.

Finally a general conclusion which was observed through this study was the excellent ability of computer simulation as an invaluable tool in the study of complex processes. A model developed by simulation can be used in designing various policies and obtaining their relevant outputs for comparison and use in the real world decision-making process. The use of a computer allows comparison of various situations quickly, examining results and varying initial conditions and policy combinations.

Futher Analysis of the Model

The purpose of this section is to summarize some of the major features of the model and to discuss various advantages and disadvantages associated with it. It is hoped that these explanations will be helpful for possible users of the model and its results.

From various discussions and analysis of the previous chapters it can be concluded that, although the model as presented here needs more work, it can provide important contributions to the famine relief logistics planning and the policy-making process. Most of the existing models in the literature dealing with the logistics have two distinct characteristics. One, they are discrete time, meaning that all entities have been modeled individually. Second, they are at a micro level, simulating the logistics of a business company. In this dissertation, the logistics systems has been looked upon from a macro point of view, thus the existing flows have been modeled at the aggregate level. In addition, the discrete modeling of the port and its interconnections with the continuous time inland transportation system provides the desired framework which can be utilized for macro level decision making.

Using an operational model is a major step forward in the task of managing a logistics system. A more direct input to the policy development process is the capability of the model to explore the consequences and implications of a wide range of logistics policy options. As discussed in Chapter V, different policies can be tested on the current model. The sensitivity analysis of Chapter IV illustrates an important application of the model to policy formulation when there is uncertainty inherent in the quality of the available information. In this way, the model can be used to evaluate the sensitivity of the policies to data uncertainty, for example, the upper limit on the capital acquisition rate (TRLIMIT). In the model description of Chapter II, it was said that since there is little information on this parameter, the model can be utilized in order to get an estimate about the range of it. This is essential information for system planners who should take any action possible to provide the necessary amount of capital needed for the fulfilment of the allocation policies which may include the use of government authority power.

In this study, significant steps forward are made in the modeling of the famine logistics system. The discrete time port model has been interconnected with the continuous time inland transportation system along with a distribution network and regional warehouses. Transshipments are possible in the case of an emergency when one of the roads becomes impassable and population movement can give a wide range of possibilities for policy experimentation. It is also possible to generate different ship arrival patterns.

Detailed analysis of the behavior of the simulated system under a range of assumptions and policy conditions provides a comprehensive view of the complex and dynamic logistics system under study. This can contribute to an improved understanding and sharpened intuitions regarding relief operations in general as well as the particular logistics system itself. Insofar as the simulated system correctly represents relevant behavioral patterns of the real system, this heightened understanding can be a valuable asset in reducing some of the uncertainty policy makers necessarily face.

The sampling component, added to the simulation model, allows study of results of a given information quality without specifying the details of surveillance and processing. Since the model has not been adequately validated against real famine data and its background is a hypothetical country, the numerical results of this study should be looked upon as indicators of the nature of expected outcomes, not as actual recommendations.

The main drawback of the model can be seen in the development of the cost function. Since the total cost is one of the main perfromance criterion used in policy evaluations, more attention is needed for this part of the model. A real-world data base is not available for much of the cost data that would allow comprehensive model validation and policy experimentation. There are some unrealistic assumptions in the model which should be kept in mind in analyzing policy results. In this model no constraints have been assumed on fuel, spare parts, and maintenance, although it is easy to incorporate them. Also, the question of needed money and technology has not been addressed. Thus, it may be desirable, if the model is to be implemented, to give high priority to modifying the current model to realistically reflect actual input constraints.

The discussions of Chapter I led to the conclusion that the food crisis can happen in any part of the world. Even though the third world countries are more susceptible to famine, they enjoy a wide spectrum of different cultures, political and economic settings. These factors are quite important and must be taken seriously in the planning and decision making processes. Thus it is probably never going to be possible to have a detailed model that addresses a particular food crisis in a particular region.

In light of above facts, the value of less specific models such as the current one is in their ability as a tool for decision makers and planners. These models can give general guidelines for crisis management under various circumstances and scenarios. They provide a decision maker with more information, help him to identify new and economically feasible policy options, and sharpen his intuition, thus making for better decisions. But the policy decision maker, in evaluating simulated results, must be aware of the assumptions and simplifications built into the model. He must appreciate limitations that exist with regard to the quesitons the model is capable of addressing. As part of the pre-planning stage these models can also be used as training devices for the perspective people involved in the managing of relief operations.

Improvements and Extensions

Any modeling effort of human behavior can never be finished. Famine relief operations simulation is of this type. The people are involved in all aspects of any relief effort and, indeed, it is done to save other people. Based on this fact, in response to the changing world, input data, structural and casual relationships and even the problem definition may have to be revised from time to time. But any modification and extension should be decided upon after a cost-benefit analysis.

There are several areas of the current model which need further development and research in order to improve its performance and conform more closely to real world behavior. The first area of work concerns the development of a cost function. Not only does the aggregate level of the current one need more detailed analysis and modification but there also is a severe need for information on numerical values for cost coefficients. The importance of this area becomes clearer in light of the poor financial situation of third world countries, and the decision on the policy choice. It was said that there are many noninferior solutions to a multi-objective problem. Thus, the total cost becomes an important factor in the selection of one of these noninferior solutions. The above discussion should not undermine the general need for accurate data in other parts of the logistics system.

One of the results of the sensitivity analysis and policy experiments stages was the importance of the role that some extra number of trucks or drivers could play in improvement of the system performance. The capital market mechanism has not been modeled in this study and its effects are considered as exogenous inputs to the decision making component of the system (Figure 5.2). Even though the current capital development model (Figure 2.6) simulates important elements of this process, it leans more toward the policy design and control parts of the logistics model rather than the market interactions. There is a need for further development of the mechanism of this market in order to model its reaction to policy inputs in more detail. This brings up, again, the question of an upper limit on the capital acquisition rate (TRLIMIT). There is a serious lack of data on this rate. Other less serious shortcomings of this component is the equal acquisition delay and TRLIMIT for both types of capital.

Many features of the current model are in aggregated form. One such case is the truck repair shop. No distinction is made between the possible various repair needs. An average constant delay has been assumed for all trucks. This needs a more detailed modeling in order for the model to portray the real world better. There are also some constraints which have not been modeled at all. These are: fuel, spare parts and maintenance inputs. Fuel is very critical considering the worldwide energy crisis and that the high prices of energy have made poorer countries more vulnerable to famine. One more factor for exploration is the driver "attrition". There is a truck attrition rate in the model.

The decision making process has been modeled continuously with constant control parameters. This continuity refers to the fact that the control values are computed at each discrete model time interval, DT. As DT shrinks, decisions are made more and more continuously. The possibility of time-varying control parameters lead to the use of dynamic programming, which should be explored as an extension to this model. Another natural extension, regarding the control and decision-making process is the optimization work which was mentioned in a previous chapter.

It was said that the multi-objectivity feature of the control problem poses new difficulties for optimization. There is usually a tendency to convert the multi-objective problems to single-objective ones, by some weighting method, since the latter is much easier and many procedures exist for its solution. The subject of multi-criterion optimization which is also known as Pareto optimization regarding the current study, is by itself a separate research topic due to the volume of work and the freshness of the subject. In what follows, it is tried to portray some of the advantages of this approach to the single-criterion one.

The consideration of many goals in the planning process accomplishes several major improvements in problem solving. Since the model, such as the current one, is most likely to be used in the decision-making and planning processes, multi-objective programming and planning promotes more appropriate roles for the participants in the above processes. The single-objective approaches often expand the analyst's role, resulting in a decrease in the decision maker's control of decision situations. Since all single-objective models require that all policy effects be measurable in terms of a single unit, the burden of decision making, not the decision of weighting function, squarely falls on the shoulders of the analyst or the model. Multi-objective approaches pursue an explicit consideration of the relative value of policy impacts. By systematically investigating policy alternatives, the range of choice and the relationship between alternatives and the relative values of the objectives are identified. In this manner the responsibility of assigning relative values remains where it belongs - with the decision makers.

Regardless of the actual nature of the decision-making process, multi-objective approaches can be useful in promoting the explicit consideration of value judgments which are implicitly made in the application of single-objective approaches. The unambiguous identification of an optimal alternative is the result of single-objective methods which are predicted on a unique measure of effectiveness. This leaves the decision makers in the position of accepting or rejecting this sole alternative identified as the best. It is generally true, however, that multi-objective approaches will present to decision makers a range of choice larger than the one "optimal" solution.

It was mentioned that there are, generally, infinitely many noninferior solutions to a multicriterion optimization problem, and one noninferior solution is as good as another. Decision makers, considering the existing circumstances, select the most satisfying noninferior solution. This is quite important, considering the generality of the current model, and diversity of conditions different relief operations face. A general rule for decision making which is assumed here is that more information (carefully presented) is better than less information. The decision to accept or reject a single optimal alternative is an uninformed decision. Informed, rational decision making requires a knoweldge of the full range of possibilities. This can be provided by multiobjective analysis. Finally, models or the analyst's perception of a problem will be more realistic if many objectives are considered. Different approaches have been suggested for the handling of this type of problem. For example, see (54), (83), (99), and (102).

The process of selection of the best means of transportation has not been modeled in the current study. This is a possibility for extension of the current model. Various modes of transportation, one mode or a combination of modes, should be modeled. In the case of the availability of more than one mode, the results of this extension could be used in the selection of the better mode. Also, in most cases, more than one means of transportation is utilized in order to deliver the allocated food to different regions. In the current study a single mode, meaning the trucks, has been modeled.

One further factor not explored in this study but which has a large effect, is the distribution of grain on ships; the distribution used for the Bangladesh case (Figures 2.2 and 2.3) is certainly open to change for other ports. The current model also uses one grain equivalent figure and has no crop breakdowns. This is done for simplicity, but logic generally dictates that others should be handled similarly. The disaggregation in modeling could be extended to the demand function. A more accurate portrayal would be the result of identifying various population groups such as rural and urban. Another important modification of the demand function is the introduction of randomness into the demand model.

Facility location is one of the modern logistical activities. The number, size, and geographical arrangement of facilities and warehouses bear a direct relationship to the service performance capabilities and corresponding logistical cost outlay (11, Chapter 2). The current model can easily be modified and used for the purpose of finding optimum regional warehouse locations. The subroutine SILOS in Appendix B can be utilized for any number and size RWH. The geographical location can be modeled by changing the distances from the port.

Another problem area which would call for an extension of the model is the transshipments issue. The current model can handle random breakdowns of any road and at any time. But no transshipments are possible from one RWH to the other. This can give extra flexibility to the system managers for emergency cases, because it is desirable that the control policies would lead to an optimum food allocation for which no transshipment becomes necessary. Finally, the hierarchical characteristic of the control problem can be used in order to utilize a vast amount of literature on multi-level control for further research. Bryds et al (14) present a technique for steady-state optimization of an important class of hierarchical control structures, namely continuous processes. Note that with the exception of ship arrivals at port, the rest of the model is in a continuous time mode.

Concluding Remarks

In what has passed, some of the shortcomings of this study have been discussed and means by which they can be dealt with in order to improve the model's predictive and prescriptive capabilities have been suggested. It was seen that some, if not most, of these shortcomings arise from the lack of needed information. This problem exists no matter what kind of technique is used. Nonetheless, it has been reasoned that the system simulation analysis as used here, with its flexible approach to many of the methodological problems found in studying famine relief operations, provided an improved framework for not only policy analysis but also gave a better understanding of the real system itself.

There are tremendous tasks to be accomplished in any relief effort. Even with limiting the scope of the current study to the role of a logistics system, many complex components have been noted. There still remains, however, the task of actual implementation of the model. Many political and cultural obstacles, some of which were discussed in Chapter I, hinder the implementation feasibility. Conflicts between social classes, politicians, religions or regions have always been the cause of the unequal distribution of food in the world. These factors must be taken into consideration when designing allocation policies and planning relief programs.

It must be stressed that the current model yields usable estimates of the consequences of several policy strategy alternatives. In the future, when more and better information becomes available, further research could correct current inadequacies. The experience and lessons learned in the present work and others like it will be valuable in future modeling and relief efforts.

APPENDICES

APPENDIX A

NUMERICAL COST COEFFICIENTS

The total cost was one of the main criterion in the process of selecting a better policy in Chapter V. It is always used in logistical systems evaluation. The equations of Chapter II, merely presented the mathematical relationships among various components of the total cost and their assumed structures. Those equations (2.58 - 2.74) explained the rationale of the assumed mathematical forms and defined different variables. But the values of the parameters and the unit costs were left undefined. These values are needed for the total cost computation of Chapter V.

This appendix is intended to fill the gap between Chapter II formulations and the analysis of Chapter V. In what follows, different unit costs are redefined and their numerical values are discussed. These values are based on limited available information and intuitive judgement. The lack of data on third world countries is apparent, but, since various logistical policies are judged on relative total cost, these numerical values do not harm the process of finding the pareto optimum solution for the control problem in this study.

The fuel unit cost is calculated as follows. It is assumed that the cost per gallon of diesel is $2 (approximately $.53/liter) and a truck can travel 5 miles per gallon. This means approximately one kilometer per .47 of a liter. Thus

$$\text{CFUEL} = \text{unit fuel cost} = .47 * .53 = .2491 \qquad (\$/\text{truck/KM})$$

A truck imported to a third world country costs $40,000, and has a life span of 10 years (considering road conditions of these countries), its depreciation value for one year has been used for the truck rental cost.

CRENT = rental cost = 4000 ($/truck/year)

Other transportation costs are as follows.

CDWAGE = driver wage = 5475 ($/driver/year)

The driver's wage is based on $5 per driver each shift. A shift is eight hours. An average repair cost has been assumed for trucks.

CRPIR = average truck repair cost = 200 ($/truck/service)

CFRPIR = fixed cost of repair shop = 2000 ($/year)

Another logistical cost is the inventory cost. The following numerical values have been assumed for it.

CSTRG = average unit inventory cost = 145 ($/ton/year)

CFSTRG = fixed cost of inventory = 5000 ($/year)

The loading and unloading of trucks were assumed to be done by manpower. A ten ton truck consists of 200 bags of grain. On the average, it usually takes two men three hours to load or unload a truck, or six hours per man. Manpower cost assumed in this study is four dollars per man per shift (eight hours). As was discussed in Chapter II, in a famine situation part of the wage is paid in food and labour is generally cheap in such a crisis. Thus, the above manpower cost translates to fifty cents an hour per man. Consequently, the cost of unloading or loading a truck becomes three dollars (6 * .5). This means that the cost of loading/unloading of a ton of grain cost $.3 (truck capacity is ten tons). Hence,

CLOAD = unit loading cost = .5 * .6 = .3 ($/ton)

CULOAD = unit unloading cost = .3 ($/ton)

CFLOAD = fixed loading cost = 1000 ($/year)

CFULOAD = fixed unloading cost = 1000 ($/year)

The following has been assumed for sampling cost. Knapp (64) gives a detailed discussion on this type of cost.

CSMPL = unit sampling cost = 2000 ($/survey/region)

CFSMPL = fixed sampling cost = 4000 ($/year)

The last item in the total cost calculation is the ship waiting cost. The contribution of this cost is an important part of the total cost. In this study, it has been assumed that this cost is proportional to the capacity of the ship and other important ship characteristics such as speed, which is assumed to be the same for all ships. The numerical value of the waiting cost is based on the cost of transporting a ton of grain from the donor country to the port of destination. This cost is $50 for a ton of grain when the travelling time is six weeks. So the ship waiting time cost becomes

CSHIPW = unit cost of ship waiting time = 50 * 52/6 = 433.33 ($/ton/year)

The above numerical values remain unchanged throughout the study.

APPENDIX B

FORTRAN Computer Program

```
      PROGRAM  MAIN( INPUT,OUTPUT,TAPE1,TAPE2,TAPE3,TAPE4,TAPE5,TAPE6,
     1             TAPE7,TAPE8 )
      COMMON / BLOCK / DUR,DT,DETPRT,SELPRT,BEGPRT,PRTCHG,PRTVL1,
     1                 PRTVL2,SAMPT,ALPHA,BETA,CCDP,SUMDEL,TRLIMIT,
     2                 BET1,BET2,BET3,DELD,SDDEM,BETSMPL,SPDFUL,SPDMTY,
     3                 CPRSTG,CPEFA,CPQUE,CPTND,QUEFLAG,POP(4),TATTC
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON / CDP / DELCDP,DELCDPP,KCDP,TRLOST,YPAST,TRMIN,TYD,DYD,
     1              STRGCDP,TRLACK,DRLACK,DYPAST,DSTGCDP
      COMMON/ ARRIVE / TRUCKAR,DELINN,DELINNP,KDP,RT(6),RD(3),DELRPR,
     1                 DELRPRP,KTP
      COMMON / FAC / TIDT,IOUTTOT,ST,DOCK,NSS,PARWT,TINPUT,TIDCAP,TIDRMS
      COMMON / UNI / A1,A2,A3,D1,D2,P1,C1,RMS,TONSH(150)
      COMMON / SILO / RSTGLST(4),PRODEM(4),TSUPPLY(4),KP,TRP(4),RMSS(4),
     1               RPT(10,4),TDEMAND(4),RTRUPUT(4),TDPR(4),TRN(4),
     2               RFT(10,4),DELF(4),DELPF(4),KF,TRNP(4),KR,STKOUT(4)
     3               ,RTR(10,4),SDEVSD(4),TAR(4),TSR(4),CIQS(4),GR(4)
     4               ,RTTP(10,4),RTTR(10,4),SROUTE(4),BRFLG(4),TBRKDN,
     5               BALANCE
      COMMON / TRNSS / KT,AUXRM(3,4),AUXRF(3,4),START(4),ENDFLG(4,4)
      COMMON / DEMDEST / DD(4),PI,TDEF,BIAS,ENID(4),BETDEM(2),DEV
     1                   ,DTOTAL,TDEM
      COMMON / DECIDE / TIDTR,TDR,DDR,THRUPUT,TTRUPUT,DTRUPUT,STGLST,RMT
     1                  ,TIDGR,TIDDR,TIDRMT,CCTRL(4)
      COMMON / COST / CDWAGE,CRPIR,CFRPIR,CRENT,CFUEL,CFTRNS,CFSTRG,
     1               CSTRG,CFLOAD,CLOAD,CFULOAD,CULOAD,CFSMPL,CDRWAGE,
     2               CRPAIR,CRNTR,CFUELS,TCTRNS,CVAINV,CVLOAD,CVULOAD,
     3               CVSMPL,CSHIPW,TCSHIP,TOTCOST,CSMPL
      COMMON / AVE / MONRUN,NAVE,MONTIME,MON,INTOTM(4),IWLM(4),STOGM(4),
     1              AVTWTM(4),TIDTM(4),THRUPM(4),TINPM(4),TIDTRM(4),
     2              IOUTM(4),TIDCM(4),PARIM(4),STKOTM1(4),STKOTM2(4),
     3              STKOTM3(4),STKOTM4(4),RSTOGM1(4),RSTOGM2(4),
     4              RSTOGM3(4),RSTOGM4(4),TTRUPM(4),DTRUPM(4),TTBSM(4),
     5              TDBSM(4),RTRUPM1(4),RTRUPM2(4),RTRUPM3(4),
     6              RTRUPM4(4),PRODEM1(4),PRODEM2(4),PRODEM3(4),
     7              PRODEM4(4),SDEVDM1(4),SDEVDM2(4),SDEVDM3(4),
     8              SDEVDM4(4),TIDGRM(4),TIDDRM(4),VAR(20),SDEV(20),
     9              TIDRMSM(4),TIDRMTM(4),TT(20,30),PARIDT,AVTWT,
     1              TCSHIPM(4),TCTRNSM(4),TOTCSTM(4),BALANCM(4)
      COMMON / FOOD / YRTONS
      COMMON / CAL / QGRW,QGRAP
      COMMON / PQUE / PTSR,PTAR,PDAR,PCIQS,PCIQSD
      DATA  NVAR,NRUN,MONRUN,MONTIME / 9,1,1,4 /
      DATA  ROUTE/ 0.0,400.,590.,480.,400.,400.,0.0,190.,330.,400.,590.,
     1            190.,0.0,116.,330.,480.,330.,116.,0.0,170.,400.,
     2            400.,330.,170.,0.0 /
C
C     *   *   *    BEGIN  RUN  LOOP
C
```

```
      DO  500  IRUN = 1,NRUN
C
C       *    *    DEFINE PARAMETERS UNCHANGED THRU SIMULATION RUN
C
C    *   *    *    RUN  PARAMETERS
C
      DUR = 1
      DT = 1./4380.
      DETPRT = 0.0
      SELPRT = 1.
      BEGPRT = .25
      PRTCHG = 2.
      PRTVL1 = .25
      PRTVL2 = .25
      NAVE = IRUN
      TGRC = 10.
      TDRC = 1.
C
C  *   *   DATA  FOR  PORT
      RMTD = 13700.
      RMT = RMTD*365.
      CAPWH = 200000.
      YRTONS = 3000000.
      NDTSKIP = 10
      RMSH = 640.
      RMS = RMSH*24.*365.
      STGLST = .1
      ALPHA = .05
      BETA = .8
C
C   *   *   DATA  FOR  REGIONAL  WAREHOUSES
      TRSHOLD = .02
      DO  1  I=1,4
       RCAPWH(I)=50000.
       RSTGLST(I)  = .1
       DELF(I)  = 1./(2.*365.)
       DELPF(I)  = DELF(I)
    1 CONTINUE
C
C    *    *   DATA  FOR  SHIPS
      AVTONS = 18500.
      P1 = .86
      A1 = 4000.
      A2 = 27000.
      A3 = 55000.
      D1 = A2-A1
      D2 = A3-A2
      C1 = 1./1460.
      C1HR = C1*1460.*6.
C
C   *   *   DATA  FOR  REGIONAL  DEFICIT  AND  DEMAND
C   *    *   DEMAND  SHIFTS  PARAMETERS
      BET1 = 0.0
      BET2 = 0.0
```

```
      BET3 = 0.0
      PI = 4. * ATAN(1.)
      TDEF = 3200000.
C
C  *   *   DATA  FOR  SAMPLING AND ESTIMATION  OF  DEMANDS
      SAMPT = 14./365.
      BETDEM(1) = .2363
      BETDEM(2) = .1133
      DEV = 2250000.
C
C    *   *   CONTROL PARAMETERS
      CPEFA = 1.
      CPTND = .06
      CPQUE = 0.0
      QUEFLAG = 5.
C
C  *    *    ROAD BREAKDOWN
      TBRKDN = 2.
      R = .4
C
C    *   *   POLICY  PARAMETERS
      SPDFUL = 35.
      SPDMTY = 40.
C
C  *  *   READ  RUN  PARAMETERS
C
      PRINT 901, IRUN
      PRINT 905, CAPWH,RMSH,RMTD,C1HR,YRTONS,P1,DT
      PRINT 906, RMS,RMT
      PRINT 914, RCAPWH(1),RCAPWH(2),RCAPWH(3),RCAPWH(4),RMSS(1),
     1           RMSS(2),RMSS(3),RMSS(4)
      ZTDEF = 1.1 * YRTONS
      PRINT 916, BETDEM(1),BETDEM(2),DEV,SAMPT,ZTDEF,BET1,BET2,BET3
      NITER = DUR / DT + .000000000001
C
C            ***     START MONTE CARLO LOOP     ***
C
      DO  450  MRUN = 1 , MONRUN
C
C  *   *   DEFINE  INITIAL  VALUES
C
C  *   *    DATA  FOR  PORT
      SUMAT = 0.0
      TPOL = TRMIN
      DPOL = TRMIN
      DOCK = 0.
      NSS = 0
      NSP = 3
      TIDT = 0.
      TIDTR = 0.
      TIDGR = 0.0
      TIDDR = 0.0
      TIDCAP = 0.0
      TIDRMS = 0.0
```

```
      TIDRMT = 0.0
      IWL = 0
      TWT = 0.
      PARWT=0.
      INTOT = 0
      INPART = 0
      IOUTTOT = 0
      TINPUT=0.
      THRUPUT = 0.
      STOG = 40000.
      TEMPC1 = C1
      TTRUPUT = 0.
      DTRUPUT = 0.
      TDR = 0.0
      DDR = 0.0
C   *   *    QUEUES AT PORT
      PTAR = 0.0
      PDAR = 0.0
      PTSR = 0.0
      PCIQS = 0.0
      PCIQSD = 0.0
C
C   *   *    DATA   FOR  REGIONAL  WAREHOUSES
      DO  5  I = 1,4
       XGT(I) = 0.0
       TRN(I) = 0.0
       TRP(I) = 0.0
       TAR(I) = 0.0
       TSR(I) = 0.0
       TDPR(I) = 0.0
       SDEVSD(I) = 0.0
       RTRUPUT(I) = 0.0
       STKOUT(I) = 0.0
       TRNP(I) = 0.0
       RWSTOG(I) = 11000.
       TRPOL(I) = 0.0
       CIQS(I) = 0.0
       TDEMAND(I) = 0.0
       TSUPPLY(I) = 0.0
       PRODEM(I) = 0.0
       RLOAD(I) = 0.0
       RUNLOAD(I) = 0.0
       PTSTRG(I) = 0.0
       FTSTRG(I) = 0.0
       RTSTRG(I) = 0.0
       BRFLG(I) = 0.0
       START(I) = 0.0
       DO  4  J = 1,4
        ENDFLG(I,J) = 0.0
    4  CONTINUE
    5 CONTINUE
      DO  7  J=1,4
       DO  6  I=1,10
         RPT(I,J) = 0.0
```

```
            RFT(I,J) = 0.0
            RTR(I,J) = 0.0
            RTTP(I,J) = 0.0
            RTTR(I,J) = 0.0
    6  CONTINUE
    7 CONTINUE
      DO  8  K = 1,150
       TONSH(K) = 0.0
    8 CONTINUE
      DO  9  J = 1,16
       TTSTRG(J) = 0.0
    9 CONTINUE
      BALANCE = 0.0
C
C        DATA  FOR  COSTS
C
C        TRUCKS AND DRIVERS WHICH WE HAVE TO PAY FOR THEIR SERVICES
      TTRIOP = 0.0
      TDRIOP = 0.0
C        TOTAL  DISTANCE  TRAVELLED  BY  TRUCKS
      TROUTE = 0.0
C        INCREMENTAL SUM OF SERVICES OF STORAGES AND LOADING AND
C        UNLOADING FACILITIES
      SUMSTOG = 0.0
      SUMR1 = 0.0
      SUMR2 = 0.0
C   *   *    GRAIN ON SHIPS WAITING AT PORT
      QGRW = 0.0
      QGRAP = 0.0
C
C   *    *    TIME  AND  PRINT  DATA
      T = 0.0
      MON = 1
      PRTIME = BEGPRT
      PRTVL = PRTVL1
C
C          ***  INITIAL  CAPITAL  DEVELOPMENT  PROCESS  ***
      CALL  CAPITAL( YD )
C
C             *** BEGIN TIME LOOP ***
C
      DO  400  ITER = 1 , NITER
C
C           CALL  MODEL
C           -----------
      T = T + DT
C
      CALL  EXGEN( T,SUMAT,AVTONS,INTOT,INPART,IWL )
      CALL FACPORT
C             *** ALLOW FOR DOWN TIME ***
      IF(NSP.LT.NDTSKIP) GO TO 15
      NSP = 0
      GO TO 25
   15 CONTINUE
```

```
C               ***     CHECK DOCKING     ***
      CALL  DOCKY( DOCK,TEMPC1,R1,RMS,C1,DT )
C
C     ****              CHECK   TRUCK   AND   DRIVER         ****
   25 CALL  ARAIVAL( TDR , DDR )
      CALL  DEMAND
C
C        CHECK FOR ROAD BREAKDOWN
C
      IF( T .GT. TBRKDN ) THEN
C        RANDOM SELECTION OF ROAD
       IF( R .GT. .75 ) XGT(1) = 1.0
       IF( R .GT. .5 .AND. R .LE. .75 ) XGT(2) = 1.0
       IF( R .GT. .25 .AND. R .LE. .5 ) XGT(3) = 1.0
       IF( R .LE. .25 ) XGT(4) = 1.0
      ENDIF
C
      CALL  CONTROL
C
      DO  80  I = 1,4
         CALL  SILOS(I)
   80 CONTINUE
      TRUCKAR = TRNP(1) + TRNP(2) + TRNP(3) + TRNP(4)
      CALL  CALCULT
C               ***     CHECK PRINT TIME     ***
      IF(T.LT.PRTIME-.00000001) GO TO 90
C
C        PRINT  RESULTS
C
      IF( T .GT. PRTCHG - .000000001 ) PRTVL = PRTVL2
      PRTIME = T + PRTVL
C
      CALL  COSTS
C
      CALL  AVERAGE( IRUN,INTOT,INPART )
C
      IF( SELPRT .EQ. 0.0 ) GOTO 90
C
C        PRINT SELECTED VARIABLES
C
      CALL  SELPRNT( DUR )
C
   90 CONTINUE
      IF( T .LT. .9999999 ) GO TO 100
C
C        VARIABLE OBSERVATION FOR CONSTRUCTION OF
C        ITS DISTRIBUTION
C
      TT(1,MRUN) = TIDT
      TT(2,MRUN) = TIDCAP
      TT(3,MRUN) = TIDGR
      TT(4,MRUN) = AVTWT
      TT(5,MRUN) = TIDTR
      TT(6,MRUN) = TIDDR
```

```
      DO  95  I = 1,4
       TT(I+6,MRUN) = PRODEM(I)
       TT(I+10,MRUN) = STKOUT(I)
   95 CONTINUE
      TT(15,MRUN) = TINPUT
      TT(16,MRUN) = THRUPUT
      TT(17,MRUN) = TCSHIP
      TT(18,MRUN) = TCTRNS
      TT(19,MRUN) = TOTCOST
      TT(20,MRUN) = BALANCE
C
  100 CONTINUE
  400 CONTINUE
  450 CONTINUE
C
C         PRINT MONTE CARLO AVERAGES
C
      CALL  MONPRNT( DETPRT )
C
  500 CONTINUE
      STOP
C
C           FORMAT  STATEMENTS
C
  901 FORMAT(38H1 NON-DEFAULT PARAMETER VALUES FOR RUN,I2,/,
     1          "======================================")
  905 FORMAT("0",5X,"PORT PARAMETERS",/,6X,"---------------",/,
     1             " GRAIN STORAGE CAPACITY AT PORT (TONS) ",F10.,/,
     2             " SHIP UNLOADING RATE (TONS/HR) ",12X,F6.0,/,
     3             " PORT TRUCK LOADING RATE (TONS/DAY) ",6X,F6.0,/,
     4             " DOCKING TIME (HRS) ",20X,F6.2,/,
     5             " TONS OF GRAIN ARRIVING PER YEAR ", 7X,F10.0,/,
     7             " SERVICE GENERATION PARAMETER FOR SHIPS ",2X,F6.2,/,
     8             " DT (TIME INCREMENT) ",18X,F10.6 )
  906 FORMAT(" SHIP UNLOADING RATE (TONS/YR) ",8X,F12.0,/,
     1        " PORT TRUCK LOADING RATE (TONS/YR) ",4X,F12.0 )
  914 FORMAT("0",5X,"R.W.H. PARAMETERS",/,6X,"-----------------",/,
     1             " STORAGE CAPACITY AT 1ST RWH (TONS)",F10.,/,
     2             " STORAGE CAPACITY AT 2ND RWH (TONS)",F10.,/,
     3             " STORAGE CAPACITY AT 3RD RWH (TONS)",F10.,/,
     4             " STORAGE CAPACITY AT 4TH RWH (TONS)",F10.,/,
     5             " MAX TRUCK UNLOADING RATE AT 1ST RWH (TONS/YR)",F10.,/
     6            ," MAX TRUCK UNLOADING RATE AT 2ND RWH (TONS/YR)",F10.,/
     7            ," MAX TRUCK UNLOADING RATE AT 3RD RWH (TONS/YR)",F10.,/
     8            ," MAX TRUCK UNLOADING RATE AT 4TH RWH (TONS/YR)",F10.)
  916 FORMAT("0",5X,"ESTIMATION,SAMPLING AND DEMAND PARAMETERS",/,
     1             6X,"------------------------------------------",/,
     2             " BETA1 =",F9.6,/," BETA2 =",F9.6,/," DEV =",F10.,/,
     3             " SAMPLING INTERVAL (YEARS)",F9.6,/,
     4             " EXPECTED TOTAL DEMAND (TONS)",F10.,/,
     5             " REGIONAL POPULATION MOVEMENT COEFFICIENTS",
     6             3(2X,F5.3))
      END
```

```
      SUBROUTINE  CONTROL
      COMMON / BLOCK / DUR,DT,DETPRT,SELPRT,BEGPRT,PRTCHG,PRTVL1,
     1                 PRTVL2,SAMPT,ALPHA,BETA,CCDP,SUMDEL,TRLIMIT,
     2                 BET1,BET2,BET3,DELD,SDDEM,BETSMPL,SPDFUL,SPDMTY,
     3                 CPRSTG,CPEFA,CPQUE,CPTND,QUEFLAG,POP(4),TATTC
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON / DECIDE / TIDTR,TDR,DDR,THRUPUT,TTRUPUT,DTRUPUT,STGLST,RMT
     1                  ,TIDGR,TIDDR,TIDRMT,CCTRL(4)
      COMMON / PQUE / PTSR,PTAR,PDAR,PCIQS,PCIQSD
      DIMENSION  GNEED(4) , GRWH(4) , RSTGMTY(4)
      DATA CCTRL / 4*.95 /
C
      IF( T .GT. DT ) GOTO 5
      DO  4  I = 1,4
       RSTGMTY(I) = CCTRL(I) * RCAPWH(I)
    4 CONTINUE
    5 TDR = 0.0
      TGRWH = 0.0
      TOTDEM = 0.0
      TOTNEED = 0.0
      CALL  FOODAR( T , YM )
      CALL  CONVDEL
      YD = YM * CONVFAC
      QUE = FLOAT(IWL) - QUEFLAG
      IF( QUE .LT. 0.0 ) QUE = 0.0
C
C        COMPUTING TOTAL NUMBER OF TRUCKS DESIRED
      SCALE = TRSHOLD * CAPWH
      ASTOG = (STOG - SCALE) / TGRC
      IF( ASTOG .LT. 0.0 ) ASTOG = 0.0
      CAPNEED = CPEFA*YD + CPQUE*(QUE*AVTONS/TGRC) + CPTND*ASTOG
C
      CALL  CAPITAL( CAPNEED )
      CALL  CHOICE( DT,RMT,TIDGR,TIDTR,TIDDR,TIDRMT )
C
C        FOOD ASSIGNMENT
C
      DO  10  I = 1,4
       IF( DEMEST(I) .LE. 0.0 ) DEMEST(I) = .001
       TOTDEM = TOTDEM + DEMEST(I)
   10 CONTINUE
C
      REST = R2 - TOTDEM
C        ALLOCATION OF EXTRA AID
      IF( REST .GT. 0.0 ) THEN
       R2 = R2 - REST
C        FULL STORAGES DO NOT GET EXTRA ALLOCATION
       DO  12  I = 1,4
        GNEED(I) = DEMEST(I)
```

```
       IF( RWSTOG(I) .GE. RSTGMTY(I) ) GNEED(I) = .000001
       TOTNEED = TOTNEED + GNEED(I)
   12  CONTINUE
C        EXTRA AID IS ALLOCATED PROPORTIONAL TO
C        ESTIMATED DEMAND
      DO  15  J = 1,4
       GNEED(J) = ( GNEED(J)/TOTNEED ) * REST
   15  CONTINUE
      ENDIF
C
      DO  20  I = 1,4
       IF( REST .LE. 0.0 ) GNEED(I) = 0.0
       GRWH(I) = GNEED(I) + ( DEMEST(I)/TOTDEM ) * R2
       TDP(I) = GRWH(I) / TGRC
       TGRWH = TGRWH + GRWH(I)
       TDR = TDR + TDP(I)
   20 CONTINUE
      DDR = TDRC*TDR
      IF( REST .GT. 0.0 ) R2 = R2 + REST
C
C        PORT OUTPUTS
C
      THRUPUT = THRUPUT + DT*TGRWH
      TTRUPUT = TTRUPUT + DT*TDR
      DTRUPUT = DTRUPUT + DT*DDR
      STOG = STOG + DT*(R1 - TGRWH - STGLST*STOG)
      IF( STOG .LT. 0.0 ) STOG = 0.0
C
C        QUEUES AT PORT
C
      PTSR = PTSR + DT*TDR
      PCIQS = PCIQS + TPOL
      PCIQSD = PCIQSD + DPOL
C
      RETURN
      END
```

```
      SUBROUTINE  CAPITAL( YD )
      COMMON / BLOCK / DUR,DT,DETPRT,SELPRT,BEGPRT,PRTCHG,PRTVL1,
     1                 PRTVL2,SAMPT,ALPHA,BETA,CCDP,SUMDEL,TRLIMIT,
     2                 BET1,BET2,BET3,DELD,SDDEM,BETSMPL,SPDFUL,SPDMTY,
     3                 CPRSTG,CPEFA,CPQUE,CPTND,QUEFLAG,POP(4),TATTC
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON / CDP / DELCDP,DELCDPP,KCDP,TRLOST,YPAST,TRMIN,TYD,DYD,
     1               STRGCDP,TRLACK,DRLACK,DYPAST,DSTGCDP
      COMMON / PQUE / PTSR,PTAR,PDAR,PCIQS,PCIQSD
      DIMENSION  RCDPT(3) , RCDPD(3)
      DATA CCDP,KCDP,TRLOST,TRMIN,TRLIMIT,TATTC / 4000.,3,.1,0.0,
     1      123000.,.25 /
C
C   *   THIS  SUBROUTINE  SIMULATES  THE  CAPITAL  DEVELOPMENT
C       PROCESS  IN TOTAL  OPERATIONS . ( ACQUSITION OF TRUCKS/DRIVERS )
C
C       TATTC = TRUCK ATTRITION RATE
C       DELCDP = ACQUSITION  DELAY
C       TRLOST = LOST  FACTOR
C       TRMIN = INITIAL  NUMBER OF  TRUCKS  IN  THE  SYSTEM
C       CCDP = CONTROL PARAMETER
C       TRLIMIT = LIMIT  ON  RATE  OF  ACQUSITION
C       STRGCDP = INVENTORY  OF  TRUCKS  IN  TRANSIT
C       DSTGCDP = INVENTORY OF DRIVERS IN TRANSIT
C
      IF( T .GT. 0.0 ) GOTO 20
      DELCDP = 14. / 365.
      DELCDPP = DELCDP
      DSTGCDP = 0.0
      STRGCDP = 0.0
      U = 0.0
      YN = 0.0
      DU = 0.0
      DYN = 0.0
      TRLACK = 0.0
      DRLACK = 0.0
      DO  5  I = 1,3
        RCDPT(I) = 0.0
        RCDPD(I) = 0.0
    5 CONTINUE
      YPAST = TRMIN
      DYPAST = TRMIN
C       CALCULATING THE INITIALLY NEEDED CAPITAL
      CALL  FOODAR(T , YM )
      CALL  CONVDEL
      YD = YM * CONVFAC
      TYD = ( 1. + DT*TATTC ) * YD
      DYD = YD
      YDINT = YD
```

```
      CDPFLAG = 0.0
      GOTO  25
C
C             EXECUTION  PHASE
C
C        ADJUSTING FOR TRUCKS IN REPAIR SHOP AND
C        DRIVERS ON LEAVE AND TRUCK ATTRITION
C
   20 TYD = YD + TTIRS
      TYD = ( 1. + DT*TATTC ) * TYD
      DYD = YD + TDOL
   25 Z = TRLOST * YPAST
      ATTRATE = TATTC * YPAST
      YDOT = U + YN - Z
      YDOT = YDOT - ATTRATE
      Y = YPAST + DT*YDOT
      IF( Y .LT. 0.0 ) Y = 0.0
      CHANGE = Y - YPAST
      YPAST = Y
      TPOL = TPOL + CHANGE + TRLACK
C
      DZ = TRLOST * DYPAST
      DYDOT = DU + DYN - DZ
      DY = DYPAST + DT * DYDOT
      IF( DY .LT. 0.0 ) DY = 0.0
      DCHANGE = DY - DYPAST
      DYPAST = DY
      DPOL = DPOL + DCHANGE + DRLACK
C
C   *   *    QUEUES AT PORT
C
      IF( CDPFLAG .LT. 1. ) GOTO 30
      IF( CHANGE .GT. 0.0 ) THEN
       PTAR = PTAR + CHANGE
      ENDIF
      IF( DCHANGE .GT. 0.0 ) THEN
       PDAR = PDAR + DCHANGE
      ENDIF
   30 CONTINUE
C
C       CHECK FOR INITIAL ACCUMULATION OF CAPITAL
      IF( TPOL .GE. YDINT  .AND. CDPFLAG .EQ. 0.0 ) THEN
       CDPFLAG = 1.
       GOTO 40
      ENDIF
      TRLACK = 0.0
      DRLACK = 0.0
      IF( TPOL .LT. 0.0 ) THEN
       TRLACK = TPOL
       TPOL = 0.0
      ENDIF
      IF( DPOL .LT. 0.0 ) THEN
       DRLACK = DPOL
       DPOL = 0.0
      ENDIF
```

```
C        CONTROL
      ERRORT = TYD - Y
      X = CCDP * ERRORT
      IF( X .LE. 0.0 ) THEN
         W = 0.0
         YN = X
       ELSE
         IF( X .LT. TRLIMIT ) W = X
         IF( X .GE. TRLIMIT ) W = TRLIMIT
         YN = 0.0
      ENDIF
C
      ERRORD = DYD - DY
      DX = CCDP * ERRORD
      IF( DX .LE. 0.0 ) THEN
         DW = 0.0
         DYN = DX
       ELSE
         IF( DX .LT. TRLIMIT ) DW = DX
         IF( DX .GE. TRLIMIT ) DW = TRLIMIT
         DYN = 0.0
      ENDIF
C
C        CAPITAL ACQUISITION DELAY
C
      IDTU = 1
      CALL  DELVF( W,U,RCDPT,STRGCDP,DELCDP,DELCDPP,DT,IDTU,KCDP )
      CALL  DELVF( DW,DU,RCDPD,DSTGCDP,DELCDP,DELCDPP,DT,IDTU,KCDP )
C
      IF( CDPFLAG .EQ. 1. ) GOTO 40
      TTRIOP = TTRIOP + TPOL
      TDRIOP = TDRIOP + DPOL
      GOTO 25
C
   40 CONTINUE
      RETURN
      END
```

```
      SUBROUTINE  CONVDEL
C
C         THIS SUB COMPUTES THE CONVERSION FACTOR FOR CAPITAL
C         DEVELOPMENT PROCESS
C
      COMMON / BLOCK / DUR,DT,DETPRT,SELPRT,BEGPRT,PRTCHG,PRTVL1,
     1                 PRTVL2,SAMPT,ALPHA,BETA,CCDP,SUMDEL,TRLIMIT,
     2                 BET1,BET2,BET3,DELD,SDDEM,BETSMPL,SPDFUL,SPDMTY,
     3                 CPRSTG,CPEFA,CPQUE,CPTND,QUEFLAG,POP(4),TATTC
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON / SILO / RSTGLST(4),PRODEM(4),TSUPPLY(4),KP,TRP(4),RMSS(4),
     1                RPT(10,4),TDEMAND(4),RTRUPUT(4),TDPR(4),TRN(4),
     2                RFT(10,4),DELF(4),DELPF(4),KF,TRNP(4),KR,STKOUT(4)
     3                ,RTR(10,4),SDEVSD(4),TAR(4),TSR(4),CIQS(4),GR(4)
     4                ,RTTP(10,4),RTTR(10,4),SROUTE(4),BRFLG(4),TBRKDN,
     5                BALANCE
      COMMON / TRNSS / KT,AUXRM(3,4),AUXRF(3,4),START(4),ENDFLG(4,4)
      DIMENSION  DISDEL(4),ESTIME(4),W(4),DUMDEL(4),DUMSTG(4)
      DATA  POP / 20.,20.,10.,10. /
      DATA IFLG,DUMDEL,DUMSTG / 0,4*0.0,4*0.0 /
C
      TW = 0.0
      SUMDEL = 0.0
      IF( T .GT. 0.0 ) GOTO 15
C        TRAVEL DELAY AND EXPECTED SERVICE TIME
      DO  5  I = 1,4
       DISDEL(I) = DELAY(SPDFUL , ROUTE(I+1,1)) +
     1             DELAY(SPDMTY , ROUTE(I+1,1))
C        EXPECTED SERVICE TIME PER DT
       ESTIME(I) = 1./(RMSS(I)/TGRC)
C        WEIGHTS FOR INITIAL CAPITAL DEVELOPMENT PROCESS
       W(I) = POP(I)
       TW = TW + W(I)
    5 CONTINUE
      DO  10  I = 1,4
       DEL = ESTIME(I) + DISDEL(I) + DELF(I)
       SUMDEL = SUMDEL + (W(I)/TW)*DEL
   10 CONTINUE
      GOTO 35
   15 CONTINUE
C
C        CHECK FOR ROAD BREAK DOWN AND DELAY-WEIGHT ADJUSTMENTS
C
      IF( T .GT. TBRKDN ) THEN
      TBRKDN = TBRKDN + DUR
C        PERMANENT DELAY CORRECTIONS
       DO  18  I = 1,4
         IF( XGT(I) .GE. 1. ) THEN
           DELP = DELAY(SPDFUL , ROUTE(I+1,1))
```

```
          DELR = DELAY(SPDMTY , ROUTE(I+1,1))
          DISDEL(I) = DISDEL(I) + DELAY(SPDFUL , SROUTE(I)) +
     1                DELAY(SPDMTY , SROUTE(I)) - DELP - DELR
          IFLG = I
          GOTO 19
        ENDIF
   18  CONTINUE
      ENDIF
C
   19 IF( IFLG .EQ. 0 ) GOTO  20
C       TEMP. CORRECTIONS
      IF( BRFLG(IFLG) .LT. 4. ) THEN
        IF( ENDFLG(1,IFLG) .LT. 1. ) THEN
          DUMDEL(IFLG) = DUMDEL(IFLG) + DELR/2.
          DUMSTG(IFLG) = DUMSTG(IFLG) + TTSTRG(IFLG)
        ENDIF
        IF( ENDFLG(2,IFLG) .LT. 1. ) THEN
          DUMDEL(IFLG) = DUMDEL(IFLG) + DELR / 2.
          DUMSTG(IFLG) = DUMSTG(IFLG) + TTSTRG(IFLG+4)
        ENDIF
        IF( ENDFLG(3,IFLG) .LT. 1. ) THEN
          DUMDEL(IFLG) = DUMDEL(IFLG) + DELP/2.
          DUMSTG(IFLG) = DUMSTG(IFLG) + TTSTRG(IFLG+8)
        ENDIF
        IF( ENDFLG(4,IFLG) .LT. 1. ) THEN
          DUMDEL(IFLG) = DUMDEL(IFLG) + DELP / 2.
          DUMSTG(IFLG) = DUMSTG(IFLG) + TTSTRG(IFLG+12)
        ENDIF
      ENDIF
      IF( BRFLG(IFLG) .GE. 4. ) IFLG = 0
   20 CONTINUE
C
C
C       WEIGHTS AFTER FOOD ARRAIVAL
C
      DO  25  I = 1,4
       W(I) = TRPOL(I) + PTSTRG(I) + FTSTRG(I) + RTSTRG(I) + DUMSTG(I)
       DUMSTG(I) = 0.0
       TW = TW + W(I)
   25 CONTINUE
C
C       QUEUE DELAY AT RWH
C
      DO  30  I = 1,4
       IF( CIQS(I) .EQ. 0.0 ) THEN
          X = 0.0
         ELSE
          X = CIQS(I) / TAR(I)
       ENDIF
       DEL = DT*X + ESTIME(I) + DISDEL(I) + DELF(I) + DUMDEL(I)
       DUMDEL(I) = 0.0
       IF( W(I) .EQ. 0.0 ) THEN
          Y = 0.0
         ELSE
          Y = W(I) / TW
```

```
        ENDIF
        SUMDEL = SUMDEL + Y * DEL
   30 CONTINUE
C
C        CONVERSION FACTOR
C
   35 CONVFAC = SUMDEL / TGRC
      RETURN
      END
```

```
      SUBROUTINE  FOODAR( T , Y )
C
C  *   * THIS  SUBROUTINE  GENERATES  FOOD  ARRAIVAL  RATE  SCENARIO .
C .       THE  AREA  UNDER  THE  CURVE  REPRESENTS  TOTAL  AMOUNT  OF
C         AID . ALSO , IT  IS  USED  FOR  CALCULATING  THE  DESIRED
C         NUMBER  OF TRUCKS  IN THE TOTAL  SYSTEM AT ANY  TIME , AND
C         GENERATING  STOCHASTIC  INTERARRIVAL  TIME FOR  SHIPS .    *  *
C
      COMMON / FOOD / YRTONS
      DIMENSION  XTAB(21) , YTAB(21)
      DATA XTAB/0.0,.1,.15,.2,.25,.3,.35,.4,.45,.5,
     1          .54,.6,.65,.7,.75,.8,.85,.9,.94,.96,1./
      DATA YTAB/1.0,1.0,1.3,2.1,2.9,3.8,4.7,4.9,5.1,5.35,5.5,5.40,
     1          5.05,4.1,3.15,2.2,1.25,.59,.19,.11,.001/
      DO  20  I=2,21
      IF( T .GT. XTAB(I)) GOTO 20
      Y =  (T-XTAB(I-1))*(YTAB(I)-YTAB(I-1))/(XTAB(I)-XTAB(I-1))
     1    + YTAB(I-1)
      Y = Y*YRTONS/3.
      GOTO  25
   20 CONTINUE
   25 RETURN
      END
```

```
      SUBROUTINE  EXGEN( CLOCK,SUMAT,AVTONS,INTOT,INPART,IWL )
C
C        THIS SUB GENERATES EXPONENTIAL ARRIVAL TIMES
C        AND DUAL-UNIFORM SHIP TONNAGE
C
      COMMON / UNI / A1,A2,A3,D1,D2,P1,C1,RMS,TONSH(150)
      COMMON / CAL / QGRW,QGRAP
C
      IF(CLOCK.LT.SUMAT) GO TO 1
      IEXOUT = 1
      R = RANF()
      CALL  FOODAR( CLOCK,YRTONR )
      T = CLOCK + AVTONS/(2.*YRTONR)
      IF( T .GT. 1. ) T = 1.
      CALL  FOODAR( T , YRTONR )
      EAT = AVTONS/YRTONR
      AT = -EAT*ALOG(R)
      SUMAT = SUMAT + AT
C        COMPUTING THE SHIP LOAD
      R = RANF()
      IF( R .GE. P1 ) THEN
         TONSH(IWL+1) = (1.-R)*D2/(1.-P1) + A2
        ELSE
         TONSH(IWL+1) = A1 + R*D1/P1
      ENDIF
      QGRAP = QGRAP + TONSH(IWL+1)
      INTOT = INTOT + IEXOUT
      INPART = INPART + IEXOUT
      IWL = IWL + IEXOUT
      IF( IWL .GE. 150 ) THEN
       PRINT  100
       STOP
      ENDIF
  100 FORMAT("1",5X,"TOO MANY SHIPS ARE WAITING")
C
    1 RETURN
      END
```

```
      SUBROUTINE FACPORT
C
      COMMON / BLOCK / DUR,DT,DETPRT,SELPRT,BEGPRT,PRTCHG,PRTVL1,
     1                 PRTVL2,SAMPT,ALPHA,BETA,CCDP,SUMDEL,TRLIMIT,
     2                 BET1,BET2,BET3,DELD,SDDEM,BETSMPL,SPDFUL,SPDMTY,
     3                 CPRSTG,CPEFA,CPQUE,CPTND,QUEFLAG,POP(4),TATTC
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON / FAC / TIDT,IOUTTOT,ST,DOCK,NSS,PARWT,TINPUT,TIDCAP,TIDRMS
      COMMON / UNI / A1,A2,A3,D1,D2,P1,C1,RMS,TONSH(150)
C
C              ***     CHECK DOWN TIME     ***
      IF(NSP.LT.NDTSKIP-1) GO TO 75
      IF(NSS.EQ.1) GO TO 70
      TIDT = TIDT+DT
      GO TO 30
   70 TWT = TWT+IWL*DT
      PARWT = PARWT+IWL*DT
      GO TO 30
   75 CONTINUE
C              ***     CHECK SERVICE STATION     ***
      IF(NSS.EQ.1) GO TO 10
      IF(IWL.NE.0) GO TO 5
      TIDT = TIDT+DT
      R1=0.
      GO TO 30
    5 IWL = IWL-1
      NSS = 1
C              ***     GENERATE SERVICE TIME     ***
      ST = C1 + TONSH(1) / RMS
      TINPUT = TINPUT + TONSH(1)
      IF( IWL .LT. 1 ) GOTO 9
      DO  8  J = 1,IWL
       TONSH(J) = TONSH(J+1)
    8 CONTINUE
    9 DOCK = 1.
      GO TO 15
C              ***     CHECK WAITING LINE     ***
   10 IF(IWL.EQ.0) GO TO 20
   15 TWT = TWT+IWL*DT
      PARWT=PARWT+IWL*DT
C              ***     CHECK STORAGE VS. CAPACITY     ***
   20 IF(STOG.GE.CAPWH) GO TO 35
C              ***     CHECK REMAINING SERVICE TIME     ***
      IF(ST.GT.DT) GO TO 25
      R1 = ST*RMS/DT
      IOUT = 1
      NSS = 0
      GO TO 40
   25 ST = ST-DT
```

```
      R1 = RMS
      TIDRMS = TIDRMS + DT
   30 IOUT = 0
      GO TO 40
   35 R1 = 0.
      IOUT = 0
      TIDCAP = TIDCAP+DT
   40 CONTINUE
      IOUTTOT = IOUTTOT+IOUT
      RETURN
      END


      SUBROUTINE  DOCKY( DOCK,TEMPC1,R1,RMS,C1,DT )
C        THIS  SUBROUTINE  COMPUTES  SHIP  OFF-LOADING  RATE
C
      IF(DOCK.EQ.0.) GO TO 30
      IF(TEMPC1.LT.DT) GO TO 20
      TEMPC1 = TEMPC1-DT
      R1 =0.
      GO TO 30
   20 R1 = (DT-TEMPC1)*RMS/DT
      DOCK = 0.
      TEMPC1 = C1
   30 RETURN
      END
```

```
      SUBROUTINE  ARAIVAL  ( TDR , DDR )
C  *    *  THIS SUB COMPUTES THE NET INPUT RATES INTO REPAIR SHOP
C          AND TRUCK / DRIVER POOLS .               *        *       *
C
      COMMON / BLOCK / DUR,DT,DETPRT,SELPRT,BEGPRT,PRTCHG,PRTVL1,
     1                 PRTVL2,SAMPT,ALPHA,BETA,CCDP,SUMDEL,TRLIMIT,
     2                 BET1,BET2,BET3,DELD,SDDEM,BETSMPL,SPDFUL,SPDMTY,
     3                 CPRSTG,CPEFA,CPQUE,CPTND,QUEFLAG,POP(4),TATTC
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON/ ARRIVE / TRUCKAR,DELINN,DELINNP,KDP,RT(6),RD(3),DELRPR,
     1                 DELRPRP,KTP
      COMMON / PQUE / PTSR,PTAR,PDAR,PCIQS,PCIQSD
      DATA  KDP,KTP / 3,6 /
C
      IF( T .GT. DT ) GOTO 4
C          TRUCK REPAIR AND DRIVER  DELAYS  AT  PORT
      DELRPR = 5./365.
      DELRPRP = DELRPR
      DELINN = 2./365.
      DELINNP = DELINN
C   ***      INITIAL TRUCK/REPAIR AND DRIVER/LEAVE  AT  PORT      ****
      TTIRS = 0.
      TDOL = 0.
      TTBS = 0.0
      TDBS = 0.0
C           TRUCK// DRIVER  ARRAIVAL  RATES
      RD(1) = 0.0
      RD(2) = 0.0
      RD(3) = 0.0
      TRUCKAR = 0.0
      DO  3  J=1 , KTP
       RT(J) = 0.0
    3 CONTINUE
    4 CONTINUE
C
      IDTU = 1
      DRIVEAR = TDRC * TRUCKAR
      TRUCKRN = TRUCKAR * ALPHA
      IF( NSP .GT. 1 ) THEN
       HOLD = 0.0
       GOTO  5
      ENDIF
      IF( NSP .LE. 0 ) THEN
       HOLD = TRUCKRN
       TRUCKRN = 0.0
       GOTO 10
      ENDIF
      IF( T .LT. 2*DT ) GOTO 5
      TRUCKRN = TRUCKRN + HOLD
```

```
C
    5 CALL DELVF(TRUCKRN,TRUCKRD,RT,TTIRS ,DELRPR,DELRPRP,DT,IDTU,KTP)
   10 TRAR = TRUCKAR - TRUCKRN
      R3 = TRAR + TRUCKRD - TDR
      PTAR = PTAR + DT*( TRAR + TRUCKRD )
      TPOL = TPOL + DT * R3
      TTBS = TTBS + DT*TRUCKRD
C
      DRIVEIN = DRIVEAR * BETA
      CALL DELVF(DRIVEIN,DRIVERD ,RD,TDOL ,DELINN,DELINNP ,DT,IDTU ,KDP)
      DRAR = DRIVEAR - DRIVEIN
      R4 = DRAR + DRIVERD - DDR
      PDAR = PDAR + DT*( DRAR + DRIVERD )
      DPOL = DPOL + DT * R4
      TDBS = TDBS + DT*DRIVERD
      RETURN
      END
      SUBROUTINE  DELVF( RIN,ROUT,R,STRG,DEL,DELP,DT,IDTU,K )
      DIMENSION  R(1)
      FK = FLOAT(K)
      B = 1. + (DEL - DELP)/(DT*FK)
      IDT = 1. + 2. *B*DT*FK/DELP
      IF( IDT .LT. IDTU ) IDT = IDTU
      A = FK*DT/(DELP*FLOAT(IDT))
      DELP = DEL
      KM1 = K - 1
      DO  20  J=1,IDT
         IF( K .EQ. 1 ) GOTO 15
         DO  10  I=1,KM1
           R(I) = R(I) + A*(R(I+1) -B*R(I))
   10    CONTINUE
   15    R(K) = R(K) + A*(RIN -B*R(K) )
   20 CONTINUE
      STRG = 0.
      DO  30  I=1,K
         STRG = STRG + R(I)*DEL/FK
   30 CONTINUE
      ROUT = R(1)
      RETURN
      END
```

```
      SUBROUTINE  CHOICE( DT,RMT,TIDGR,TIDTR,TIDDR,TIDRMT )
C
C  *   *  THIS SUB SIMULATES THE ASSIGNMENT OPERATION AT THE PORT . IT
C         CALCULATES THE OUTPUT RATES OF THE PORT .           *       *
C
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      SCALE = TRSHOLD * CAPWH
      IF( NSP .GE. NDTSKIP .OR. STOG .LE. SCALE ) THEN
          R2 = 0.0
          TIDGR = TIDGR + DT
          IF( TPOL .LE. 0.0 ) TIDTR = TIDTR + DT
          IF( DPOL .LE. 0.0 ) TIDDR = TIDDR + DT
          GOTO  10
      ENDIF
C
      IF( TPOL .LE. 0.0 ) THEN
          R2 = 0.0
          TIDTR = TIDTR + DT
          IF( DPOL .LE. 0.0 ) TIDDR = TIDDR + DT
          GOTO  10
      ENDIF
C
      IF( DPOL .LE. 0.0 ) THEN
          R2 = 0.0
          TIDDR = TIDDR + DT
          GOTO  10
      ENDIF
C
      DD = 0.
      DPO =  (TGRC*DPOL)/TDRC
      RDD = CHECK( DPO,DT,RMT,DD )
      TT = 0.
      TPO = TGRC * TPOL
      RTT = CHECK( TPO,DT,RMT,TT )
      SS =0.
      RSS = CHECK( STOG,DT,RMT,SS )
      CODE = DD*TT *SS
      IF( CODE .EQ. 1. ) THEN
       R2 = RMT
       TIDRMT = TIDRMT + DT
       GO TO 10
      ENDIF
      R2 = RDD
      IF( R2 .GT. RTT ) R2 = RTT
      IF( R2 .GT. RSS ) R2 = RSS
C
```

```
      IF( R2 .EQ. RSS ) TIDGR = TIDGR + DT
      IF( R2 .EQ. RDD ) TIDDR = TIDDR + DT
      IF( R2 .EQ. RTT ) TIDTR = TIDTR + DT
C
   10 RETURN
      END


      FUNCTION  CHECK( DATA,DT,RMT,W )
C
      X = DT*RMT
      IF( DATA .GE. X ) W = 1.
      CHECK = DATA / DT
C
      RETURN
      END
```

```
      SUBROUTINE  SILOS ( I )
C
      COMMON / BLOCK / DUR,DT,DETPRT,SELPRT,BEGPRT,PRTCHG,PRTVL1,
     1                 PRTVL2,SAMPT,ALPHA,BETA,CCDP,SUMDEL,TRLIMIT,
     2                 BET1,BET2,BET3,DELD,SDDEM,BETSMPL,SPDFUL,SPDMTY,
     3                 CPRSTG,CPEFA,CPQUE,CPTND,QUEFLAG,POP(4),TATTC
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON / SILO / RSTGLST(4),PRODEM(4),TSUPPLY(4),KP,TRP(4),RMSS(4),
     1                RPT(10,4),TDEMAND(4),RTRUPUT(4),TDPR(4),TRN(4),
     2                RFT(10,4),DELF(4),DELPF(4),KF,TRNP(4),KR,STKOUT(4)
     3                ,RTR(10,4),SDEVSD(4),TAR(4),TSR(4),CIQS(4),GR(4)
     4                ,RTTP(10,4),RTTR(10,4),SROUTE(4),BRFLG(4),TBRKDN,
     5                BALANCE
      DIMENSION  COUNT(4)
      DATA KF,KP,KR,RMSS / 1,6,6,2000000.,2000000.,1000000.,1000000.  /
      DATA SROUTE / 780.,590.,570.,650. /
C
      IF( T .GT. DT ) GOTO 1
      TOTDEM = 0.0
      TOTSUP = 0.0
      SUM = 0.0
    1 CONTINUE
C
C  * * *  DELAYS  OF  TRUCKS  AND DRIVERS  RETURNING  TO  PORT    * *
C
      IDTU = 4
C        CHECK FOR ROAD BREAKDOWN AND TRANSSHIPMENT
C
      IF( XGT(I)  .LT. 1. ) GOTO 2
      DELR = DELAY( SPDMTY , SROUTE(I) )
      DELPR = DELR
      CALL  DELVF( TRN(I),TRNP(I),RTTR(1,I),RTSTRG(I),DELR,DELPR,DT,
     1             IDTU , KR )
      GOTO 3
    2 CONTINUE
C
      DELR = DELAY( SPDMTY , ROUTE(I+1,1) )
      DELPR = DELR
      CALL  DELVF( TRN(I),TRNP(I),RTR(1,I),RTSTRG(I),DELR,DELPR,DT,
     1             IDTU , KR )
C
C   * * *  DELAYS  DUE TO  OVERNIGHT  STAYS  OF  DRIVERS  AT  R.W.H.
    3 IDTU = 1
      CALL  DELVF( TDPR(I),TRN(I),RFT(1,I),FTSTRG(I),DELF(I),DELPF(I),
     1             DT,IDTU,KF )
C
C         DOWN TIME FOR SILOS
C
      IF( NSP .GE. NDTSKIP ) THEN
```

```
        SR1(I) = 0.0
        SR2(I) =0.0
        SUP = 0.0
        TDPR(I) = 0.0
        RLOAD(I) = 0.0
        RUNLOAD(I) = 0.0
        GOTO  15
      ENDIF
C
C  ****   UNLOADING  AND  LOADING  OPERATIONS  IN  REGIONAL  WAREHOUSES
C
      TRPOL(I) = TRPOL(I) + DT*TRP(I)
      GR(I) = TGRC * TRPOL(I) / DT
C        CHECK FOR MAX RATE OF UNLOADING
      IF( GR(I) .GT. RMSS(I) ) THEN
         TGR = RMSS(I)
        ELSE
         TGR = GR(I)
      ENDIF
C        SATISFYING THE DEMAND
      REST = DEM(I) - TGR
      IF( REST .GE. 0.0 ) GOTO 10
C        STORING EXCESS FOOD
      IF( RWSTOG(I) .GE. RCAPWH(I) ) THEN
         SR1(I) = 0.0
         GOTO 5
      ENDIF
      REST = ABS(REST)
C      CHECK FOR CAPACITY
      ACAP = (RCAPWH(I) - RWSTOG(I))/DT
      IF( ACAP .LT. REST ) REST = ACAP
      SR1(I) = REST
    5 SR2(I) = 0.0
      SUP = DEM(I)
      TDPR(I) = (DEM(I) + SR1(I)) / TGRC
      RLOAD(I) = DEM(I)
      RUNLOAD(I) = DEM(I) + SR1(I)
      GOTO 15
C
   10 SR1(I) = 0.0
C        SUPPLYING EXCESS DEMAND
C
C         CHECK FOR GRAIN IN STORAGE
      SCALE = TRSHOLD*RCAPWH(I)
      ASTOG = (RWSTOG(I) - SCALE) / DT
      IF( ASTOG .LT. 0.0 ) ASTOG = 0.0
      IF( ASTOG .LT. REST ) THEN
         SR2(I) = ASTOG
         STKOUT(I) = STKOUT(I) + DT
        ELSE
         SR2(I) = REST
      ENDIF
      SUP = TGR + SR2(I)
      TDPR(I) = TGR / TGRC
      RLOAD(I) = TGR + SR2(I)
```

```
      RUNLOAD(I) = TGR
C
C         MEASURES OF  PERFORMANCE  -   SUPPLY  AND  DEMAND
C
   15 COUNT(I) = SUP / DEM(I)
      TOTDEM = TOTDEM + DEM(I)
      TOTSUP = TOTSUP + SUP
      IF( I .LT. 4 ) GOTO  22
       TOTPRO = TOTSUP / TOTDEM
       DO  20  JK = 1,4
         DUMMY = DEMEST(JK)*AMAX1((TOTPRO - COUNT(JK)) , 0.0)
         SUM = SUM + DUMMY
         SDEVSD(JK) = SDEVSD(JK) + DT*DUMMY
   20  CONTINUE
       BALANCE = BALANCE + DT*SUM
       TOTDEM = 0.0
       TOTSUP = 0.0
       SUM = 0.0
   22 CONTINUE
      TSUPPLY(I) = TSUPPLY(I) + SUP
      TDEMAND(I) = TDEMAND(I) + DEM(I)
      PRODEM(I) = TSUPPLY(I) / TDEMAND(I)
C
      RTRUPUT(I) = RTRUPUT(I) + DT * SUP
      RWSTOG(I) = RWSTOG(I) + DT*(SR1(I) - SR2(I)-RSTGLST(I)*RWSTOG(I))
      IF( RWSTOG(I) .LT. 0.0 ) RWSTOG(I) = 0.0
C
C  *  * TRUCKS AND DRIVERS  RETURNING  BACK TO  PORT   *  *  *
      TRPOL(I) = TRPOL(I) - DT*TDPR(I)
C
C         CALCULATIONS  FOR  QUEUES
      CIQS(I) = CIQS(I) + TRPOL(I)
      TAR(I) = TAR(I) + DT*TRP(I)
      TSR(I) = TSR(I) + DT*TDPR(I)
C
C     ****    DELAYS  FROM  PORT  TO REGIONAL  WAREHOUSES     ****
C
      IDTU = 4
C         CHECK FOR ROAD BREAKDOWN
C
      IF( XGT(I) .LT. 1. ) GOTO 25
C
C         CHECK FOR TRUCKS REMAINING ON THE OLD ROAD
C
      IF( BRFLG(I) .LT. 4. ) THEN
       CALL  TRNSHIP( I , RFTR , RMTR )
      ENDIF
C
      DELPR = DELAY( SPDFUL , SROUTE(I) )
      DELPPR = DELPR
      CALL  DELVF( TDP(I),TRP(I),RTTP(1,I),PTSTRG(I),DELPR,DELPPR,DT,
     1              IDTU , KP )
C
      TRP(I) = TRP(I) + RFTR
C
```

```
C        COST CALCULATIONS FOR DISTANCES TRAVELED
C
      TROUTE = TROUTE + DT*(TRP(I)+TRNP(I)-RFTR-RMTR)*SROUTE(I)
      RFTR = 0.0
      RMTR = 0.0
C
      GOTO 30
   25 CONTINUE
C
      DELPR = DELAY( SPDFUL , ROUTE( I+1 , 1 ) )
      DELPPR = DELPR
      CALL  DELVF( TDP(I),TRP(I),RPT(1,I),PTSTRG(I),DELPR,DELPPR,DT,
     1                IDTU , KP )
C
C        CALCULATIONS FOR COST  -  SUM OF DISTANCES TRAVELED
      TROUTE = TROUTE + DT*(TRP(I) + TRNP(I)) * ROUTE(I+1,1)
C
   30 CONTINUE
C
      RETURN
      END
      FUNCTION  DELAY( SPEED , DISTANC )
C
      W = DISTANC / (SPEED * 24. )
      DELAY = W/365.
C
      RETURN
      END
```

```
      SUBROUTINE  TRNSHIP( I , RFTR , RMTR )
C
      COMMON / BLOCK / DUR,DT,DETPRT,SELPRT,BEGPRT,PRTCHG,PRTVL1,
     1                 PRTVL2,SAMPT,ALPHA,BETA,CCDP,SUMDEL,TRLIMIT,
     2                 BET1,BET2,BET3,DELD,SDDEM,BETSMPL,SPDFUL,SPDMTY,
     3                 CPRSTG,CPEFA,CPQUE,CPTND,QUEFLAG,POP(4),TATTC
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON / SILO / RSTGLST(4),PRODEM(4),TSUPPLY(4),KP,TRP(4),RMSS(4),
     1                RPT(10,4),TDEMAND(4),RTRUPUT(4),TDPR(4),TRN(4),
     2                RFT(10,4),DELF(4),DELPF(4),KF,TRNP(4),KR,STKOUT(4)
     3                ,RTR(10,4),SDEVSD(4),TAR(4),TSR(4),CIQS(4),GR(4)
     4                ,RTTP(10,4),RTTR(10,4),SROUTE(4),BRFLG(4),TBRKDN,
     5                BALANCE
      COMMON / TRNSS / KT,AUXRM(3,4),AUXRF(3,4),START(4),ENDFLG(4,4)
      DATA KT / 3 /
C
      IF( START(I) .GT. 0.0 ) GOTO 15
       START(I) = 1.0
       COST1 = 0.0
       COST2 = 0.0
       DO  10  J = 1,KT
         K = 7 - J
         AUXRM(J,I) = RTR(K,I)
         RTR(K,I) = 0.0
         AUXRF(J,I) = RPT(K,I)
         RPT(K,I) = 0.0
   10  CONTINUE
   15 CONTINUE
C
C        DUMMY VARIABLES FOR DELAY AND COST
      RIN = 0.0
      TROAD = 0.0
C
C        EMPTY TRUCKS RETURNING TO PORT
C
      IF( ENDFLG(1,I) .GT. 0.0 ) GOTO 20
      IDTU = 4
      DELR = DELAY( SPDMTY , ROUTE(I+1,1) )
      DELPR = DELR
      CALL  DELVF( RIN,RMTR,RTR(1,I),TTSTRG(I),DELR,DELPR,DT,IDTU,KR )
      TRNP(I) = TRNP(I) + RMTR
      TROAD = TROAD + RMTR
      IF( TTSTRG(I) .LE. 0.0 ) THEN
       BRFLG(I) = BRFLG(I) + 1.
       ENDFLG(1,I) = 1.
      ENDIF
C
C        EMPTY TRUCKS TURNING BACK TO RWH
C
```

```
   20 IF( ENDFLG(2,I) .GT. 0.0 ) GOTO 25
      IDTU = 8
      DELTSM = DELR/2.
      DELTSMP = DELTSM
C
      IF( COST1 .LT. 1. ) THEN
       DO  22  J = 1,KT
         TROUTE = TROUTE + (DELTSM/KT)*AUXRM(J,I)*(J/KT)*ROUTE(I+1,1)
   22  CONTINUE
       COST1 = 1.
      ENDIF
C
      CALL  DELVF( RIN,ROUT,AUXRM(1,I),TTSTRG(I+4),DELTSM,DELTSMP,DT,
     1              IDTU , KT )
C        EMPTY TRUCKS DO NOT STAY OVERNIGHT
      TRN(I) = TRN(I) + ROUT
      IF( TTSTRG(I+4) .LE. 0.0 ) THEN
       BRFLG(I) = BRFLG(I) + 1.
       ENDFLG(2,I) = 1.
      ENDIF
C
C        FULL TRUCKS COMING TO RWH
C
   25 IF( ENDFLG(3,I) .GT. 0.0 ) GOTO 30
      IDTU = 4
      DELPR = DELAY( SPDFUL , ROUTE(I+1,1) )
      DELPPR = DELPR
      CALL  DELVF( RIN,RFTR,RPT(1,I),TTSTRG(I+8),DELPR,DELPPR,DT,
     1              IDTU , KP )
      TROAD = TROAD + RFTR
      IF( TTSTRG(I+8) .LE. 0.0 ) THEN
       BRFLG(I) = BRFLG(I) + 1.
       ENDFLG(3,I) = 1.
      ENDIF
C
C        FULL TRUCKS TURNING BACK TO PORT
C
   30 IF( ENDFLG(4,I) .GT. 0.0 ) GOTO 35
      IDTU = 8
      DELTSF = DELPR/2.
      DELTSFP = DELTSF
C
      IF( COST2 .LT. 1. ) THEN
       DO  32  J = 1,KT
         TROUTE = TROUTE + (DELTSF/KT)*AUXRF(J,I)*(J/KT)*ROUTE(I+1,1)
   32  CONTINUE
       COST2 = 0.0
      ENDIF
C
      CALL  DELVF( RIN,ROUT,AUXRF(1,I),TTSTRG(I+12),DELTSF,DELTSFP,DT,
     1              IDTU , KT )
      TDP(I) = TDP(I) + ROUT
      IF( TTSTRG(I+12) .LE. 0.0 ) THEN
       BRFLG(I) = BRFLG(I) + 1.
       ENDFLG(4,I) = 1.
```

```
      ENDIF
C
C        SUM OF THE DISTANCES TRAVELED
C
   35 TROUTE = TROUTE + DT*TROAD*ROUTE(I+1,1)
C
      RETURN
      END
```

```
      SUBROUTINE  COSTS
C
C          THIS  SUBROUTINE  COMPUTES  ACCUMULATED  COST AT ANY  TIME
C
      COMMON / BLOCK / DUR,DT,DETPRT,SELPRT,BEGPRT,PRTCHG,PRTVL1,
     1                 PRTVL2,SAMPT,ALPHA,BETA,CCDP,SUMDEL,TRLIMIT,
     2                 BET1,BET2,BET3,DELD,SDDEM,BETSMPL,SPDFUL,SPDMTY,
     3                 CPRSTG,CPEFA,CPQUE,CPTND,QUEFLAG,POP(4),TATTC
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON / COST / CDWAGE,CRPIR,CFRPIR,CRENT,CFUEL,CFTRNS,CFSTRG,
     1                CSTRG,CFLOAD,CLOAD,CFULOAD,CULOAD,CFSMPL,CDRWAGE,
     2                CRPAIR,CRNTR,CFUELS,TCTRNS,CVAINV,CVLOAD,CVULOAD,
     3                CVSMPL,CSHIPW,TCSHIP,TOTCOST,CSMPL
      COMMON / CAL / QGRW,QGRAP
      DATA CDWAGE,CRPIR,CFRPIR,CRENT,CFUEL,CFSTRG,CLOAD,CSTRG,CULOAD,
     1     CFLOAD,CFULOAD,CSMPL,CFSMPL,CSHIPW / 5475.,200.,2000.,4000.,
     2     .2491,5000.,.3,145.,.3,1000.,1000.,2000.,4000.,433.33 /
C
C            TRANSPORTATION  COSTS
C
C        DRIVERS  WAGES
      CDRWAGE = CDWAGE * DT * TDRIOP
C        TRUCK  REPAIR  COSTS
      CRPAIR = CRPIR * TTBS
C        RENTED  TRUCKS  COSTS
      CRNTR = CRENT * DT * TTRIOP
C        FUEL  COST
      CFUELS = CFUEL * TROUTE
C
C          TOTAL VARIABLE COST OF TRANSPORTATION
      CVTRNS = CDRWAGE + CRPAIR + CRNTR + CFUELS
C        FIXED  COST  OF  TRANSPORTATION
      CFTRNS = ( T / DUR ) * CFRPIR
C
C        TOTAL  COST  OF  TRANSPORTATION
      TCTRNS = CFTRNS + CVTRNS
C
C        INVENTORY  COSTS
      CVAINV = CSTRG * DT * SUMSTOG
C        LOADING  FACILITIES  COSTS
      CVLOAD = CLOAD * SUMR2
C        UNLOADING  FACILITIES  COSTS
      CVULOAD = CULOAD * SUMR1
C        INFORMATION  COSTS
      CVSMPL = 4. * ( T / SAMPT ) * CSMPL
C            TOTAL SHIPS WAITING TIME COST
      TCSHIP = CSHIPW * DT * QGRW
C
C            TOTAL VARIABLE COST OF OPERATIONS
```

```
      TVCOST = CVTRNS + CVAINV + CVLOAD + CVULOAD + CVSMPL + TCSHIP
C            TOTAL FIXED COST OF OPERATIONS
      TFCOST = (T/DUR)*(CFRPIR + CFSTRG + CFLOAD + CFULOAD + 4.*CFSMPL)
C
C        TOTAL  COST  OF  OPERATIONS
      TOTCOST = TFCOST + TVCOST
      RETURN
      END
```

```
      SUBROUTINE  CALCULT
C        THIS SUBROUTINE KEEPS TRACK OF VARIABLES NECESSARY FOR
C        COST CALCULATIONS
C
      COMMON / BLOCK / DUR,DT,DETPRT,SELPRT,BEGPRT,PRTCHG,PRTVL1,
     1                 PRTVL2,SAMPT,ALPHA,BETA,CCDP,SUMDEL,TRLIMIT,
     2                 BET1,BET2,BET3,DELD,SDDEM,BETSMPL,SPDFUL,SPDMTY,
     3                 CPRSTG,CPEFA,CPQUE,CPTND,QUEFLAG,POP(4),TATTC
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON / CAL / QGRW,QGRAP
C
      TRIOP = 0.0
      CL = 0.0
      CUL = 0.0
      DO  5  K= 1 , 4
      TRIOP =TRIOP+TRPOL(K)+PTSTRG(K)+FTSTRG(K)+RTSTRG(K)
     1       +TTSTRG(K)+TTSTRG(K+4)+TTSTRG(K+8)+TTSTRG(K+12)
      CL = CL + RLOAD(K)
      CUL = CUL + RUNLOAD(K)
    5 CONTINUE
      DRIOP = TDRC * TRIOP + DPOL
      TRIOP = TRIOP + TPOL + TTIRS
      TDRIOP = TDRIOP + DRIOP
      TTRIOP = TTRIOP + TRIOP
      SUMSTOG = SUMSTOG + STOG + RWSTOG(1) + RWSTOG(2) + RWSTOG(3) +
     1          RWSTOG(4)
      SUMR1 = SUMR1 + DT * CUL
      SUMR2 = SUMR2 + DT * CL
      QGRAP = QGRAP - DT * R1
      IF( QGRAP .LE. 0.0 ) QGRAP = 0.0
      QGRW = QGRW + QGRAP
      RETURN
      END
```

```
      SUBROUTINE  DEMAND
C
C   *   *  THIS  PROGRAM  GENERATES  THE  DELAYED  ESTIMATED
C          STOCHASTIC  REGIONAL  FOOD  DEFICIT              *   *
C
      COMMON / BLOCK / DUR,DT,DETPRT,SELPRT,BEGPRT,PRTCHG,PRTVL1,
     1                 PRTVL2,SAMPT,ALPHA,BETA,CCDP,SUMDEL,TRLIMIT,
     2                 BET1,BET2,BET3,DELD,SDDEM,BETSMPL,SPDFUL,SPDMTY,
     3                 CPRSTG,CPEFA,CPQUE,CPTND,QUEFLAG,POP(4),TATTC
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON / DEMDEST / DD(4),PI,TDEF,BIAS,ENID(4),BETDEM(2),DEV
     1                   ,DTOTAL,TDEM
      DIMENSION  ALF(4) , RI(50,4)
      DATA DD,SDDEM,BIAS / .4,.4,.1,.1,.15,0.0 /
      DATA DEM,DEMEST / 4*0.0 , 4*0.0 /
C
      IF( T .GT. DT ) GOTO 3
C        INITIAL  DEMAND
      DTOTAL = .2*2.*TDEF
      TDEM = ACOS(1. - DTOTAL/TDEF)/(2.*PI)
C        INITIAL VALUES FOR REGIONAL DEMANDS
      DO  2  I=1,4
        ENID(I) = DD(I) * DTOTAL
    2 CONTINUE
C        ESTIMATION DELAY
      DELD = 2./365.
    3 CONTINUE
C
C         CALCULATING  WEIGHTS  FOR REGIONAL  DEMANDS  (TIME  VARYING)
      ALF(1) = DD(1) + BET1 * T
      ALF(2) = DD(2) + BET2 * T
      ALF(3) = DD(3) + BET3 * T
      ALF(4) = 1. - ( ALF(1) + ALF(2) + ALF(3) )
      IF( ALF(4)  .LT. 0.0 ) ALF(4) = 0.0
C
C       ESTIMATION AND DATA PROCESSING OF REGIONAL FOOD DEFICIT
C       INCLUDING TRANSMISSION DELAY
C
      IF( T .LT. TDEM ) GOTO 5
      IF( T .GT. .96 ) GOTO 5
      DTOTAL = TDEF * ( 1. - COS( 2.*PI*T ) )
    5 CONTINUE
      DO  10  I=1,4
       DEM(I) = ALF(I) * DTOTAL
       DEVS = DD(I) * DEV
       IF( DEM(I)  .LE. DEVS ) BETSMPL = BETDEM(1)
       IF( DEM(I)  .GT. DEVS ) BETSMPL = BETDEM(2)
       DUMMY = DEMEST(I)
       CALL  SAMPL( DEM(I),DEMEST(I),RI(1,I),ENID(I),SAMPT,DELD,BIAS,
```

```
     1                SDDEM,I,DT,T,BETSMPL )
        IF( DEMEST(I)  .LT. 0.0 ) DEMEST(I) = DUMMY
  10 CONTINUE
        RETURN
        END
```

```
      SUBROUTINE  SAMPL( VAL,VALEST,VALAR,ENIT,SAMPT,DEL,BIAS,SD,NK,
     1                  DT,T,BETA )
C
C            VAL  =  ACTUAL VALUE  ,  VALEST  =  ESTIMATE OF VAL
C            VALAR  =  ARRAY OF INFORMATION IN DELAY PIPLINE
C            ENIT  =  INITIAL ESTIMATE VALUE
C            SAMPT  =  SAMPLING  INTERVAL (YEAR)
C            BIAS  =  MEASUREMENT  BIAS
C            SD    =  MEASUREMENT  STANDARD  DEVIATION
C            NK  =  COUNTER , NUMBER OF ITEM MEASURED
C            DEL  =  DELAY  LENGTH.
      DIMENSION  HOLD(12),NCNT(12),NSAMP(12),NN(12),VALAR(1)
      DIMENSION  YP(12) , YY(12) , YD(12) , NMLVAL(41)
      REAL  NMLVAL
      DATA  N/50/
      DATA  NMLVAL/-3.5,-1.96,-1.645,-1.439,-1.281,-1.15,-1.037,-.925,
     1             -.841,-.755,-.674,-.598,-.524,-.454,-.386,-.312,-.253
     2             ,-.189,-.126,-.056,0.0,.056,.126,.189,.253,.312,.386,
     3             .454,.524,.598,.674,.755,.841,.925,1.037,1.15,1.281,
     4             1.439,1.645,1.96,3.5 /
      IF( T .GT. DT+.00001 ) GO TO 20
C            INITIALIZATION  OF  ARRAY  AND  COUNTERS
      DO  21  KK = 1,N
   21 VALAR(KK) = ENIT
C
C            HOLD  =  MEASURED VALUE HELD UNTIL NEXT SAMPLE TIME
C            NCNT  =  NUMBER OF DTS  SINCE  LAST  SAMPLING
C            NSAMP  =  NUMBER  OF  DTS  BETWEEN  SAMPLING
C            NN  =  NUMBER  OF  DTS  DELAY  LAST
      HOLD(NK) = 0.0
      NCNT(NK) = 0
      NSAMP(NK) = 0
      NN(NK) = DEL/DT + .5
      YY(NK) = ENIT
      YD(NK) = 0.0
C
C            EXECUTION  PHASE
   20 NCNT(NK) = NCNT(NK) + 1
      IF( NCNT(NK)  .LT.  NSAMP(NK) )  GOTO 1
C
C   .        SAMPLING  PRECEDURE
C            Y  IS  STANDARD  NORMAL  RANDOM  VARIABLE
      NSAMP(NK) = SAMPT/DT + .5
      R = RANF()
      Y = TABLIE( NMLVAL,0.0,.025,40,R )
      HOLD(NK) = VAL*(1. + SD*Y) + BIAS
C
C            DATA  PROCESSING  PHASE
      ALPHA = 2.*SQRT(BETA) - BETA
      YP(NK) = YY(NK) + SAMPT*YD(NK)
```

```
      YY(NK)= YP(NK) + ALPHA*(HOLD(NK) - YP(NK))
      YD(NK) = YD(NK) + (BETA/SAMPT)*(HOLD(NK) - YP(NK))
      NCNT(NK) = 0
    1 CONTINUE
      CALL  VDTDLI( YY(NK),VALEST,VALAR,N,NN(NK),DEL,DT )
      RETURN
      END
      FUNCTION  TABLIE( VAL,SMALL,DIFF,K,DUMMY )
      DIMENSION  VAL(1)
      DUM = AMIN1(AMAX1(DUMMY - SMALL,0.0),FLOAT(K)*DIFF)
      I = 1. + DUM/DIFF
      IF( I .EQ. K+1 ) I=K
      TABLIE = (VAL(I+1) - VAL(I))*(DUM - FLOAT(I-1)*DIFF)/DIFF + VAL(I)
      RETURN
      END
```

```
      SUBROUTINE  VDTDLI( VIN,VOUT,VINT,N,NN,DEL,DT )
C            N  =  MAXIMUM  SIZE  OF  ORDER
C            NN  =  SIZE  OF  ORDER  AT  TIME  (T-DT)
C
      DIMENSION  VINT(1)
      NNNEW = DEL/DT + .5
      IF( NNNEW .LT. 2 ) NNNEW=2
      IF( NNNEW .GT. N ) NNNEW=N
      VOUT = VINT(1)
      NDIF = NNNEW - NN
      IF( NDIF .LE. 0 ) GOTO 4
C            DEL  INCREASES , RECENT  DATA  HELD  LONGER
      DO  3  II=1,NDIF
    3 VINT(II+NN) = VINT(NN)
    4 CONTINUE
C            DEL  UNCHANGED , CURRENT  DATA  KEPT
C            DEL  SHRINKS , OLDEST  DATA  SAVED
      NN  = NNNEW
      DO  6  I=2,NN
    6 VINT(I-1) = VINT(I)
      VINT(NN) = VIN
      RETURN
      END
```

```
      SUBROUTINE  AVERAGE( IRUN,INTOT,INPART )
C
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON / FAC / TIDT,IOUTTOT,ST,DOCK,NSS,PARWT,TINPUT,TIDCAP,TIDRMS
      COMMON / DECIDE / TIDTR,TDR,DDR,THRUPUT,TTRUPUT,DTRUPUT,STGLST,RMT
     1                  ,TIDGR,TIDDR,TIDRMT,CCTRL(4)
      COMMON / SILO / RSTGLST(4),PRODEM(4),TSUPPLY(4),KP,TRP(4),RMSS(4),
     1                RPT(10,4),TDEMAND(4),RTRUPUT(4),TDPR(4),TRN(4),
     2                RFT(10,4),DELF(4),DELPF(4),KF,TRNP(4),KR,STKOUT(4)
     3                ,RTR(10,4),SDEVSD(4),TAR(4),TSR(4),CIQS(4),GR(4)
     4                ,RTTP(10,4),RTTR(10,4),SROUTE(4),BRFLG(4),TBRKDN,
     5                BALANCE
      COMMON / COST / CDWAGE,CRPIR,CFRPIR,CRENT,CFUEL,CFTRNS,CFSTRG,
     1                CSTRG,CFLOAD,CLOAD,CFULOAD,CULOAD,CFSMPL,CDRWAGE,
     2                CRPAIR,CRNTR,CFUELS,TCTRNS,CVAINV,CVLOAD,CVULOAD,
     3                CVSMPL,CSHIPW,TCSHIP,TOTCOST,CSMPL
      COMMON / AVE / MONRUN,NAVE,MONTIME,MON,INTOTM(4),IWLM(4),STOGM(4),
     1               AVTWTM(4),TIDTM(4),THRUPM(4),TINPM(4),TIDTRM(4),
     2               IOUTM(4),TIDCM(4),PARIM(4),STKOTM1(4),STKOTM2(4),
     3               STKOTM3(4),STKOTM4(4),RSTOGM1(4),RSTOGM2(4),
     4               RSTOGM3(4),RSTOGM4(4),TTRUPM(4),DTRUPM(4),TTBSM(4),
     5               TDBSM(4),RTRUPM1(4),RTRUPM2(4),RTRUPM3(4),
     6               RTRUPM4(4),PRODEM1(4),PRODEM2(4),PRODEM3(4),
     7               PRODEM4(4),SDEVDM1(4),SDEVDM2(4),SDEVDM3(4),
     8               SDEVDM4(4),TIDGRM(4),TIDDRM(4),VAR(20),SDEV(20),
     9               TIDRMSM(4),TIDRMTM(4),TT(20,30),PARIDT,AVTWT,
     1               TCSHIPM(4),TCTRNSM(4),TOTCSTM(4),BALANCM(4)
C
      IF( NAVE .NE. IRUN ) GOTO 5
      NAVE = 0
C          ***      INITIALIZE AVERAGES      ***
      DO 2 I=1,MONTIME
      IWLM(I) = 0
      AVTWTM(I)=0
      TIDTM(I) = 0.
      STOGM(I)=0
      THRUPM(I) =0.0
      TINPM(I) = 0.0
      INTOTM(I) = 0
      IOUTM(I)=0
      TIDCM(I)=0
      TIDTRM(I)=0
      TIDGRM(I) = 0.0
      TIDDRM(I) = 0.0
      TIDRMSM(I) = 0.0
      TIDRMTM(I) = 0.0
      PARIM(I)=0
      TTRUPM(I) = 0.
      DTRUPM(I) = 0.
```

```
      TTBSM(I) = 0.0
      TDBSM(I) = 0.0
      RTRUPM1(I) = 0.0
      RTRUPM2(I) = 0.0
      RTRUPM3(I) = 0.0
      RTRUPM4(I) = 0.0
      STKOTM1(I) = 0.0
      STKOTM2(I) = 0.0
      STKOTM3(I) = 0.0
      STKOTM4(I) = 0.0
      RSTOGM1(I) = 0.0
      RSTOGM2(I) = 0.0
      RSTOGM3(I) = 0.0
      RSTOGM4(I) = 0.0
      PRODEM1(I) = 0.0
      PRODEM2(I) = 0.0
      PRODEM3(I) = 0.0
      PRODEM4(I) = 0.0
      SDEVDM1(I) = 0.0
      SDEVDM2(I) = 0.0
      SDEVDM3(I) = 0.0
      SDEVDM4(I) = 0.0
      TCTRNSM(I) = 0.0
      TCSHIPM(I) = 0.0
      TOTCSTM(I) = 0.0
      BALANCM(I) = 0.0
    2 CONTINUE
      DO 3 I = 1,20
       VAR(I) = 0.0
    3 CONTINUE
    5 CONTINUE
      AVTWT = TWT/INTOT
      PARIDT=PARWT/INPART
      PARWT=0.
      INPART = 0
      IWLM(MON) = IWLM(MON)+IWL
      AVTWTM(MON) = AVTWTM(MON)+AVTWT/MONRUN
      TIDTM(MON) = TIDTM(MON)+TIDT/MONRUN
      STOGM(MON) = STOGM(MON)+STOG/MONRUN
      THRUPM(MON) = THRUPM(MON)+THRUPUT/MONRUN
      TINPM(MON) = TINPM(MON) + TINPUT/MONRUN
      INTOTM(MON) = INTOTM(MON)+INTOT
      IOUTM(MON) = IOUTM(MON)+IOUTTOT
      TIDCM(MON) = TIDCM(MON)+TIDCAP/MONRUN
      TIDTRM(MON) = TIDTRM(MON)+TIDTR/MONRUN
      TIDGRM(MON) = TIDGRM(MON) + TIDGR/MONRUN
      TIDDRM(MON) = TIDDRM(MON) + TIDDR/MONRUN
      TIDRMSM(MON) = TIDRMSM(MON) + TIDRMS/MONRUN
      TIDRMTM(MON) = TIDRMTM(MON) + TIDRMT/MONRUN
      PARIM(MON) = PARIM(MON)+PARIDT/MONRUN
      TTRUPM(MON) = TTRUPM(MON) + TTRUPUT
      DTRUPM(MON) = DTRUPM(MON) + DTRUPUT
      TTBSM(MON) = TTBSM(MON) + TTBS
      TDBSM(MON) = TDBSM(MON) + TDBS
      RTRUPM1(MON) = RTRUPM1(MON) + RTRUPUT(1) / MONRUN
```

```
RTRUPM2(MON) = RTRUPM2(MON) + RTRUPUT(2) / MONRUN
RTRUPM3(MON) = RTRUPM3(MON) + RTRUPUT(3) / MONRUN
RTRUPM4(MON) = RTRUPM4(MON) + RTRUPUT(4) / MONRUN
STKOTM1(MON) = STKOTM1(MON) + STKOUT(1) / MONRUN
STKOTM2(MON) = STKOTM2(MON) + STKOUT(2) / MONRUN
STKOTM3(MON) = STKOTM3(MON) + STKOUT(3) / MONRUN
STKOTM4(MON) = STKOTM4(MON) + STKOUT(4) / MONRUN
RSTOGM1(MON) = RSTOGM1(MON) + RWSTOG(1) / MONRUN
RSTOGM2(MON) = RSTOGM2(MON) + RWSTOG(2) / MONRUN
RSTOGM3(MON) = RSTOGM3(MON) + RWSTOG(3) / MONRUN
RSTOGM4(MON) = RSTOGM4(MON) + RWSTOG(4) / MONRUN
PRODEM1(MON) = PRODEM1(MON) + PRODEM(1) / MONRUN
PRODEM2(MON) = PRODEM2(MON) + PRODEM(2) / MONRUN
PRODEM3(MON) = PRODEM3(MON) + PRODEM(3) / MONRUN
PRODEM4(MON) = PRODEM4(MON) + PRODEM(4) / MONRUN
SDEVDM1(MON) = SDEVDM1(MON) + SDEVSD(1) / MONRUN
SDEVDM2(MON) = SDEVDM2(MON) + SDEVSD(2) / MONRUN
SDEVDM3(MON) = SDEVDM3(MON) + SDEVSD(3) / MONRUN
SDEVDM4(MON) = SDEVDM4(MON) + SDEVSD(4) / MONRUN
TCTRNSM(MON) = TCTRNSM(MON) + TCTRNS / MONRUN
TCSHIPM(MON) = TCSHIPM(MON) + TCSHIP / MONRUN
TOTCSTM(MON) = TOTCSTM(MON) + TOTCOST / MONRUN
BALANCM(MON) = BALANCM(MON) + BALANCE / MONRUN
MON = MON+1
RETURN
END
```

```
      SUBROUTINE  SELPRNT( DUR )
C
      COMMON / SYSVAR / T,ROUTE(5,5),TROUTE,TTBS,TDRIOP,TTRIOP,TR(4),
     1                  TRPOL(4),SUMSTOG,SUMR1,SUMR2,NSP,NDTSKIP,DEM(4),
     2                  DEMEST(4),TGRC,TDRC,CAPWH,IWL,TWT,RCAPWH(4),
     3                  TDP(4),XGT(4),PTSTRG(4),AVTONS,
     4                  TRSHOLD,CONVFAC,TTSTRG(16),RLOAD(4),RUNLOAD(4),
     5                  FTSTRG(4),RTSTRG(4),DPOL,TPOL,TTIRS,TDOL,
     6                  TDBS,STOG,RWSTOG(4),R1,R2,SR1(4),SR2(4),ATTRATE
      COMMON / CDP / DELCDP,DELCDPP,KCDP,TRLOST,YPAST,TRMIN,TYD,DYD,
     1               STRGCDP,TRLACK,DRLACK,DYPAST,DSTGCDP
      COMMON / SILO / RSTGLST(4),PRODEM(4),TSUPPLY(4),KP,TRP(4),RMSS(4),
     1                RPT(10,4),TDEMAND(4),RTRUPUT(4),TDPR(4),TRN(4),
     2                RFT(10,4),DELF(4),DELPF(4),KF,TRNP(4),KR,STKOUT(4)
     3                ,RTR(10,4),SDEVSD(4),TAR(4),TSR(4),CIQS(4),GR(4)
     4                ,RTTP(10,4),RTTR(10,4),SROUTE(4),BRFLG(4),TBRKDN,
     5                BALANCE
      COMMON / COST / CDWAGE,CRPIR,CFRPIR,CRENT,CFUEL,CFTRNS,CFSTRG,
     1                CSTRG,CFLOAD,CLOAD,CFULOAD,CULOAD,CFSMPL,CDRWAGE,
     2                CRPAIR,CRNTR,CFUELS,TCTRNS,CVAINV,CVLOAD,CVULOAD,
     3                CVSMPL,CSHIPW,TCSHIP,TOTCOST,CSMPL
      COMMON / PQUE / PTSR,PTAR,PDAR,PCIQS,PCIQSD
C
      PRINT  901, T
      PRINT  902
      PRINT  909, TPOL,TTIRS,YPAST,TRLACK,STRGCDP,TTRIOP
      PRINT  913, DPOL,TDOL,DYPAST,DRLACK
      PRINT  904, (PTSTRG(I),I=1,4),(FTSTRG(I),I=1,4),(RTSTRG(I),I=1,4)
C
      DO  6  I = 1,4
       IF( XGT(I) .LT. 1. ) GOTO 6
      TBR = TBRKDN - DUR
      PRINT  907, I,TBR
       IF( BRFLG(I) .GE. 4. ) GOTO 6
       PRINT  906, I,TTSTRG(I),TTSTRG(I+4),TTSTRG(I+8),TTSTRG(I+12)
    6 CONTINUE
C
      PRINT  905, (TRPOL(I) , I=1,4)
      PRINT  915
      PRINT  916, (TAR(I),I=1,4),(TSR(I),I=1,4),(CIQS(I),I=1,4)
      PRINT  917, PTAR,PDAR,PTSR,PCIQS,PCIQSD
      PRINT  919
      PRINT  920, CDRWAGE,CRPAIR,CRNTR,CFUELS,TCTRNS,
     1            CVAINV,CVLOAD,CVULOAD,CVSMPL,TCSHIP,TOTCOST
C
C        FORMAT STATEMENTS
C
  901 FORMAT("1",2X,"SELECTED AND NON MONTE CARLO VARIABLES AT TIME",
     1       F9.6,/,3X,"=============================================",
     2       "=========")
  902 FORMAT("0",5X,"DATA ON CAPITAL",/,6X,"---------------")
  904 FORMAT("0",5X,"TRUCKS AND DRIVERS ON THE ROAD",/,2X,
     2       "PTSTRG(1)=",F10.,4X,"PTSTRG(2)=",F10.,4X,"PTSTRG(3)=",
     3       F10.,4X,"PTSTRG(4)=",F10.,/,2X,"FTSTRG(1)=",F10.,4X,
     4       "FTSTRG(2)=",F10.,4X,"FTSTRG(3)=",F10.,4X,"FTSTRG(4)=",
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     5         F10.,/,2X,"RTSTRG(1)=",F10.,4X,"RTSTRG(2)=",F10.,4X,
     6         "RTSTRG(3)=",F10.,4X,"RTSTRG(4)=",F10.)
  905 FORMAT("0",5X,"REGIONAL POOLS",/,1X,"TRPOL(1) =",F10.,4X,
     1         "TRPOL(2) =",F10.,4X,"TRPOL(3) =",F10.,4X,"TRPOL(4) =",
     2         F10.)
  906 FORMAT("0",2X,"TTSTRG OF",I2,2X,4F10.)
  907 FORMAT("0",2X,"THERE HAS BEEN A BREAK DOWN IN ROAD #",I2,
     1            " AT TIME",F9.6)
  909 FORMAT("0",5X,"NUMBER OF TRUCKS AT PORT =",F12.,/,
     1             6X,"NUMBER OF TRUCKS IN REPAIR SHOP =",F10.,/,
     2             6X,"TOTAL TRUCKS IN THE SYSTEM =",2X,F10.,/,
     3             6X,"EXCESS TRUCK IN THE SYSTEM =",2X,F10.,/,
     4             6X,"TRUCK AQUSITION IN TRANSIT=",2X,F10.,/,
     5             6X,"TOTAL DT-HOURS OF TRUCK USE =",2X,F10.)
  913 FORMAT("0",5X,"TOTAL DRIVERS AT PORT =",F12.,/,6X,
     1             "NUMBER OF DRIVERS ON LEAVE =",F12.,/,6X,
     2             "TOTAL DRIVERS IN THE SYSTEM =",F12.,/,6X,
     3             "EXCESS DRIVER IN THE SYSTEM =",F12. )
  915 FORMAT("0",5X,"DATA ON QUEUES",/,6X,"--------------")
  916 FORMAT("0",5X,"QUEUES AT REGIONAL SILOS",/,3X,"ARRAIVAL RATES",
     1         1X,4F10.,/,3X,"SERVICE RATES",1X,4F10.,/,3X,
     2         "SUM OF THE QUEUES",4F10.)
  917 FORMAT("0",5X,"PORT QUEUES",/,3X,"PTAR=",F12.,2X,"PDAR=",
     1         F12.,2X,"PTSR=",F12.,2X,"PCIQS=",F12.,2X,"PCIQSD=",F12.)
  919 FORMAT("0",5X,"COSTS  INFORMATION",/,6X,"------------------")
  920 FORMAT("0",2X,"DRIVERS WAGE =",1X,F10.,/,3X,"TRUCKS REPAIR =",
     1         F10.,/,3X,"TRUCKS RENT =",2X,F10.,/,3X,"FUEL COST =",3X,
     2         F11.,/,3X,"TOTAL COST OF TRANSPORTATION =",F12.,/,3X,
     3         "INVENTORY EXPENSE =",2X,F10.,/,3X,"LOADING COST =",7X,
     4         F10.,/,3X,"UNLOADING COST =",5X,F10.,/,3X,"COST OF ",
     5         "INFORMATION =",F10.,/,3X,"SHIP WAITING COST =",1X,F11.,/,
     6         3X,"TOTAL COST OF OPERATIONS =",F12.)
C
      RETURN
      END
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      SUBROUTINE  MONPRNT( DETPRT )
C
      COMMON / AVE / MONRUN,NAVE,MONTIME,MON,INTOTM(4),IWLM(4),STOGM(4),
     1               AVTWTM(4),TIDTM(4),THRUPM(4),TINPM(4),TIDTRM(4),
     2               IOUTM(4),TIDCM(4),PARIM(4),STKOTM1(4),STKOTM2(4),
     3               STKOTM3(4),STKOTM4(4),RSTOGM1(4),RSTOGM2(4),
     4               RSTOGM3(4),RSTOGM4(4),TTRUPM(4),DTRUPM(4),TTBSM(4),
     5               TDBSM(4),RTRUPM1(4),RTRUPM2(4),RTRUPM3(4),
     6               RTRUPM4(4),PRODEM1(4),PRODEM2(4),PRODEM3(4),
     7               PRODEM4(4),SDEVDM1(4),SDEVDM2(4),SDEVDM3(4),
     8               SDEVDM4(4),TIDGRM(4),TIDDRM(4),VAR(20),SDEV(20),
     9               TIDRMSM(4),TIDRMTM(4),TT(20,30),PARIDT,AVTWT,
     1               TCSHIPM(4),TCTRNSM(4),TOTCSTM(4),BALANCM(4)
C
      DO 470 MON=1,MONTIME
      IWLM(MON)  =  IWLM(MON)/MONRUN
      INTOTM(MON)  =  INTOTM(MON)/MONRUN
      IOUTM(MON)  =  IOUTM(MON)/MONRUN
      TTRUPM(MON)  =  TTRUPM(MON)/MONRUN
      DTRUPM(MON)  =  DTRUPM(MON)/MONRUN
      TTBSM(MON)  =  TTBSM(MON)  /  MONRUN
      TDBSM(MON)  =  TDBSM(MON)  /  MONRUN
      T = FLOAT(MON)/FLOAT(MONTIME)
C
      IF( DETPRT .EQ. 1. ) GOTO 470
C
      PRINT  910, MONRUN , T
      PRINT  900
      PRINT 912,IWLM(MON),AVTWTM(MON),TIDTM(MON),STOGM(MON),THRUPM(MON)
     2     ,TINPM(MON)
      PRINT 902, INTOTM(MON),IOUTM(MON)
      PRINT 903, TIDCM(MON),TIDGRM(MON),TIDTRM(MON),TIDDRM(MON)
     1           ,PARIM(MON),TIDRMSM(MON),TIDRMTM(MON)
      PRINT 904, TTRUPM(MON),DTRUPM(MON),TTBSM(MON),TDBSM(MON)
      PRINT  905, RTRUPM1(MON),RTRUPM2(MON),RTRUPM3(MON),RTRUPM4(MON)
      PRINT 908, RSTOGM1(MON),RSTOGM2(MON),RSTOGM3(MON),RSTOGM4(MON)
     1          ,STKOTM1(MON),STKOTM2(MON),STKOTM3(MON),STKOTM4(MON)
     2          ,PRODEM1(MON),PRODEM2(MON),PRODEM3(MON),PRODEM4(MON)
      PRINT 922, SDEVDM1(MON),SDEVDM2(MON),SDEVDM3(MON),SDEVDM4(MON),
     1           BALANCM(MON)
      PRINT 921, TCSHIPM(MON),TCTRNSM(MON),TOTCSTM(MON)
  470 CONTINUE
C
      IF( MONRUN .LE. 1 ) RETURN
C
      M = 4
      DO 480 IT=1,MONRUN
      VAR(1)  =  VAR(1)+((TT(1,IT)- TIDTM(M))**2)/MONRUN
      VAR(2)  =  VAR(2)+((TT(2,IT)- TIDCM(M))**2)/MONRUN
      VAR(3)  =  VAR(3)+((TT(3,IT)-TIDGRM(M))**2)/MONRUN
      VAR(4)  =  VAR(4)+((TT(4,IT)-AVTWTM(M))**2)/MONRUN
      VAR(5)  =  VAR(5)+((TT(5,IT)-TIDTRM(M))**2)/MONRUN
      VAR(6)  =  VAR(6)+((TT(6,IT)-TIDDRM(M))**2)/MONRUN
      VAR(7)  =  VAR(7)+((TT(7,IT)-PRODEM1(M))**2)/MONRUN
      VAR(8)  =  VAR(8)+((TT(8,IT)-PRODEM2(M))**2)/MONRUN
      VAR(9)  =  VAR(9)+((TT(9,IT)-PRODEM3(M))**2)/MONRUN
      VAR(10)  =  VAR(10)+((TT(10,IT)-PRODEM4(M))**2)/MONRUN
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      VAR(11)  = VAR(11)+((TT(11,IT)-STKOTM1(M))**2)/MONRUN
      VAR(12)  = VAR(12)+((TT(12,IT)-STKOTM2(M))**2)/MONRUN
      VAR(13)  = VAR(13)+((TT(13,IT)-STKOTM3(M))**2)/MONRUN
      VAR(14)  = VAR(14)+((TT(14,IT)-STKOTM4(M))**2)/MONRUN
      VAR(15)  = VAR(15)+((TT(15,IT)-TINPM(M))**2)/MONRUN
      VAR(16)  = VAR(16)+((TT(16,IT)-THRUPM(M))**2)/MONRUN
      VAR(17)  = VAR(17)+((TT(17,IT)-TCSHIPM(M))**2)/MONRUN
      VAR(18)  = VAR(18)+((TT(18,IT)-TCTRNSM(M))**2)/MONRUN
      VAR(19)  = VAR(19)+((TT(19,IT)-TOTCSTM(M))**2)/MONRUN
      VAR(20)  = VAR(20)+((TT(20,IT)-BALANCM(M))**2)/MONRUN
  480 CONTINUE
C
      DO  485  IT = 1,20
  485 SDEV(IT) = SQRT(VAR(IT))
C
      PRINT 907, ( VAR(KT) , SDEV(KT) , KT = 1,14 )
      PRINT 909, ( VAR(KT) , SDEV(KT) , KT = 15,20 )
C
      PRINT 925
      DO  490  IT = 1,MONRUN
       PRINT  923, ( TT(KT,IT) , KT = 1,14 )
  490 CONTINUE
      PRINT 926
      DO  495  IT = 1,MONRUN
       PRINT  924, ( TT(KT,IT) , KT = 15,20 )
  495 CONTINUE
C
C        FORMAT STATEMENTS
C
  900 FORMAT("0",5X,"PORT DATA AND PERFORMANCE MEASURES",/,6X,
     1           "----------------------------------",/,
     1           10X,"LENGTH OF",10X,"AVERAGE PER-SHIP",4X,
     2     "IDLE TIME OF",10X,"STORAGE",10X,"THRUPUT",13X,"INPUT",/,
     3   10X,"WAIT LINE",10X,"WAIT TIME(YRS)",6X,"SHIP SERVICE-CENTER"
     4   ,3X,"AT PORT",10X,"(PORT)",14X,"(PORT)")
  902 FORMAT(1H0,"NUMBER OF SHIPS IN",I5,"    NUMBER OF SHIPS OUT",I5)
  903 FORMAT("0","IDLE TIME OF OFFLOAD EQUIP/SHIPS DUE TO OVERAGE ",
     1          "STORAGE CAPACITY",F9.6,/, " IDLE TIME OF TRUCK/DRIVER "
     2          ,"DUE TO SHORTAGE OF GRAIN",14X,F9.6,/,
     3           " IDLE TIME OF DRIVER/LOAD EQUIP CAUSED BY ",
     3"SHORTAGE OF TRUCKS", 5X,F9.6,/," IDLE TIME OF TRUCKS/LOAD EQUIP",
     4" DUE TO SHORTAGE OF DRIVERS", 7X,F9.6,/," AVERAGE SHIP WAIT TIME
     5FOR SERVICE CENTER (LAST PERIOD)", 9X,F9.6,/," TOTAL TIME WHEN ",
     6 "PORT IS WORKING AT LIMIT UNLOADING CAPACITY", 5X,F9.6,/,
     7" TOTAL TIME WHEN PORT IS WORKING AT LIMIT LOADING CAPACITY", 7X,
     8 F9.6)
  904 FORMAT("0",9X," NUMBER OF TRUCKS BEING UTILIZED =",F14.,/,
     1          10X," NUMBER OF DRIVERS BEING UTILIZED=",F14.,/,
     2          10X," TOTAL NUMBER OF TRUCKS REPAIRED =",F14.,/,
     3          10X," TOTAL NUMBER OF DRIVERS ON LEAVE=",F14.)
  905 FORMAT("0",5X,"DATA AND PERFORMANCE INDICES ON REGIONAL SILOS",/,
     1          6X,"----------------------------------------------",/,
     2          11X,"GRAIN THRUPUT FROM RWH1 (TONS) =",F14.,/,
     3          11X,"GRAIN THRUPUT FROM RWH2 (TONS) =",F14.,/,
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     4          11X,"GRAIN THRUPUT FROM RWH3 (TONS) =",F14.,/,
     5          11X,"GRAIN THRUPUT FROM RWH4 (TONS) =",F14.)
 907 FORMAT("1",15X,"VARIANCES AND STANDARD DEVAITIONS AT TIME 1.0",/,
     1          15X,"=============================================",/,
     1          4X,"IDLE TIME OF SHIP SERVICE CENTER",27X,2F9.5,/,
     2          4X,"IDLE TIME OF OFF-LOADING EQUIP/SHIP DUE TO FULL",1X,
     3          "STORAGE",2F9.5,/,4X,"IDLE TIME OF TRUCKS/DRIVERS DUE",
     4          " TO EMPTY STORAGE",11X,2F9.5,/,4X,
     5          "SHIP WAIT TIME FOR SERVICE CENTER",26X,2F9.5,/,
     6          4X,"IDLE TIME OF DRIVER/LOAD EQUIP DUE TO SHORTAGE OF ",
     7          "TRUCKS",2F9.5,/,4X,"IDLE TIME OF TRUCK/LOAD EQUIP DUE",
     8          " TO SHORTAGE OF DRIVERS",2F9.5,/,
     9          4X,"RATIO OF SUPPLY TO DEMAND AT RWH1",10X,2F9.5,/,
     1          4X,"RATIO OF SUPPLY TO DEMAND AT RWH2",10X,2F9.5,/,
     1          4X,"RATIO OF SUPPLY TO DEMAND AT RWH3",10X,2F9.5,/,
     2          4X,"RATIO OF SUPPLY TO DEMAND AT RWH4",10X,2F9.5,/,
     3          4X,"STOCK-OUT TIME AT RWH1",10X,2F9.5,/,
     4          4X,"STOCK-OUT TIME AT RWH2",10X,2F9.5,/,
     5          4X,"STOCK-OUT TIME AT RWH3",10X,2F9.5,/,
     6          4X,"STOCK-OUT TIME AT RWH4",10X,2F9.5)
 908 FORMAT("0",10X," STORAGE AT R.W.H. 1 (TONS) =",F14.,/,
     1           11X," STORAGE AT R.W.H. 2 (TONS) =",F14.,/,
     2           11X," STORAGE AT R.W.H. 3 (TONS) =",F14.,/,
     3           11X," STORAGE AT R.W.H. 4 (TONS) =",F14.,/,
     4           11X," STOCK-OUT  AT R.W.H. 1 (YEARS) =",F14.7,/,
     5           11X," STOCK-OUT  AT R.W.H. 2 (YEARS) =",F14.7,/,
     6           11X," STOCK-OUT  AT R.W.H. 3 (YEARS) =",F14.7,/,
     7           11X," STOCK-OUT  AT R.W.H. 4 (YEARS) =",F14.7,/,
     8           11X," RATIO OF SUPPLY TO DEMAND AT RWH1=",F14.7,/,
     9           11X," RATIO OF SUPPLY TO DEMAND AT RWH2=",F14.7,/,
     1           11X," RATIO OF SUPPLY TO DEMAND AT RWH3=",F14.7,/,
     2           11X," RATIO OF SUPPLY TO DEMAND AT RWH4=",F14.7)
 909 FORMAT("0",3X,"TOTAL GRAIN INPUT (PORT)",4X,2F20.,/,
     1          4X,"TOTAL GRAIN THRUPUT (PORT)",2X,2F20.,/,
     2          4X,"SHIP WAITING COST",11X,2F20.,/,
     3          4X,"TOTAL COST OF TRANSPORTATION",2F20.,/,
     4          4X,"TOTAL COST OF OPERATIONS",4X,2F20.,/,
     5          4X,"BALANCE DISTRIBUTION INDEX (SYSTEM)",2F20.)
 910 FORMAT("1",6X,"MONTE CARLO AVERAGES FOR",I3," RUNS AT TIME",F9.6,
     1          /,7X,"============================================",
     2          "====")
 912 FORMAT(1H0,12X,I3,10X,F10.4,15X,F5.3,12X,F10.0, 8X,F10.0,10X,F10.)
 921 FORMAT("0",5X,"DATA ON COST",/,6X,"------------",/,
     1               12X,"SHIP WAITING COST (DOLLARS) =",11X,F12.,/,
     2               12X,"TOTAL COST OF TRANSPORTATION (DOLLARS) =",F12.,
     3               /,12X,"TOTAL COST OF OPERATIONS (DOLLARS) =",4X,
     4               F12.)
 922 FORMAT("0",10X,"BALANCE DISTRIBUTION MEASURES FOR FOUR SILOS ARE",
     1          /,5X,4F20.,/,11X,"AND FOR TOTAL SYSTEM IS",F20.)
 923 FORMAT("0",2X,14F8.5)
 924 FORMAT("0",2X,6F14.)
 925 FORMAT("1",15X,"OBSERVATIONS ON SELECTED RANDOM VARIABLES",/,
     1          16X,"=========================================",/,
     2          14X,"VARIOUS IDLE TIMES AT PORT",14X,"RATIOS OF SUPPLY",
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     3          " TO DEMAND",11X,"STOCK-OUT TIMES",/,14X,
     4          "-------------------------",14X,"--------------------",
     5          "------",11X,"---------------")
  926 FORMAT("0",5X,"GRAIN INPUT",2X,"PORT THRUPUT",4X,"SHIP COST",4X,
     1          "TRANS COST",4X,"TOTAL COST",5X,"BALANCE",/,6X,
     2          "-----------",2X,"------------",4X,"---------",4X,
     3          "----------",4X,"----------",5X,"-------")
C
      RETURN
      END
```

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