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A RELATIONAL DATABASE APPROACH TO SHOP FLOOR INFORMATION MANAGEMENT AND PERFORMANCE EVALUATION

presented by

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has been accepted towards fulfillment of the requirements for

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A RELATIONAL DATABASE APPROACH TO SHOP FLOOR INFORMATION MANAGEMENT AND PERFORMANCE EVALUATION

By

Robert James Marsh

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ABSTRACT

A RELATIONAL DATABASE APPROACH TO SHOP FLOOR INFORMATION MANAGEMENT AND PERFORMANCE EVAULATION

By

Robert James Marsh

Current shop floor performance reporting procedures, which stress aggregate and mean measures, do not provide an adequate assessment of shop floor performance. Such existing measures prevent an in depth evaluation of operations and normally do not allow the identification and detailed description of complex shop floor phenomena. This research addressed this problem by utilizing non-traditional data modeling and database management techniques to provide managers with a more descriptive set of shop floor performance measures. Various conceptual modeling methods from the Information Systems field were used in this research as was an actual implementation of a relational database of historical, disaggregated shop floor operational data. Both traditional aggregate and non-traditional disaggregate performance measures and information were derived from the database and presented to information users for evaluation. The performance of the users was evaluated to determine which type of information was more effective in the identification of underlying shop floor problems and conditions.

It was found that the conceptual and implemented modeling methods were quite effective in providing a more descriptive dataset. However, the effectiveness of the different information types appeared to be dependent on the nature of the problem on the shop floor.

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ACKNOWLEDGMENTS

I would like to acknowledge the efforts of my committee in helping me to complete this work. I was fortunate to have four outstanding members, two in my field of Operations Management and two in Accounting/Information Systems. My chair, Dr. Steven Melnyk and another member, Dr. William McCarthy, were instrumental in taking my initial somewhat fuzzy idea and helping to form it into something researchable. This included many meetings and many cups of coffee several years ago, particularly with Dr. McCarthy, while this idea was taking shape. Another member of my committee, Dr. Gary Ragatz, provided additional guidance in the early phases of this work, helping me to decide what was meaningful to Operations Management researchers and what was not. The final member of my committee, Dr. Severin Grabski, provided an excellent link between the Accounting/Information Systems and Operations fields. He was able to see the relevance of my topic to both fields and was really was the "glue" that brought them together. My thanks go to all of them.

I would also like to acknowledge the support provided by my current department at Lake Superior State University and in particular that provided by my Dean, Professor Ray Adams. Their encouragement throughout this process is greatly appreciated.

Last, but certainly not least, I would like to offer my thanks and love to my wife Jill and our sons Michael, David and Christopher. Their patience and understanding throughout this process helped me to have the proper perspective on what is really important. We all look forward to enjoying our post-dissertation life together.

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1.0 Introduction and Overview

1.1 Introduction

Despite the extensive use of information in manufacturing, very little research has been done identifying and evaluating the actual structure of information on the shop floor and what impact that structure may have on managerial decision making. This is particularly true with one of the most commonly used methods of researching the shop floor- computer simulation. Such evaluation has not been feasible in the past, due largely to the current nature of shop floor data and information management techniques within a simulation environment. Traditionally, simulation-based research has been focused primarily on the evaluation of the effects of certain decision rules and operational conditions and problems, rather than on the actual diagnosis and identification of such problems. Such *a priori* specification of problems and conditions, while providing insights to researchers, has not explored the issue facing many practitioners, namely how to determine what is wrong with the shop floor, or in other words, how to identify the underlying problems that are causing poor performance.

In an attempt to establish a more descriptive information framework, one that allows the identification of specific operational problems, this dissertation proposes combining elements of traditional Operations Management (OM) research, i.e., a simulated shop floor, with modeling and analysis techniques of the Information Systems (IS) field to explicitly evaluate manufacturing's information structure. In doing so, this work is designed to link the two areas of research and practice in a new and unique way. It is intended to show, by combining these two areas on both a theoretical and implementation level, how improved cross functional integration may be achievable.

To aid in establishing a linkage between OM and IS work, this dissertation proposes using an information system based on a relational database to exploit shop floor data. While relational databases themselves have been widely used in actual manufacturing

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settings, their theoretical implementation has not been significantly explored in the manufacturing literature. Moreover, the specific approach being proposed, which makes use of previous research in the accounting information systems field (McCarthy, 1979; McCarthy, 1982; Colantoni, Manes and Whinston, 1971), has not been explored in manufacturing to any meaningful extent. Elements of IS research, such as conceptual database modeling, are used in this research to develop a method of managing shop floor data and information that may result in improved evaluation of the shop floor.

Thus this research is examining not only the issue of performance measurement and reporting, but also the way in which information is handled on the shop floor. It looks explicitly at the actual means by which shop floor data can be structured and managed and whether the structure itself has an impact on both the performance measures used and the insights gained.

In addition to exploring the enhancement of shop floor information management, this work also proposes to employ actual information users to evaluate the benefits of such management. This is done with a controlled laboratory experiment in which users/subjects have available to them different types of shop floor information and are given the task of evaluating shop floor performance and identifying problems in its operation. The users' performance is subsequently evaluated to determine if information type has an effect on problem identification.

1.2 Problem Statement

Current shop floor performance reporting procedures, which stress aggregate and mean measures, do not provide an adequate assessment of shop floor performance. Such existing measures prevent an in depth evaluation of operations and normally do not allow the identification and detailed description of complex shop floor phenomena. This deficiency is also evidenced in one of the most common methods of shop floor research, simulation modeling. As a result, it is difficult to use simulation to identify and diagnosis specific operational con

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specific operational conditions that may be causing shop floor performance to degrade. That is, actual interactions on the shop floor can go unnoticed. This emphasis on aggregate and mean point measures also prevents simulation from being widely used as a managerial or enterprise level decision tool.

1.3 Discussion of Research

This research is investigating the actual structure, management and processing of shop floor data and its subsequent presentation as potentially useful information. A simulated environment will be utilized to evalute different methods of shop floor data and information management and will act as the vehicle by which operational performance measures will be generated. The resulting measures and information, of primarily two different types (to be discussed later), will then be evaluated by actual information users in a controlled laboratory setting.

1.3.1 Importance of the Research

It is critical that researchers and practitioners have a thorough understanding of the shop floor. At its essence, shop floor control is the foundation upon which the Manufacturing Planning and Control Hierarchy is based, as indicated in figure 1.

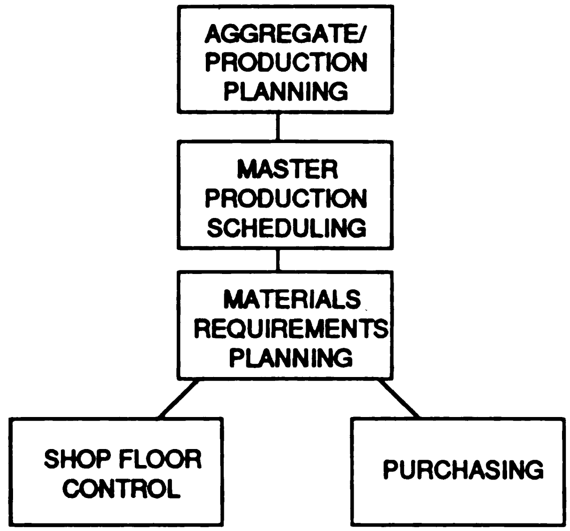

Figure 1: Manufacturing Planning and Control Hierarchy

However, unlike the upper levels of the hierarchy, such as Aggregate Planning or Master Production Scheduling, shop floor control is very detailed, requiring information and decisions on a daily or hourly basis (Stevenson, 1999). Aggregate and mean measures of capacity and performance are not sufficient at such a detailed level, although shop floor managers and researchers have traditionally had to use such measures solely within an OM environment to evaluate performance (Blackstone, *et. al.*, 1982).

This research is attempting to increase the descriptive power of shop floor performance measures by incorporating certain IS methods into what traditionally has been an OM area. By doing so, such performance measures may provide a level of detail commensurate with that of the nature of shop floor operations and allow additional insight of those operations. In addition, the combination of IS and OM techniques being proposed provide a substantial extension of previous work towards the development of a new methodology of information management and evaluation, as will be reviewed in the next chapter.

This research has elements of interest to various fields of research and practice. The simulation model used is based very closely on an actual shop floor that was studied over a period of time

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over a period of time and incorporates features not normally included in simulation models (see Chapter 4). The development of such a detailed empirically based model acts to lend validity to the use of simulation models. In addition, this research will utilize a relatively standard IS management tool, the relational database, in ways not previously explored in the OM field, allowing both OM and IS researchers the opportunity to observe how their respective methodologies can work together to create and use information. Finally, this research makes use of a methodology not normally associated with OM, the laboratory environment. Rather than statistically analyze a factorial simulation experiment, this research will allow actual information users to evaluate two different types of information in an attempt to determine which is more effective in identifying shop floor problems. Not only will this demonstrate how managers may use information, but it also will allow OM researchers to evaluate the utility of the lab experiment, a methodology normally associated with Organizational Behavior or Industrial Organizational Psychology (OB/IO Psych).

1.4 Methods and Key Results

As described earlier, this research proposes to combine a variety of methodologies in an attempt to develop more descriptive and meaningful performance measures. A literature review will be conducted as will interviews with two shop floor experts to develop an initial listing of both traditional and non-traditional measures. Modeling techniques from the IS field will then used in conjunction with a simulation model to collect a larger, more disaggregated dataset from the model's runs. This dataset will in turn be converted into performance measures, some traditional, some non-traditional, with the use of a relational database. A laboratory experiment will then be conducted to evaluate the usefulness of the various types of measures.

On the key question of the measures' utility, several interesting findings are reported. It was found that information type did have a significant effect in identifying some conditions. It appears that users evaluating the effect of more dynamic and changing conditions can benefit

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conditions can benefit from the use of more disaggregate measures, while for other conditions the information type made no significant difference. The ramifications of this are discussed in later sections.

1.5 Conclusions and Organization

As discussed, this work is attempting to address the issues of shop floor information sufficiency and utility through the use of several different methodologies. Through the combination of OM, IS and OB/IO Psych methods, it is hoped to present a unique and useful approach to shop floor data management and performance reporting. The multi-disciplinary nature of this work is such that the results may have application in not only the OM field, but other functional areas of a typical enterprise.

1.5.1 Organization of the Remaining Dissertation

Chapter 2 surveys the literature of information management in both the OM and IS fields, with special emphasis on data and database modeling techniques. Chapter 3 presents the research questions and hypotheses and discusses them further in terms of their relationship to the problem statement. Chapter 4 lays out in some detail the research experimental design methodology and the proposed data analysis. The results of the research are presented and discussed in Chapter 5 and Chapter 6 concludes this work and suggests directions for future research.

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2.0 Literature Review

2.1 Overview

This chapter synthesizes previous work done in both the OM and IS fields that deals with the uses and structure of information. This review initially discusses the overall methods by which information has been approached and managed in manufacturing environments. Upon such a review, it will be seen that while data and information are, understandably, used extensively in OM, there is very little discussion of their actual structure. The vast majority of work dealing with data and information structure has been done in the IS field, which has developed a solid theoretical foundation for research. Various conceptual and practical applications of data management techniques in both the IS and OM fields are discussed, including the use of relational databases, which will become a key element of this research.

Various traditional shop floor operational conditions, such as dispatch, order release and due date assignment rules, are reviewed to establish their importance in the OM field. These conditions will be among those evaluated and identified by actual information users in the lab portion of this research. Finally, a review is made of performance evaluation of the shop floor, discussing the use of both tactical and non-tactical measures and information.

2.2 Background

The increasing importance of information in manufacturing has been noticed by past OM researchers. Skinner maintained that a factory is "75% information handling and only 25% a materials transforming system" (1969, p. 63). He further maintained that this relationship has led to a more critical role in the organization for information systems and information specialists. Hollander, Denna and Cherrington (1995) also suggested a more core role for the information system within a manufacturing organization with their suggestion that manufa

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suggestion that manufacturing, along with the entire organization, needs to be viewed as a collection of business processes that are closely supported by the company's information system. That is, even physical processes should be described primarily as information generating events and should be recorded as such. In fact, manufacturing information management is becoming so important in today's business environment, some feel, that it has become necessary to define and evaluate "information-oriented" performance (Hill, Koelling and Kurstedt, 1993), in which it is the actual quality of the information produced and managed that is assessed.

However, despite this growing recognition of information's importance, one element which has not seen much attention in the OM literature is the *specific* treatment of information management on the shop floor. While discussed peripherally, information has not had a central role in the literature. In the most commonly used method of shop floor analysis– simulation– information management has been restricted to the very limited collection of data to support performance measures such as the mean or variance of time in system or of job tardiness. And since means and variances can be derived from only two or three cumulative values, very limited data are stored during the simulation run and those that are stored have a very simple structure, designed to support the relatively simple measures being used. There has been very little attention paid to developing more extensive or theoretically based data structures for the shop floor; it has been considered sufficient merely to collect and analyze data to report certain aggregate performance measures.

2.3 Information Systems in Manufacturing

In order to accurately gauge performance, Kaplan and Norton (1992) maintained that it is necessary to properly manage manufacturing information. Indeed, an unresponsive information system can be the "Achilles heel" of performance measurement (p.75). They maintained that for a shop floor information system to be effective in aiding performance evalu

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performance evaluation, it should be integrated with not only the shop floor operational areas but other functional areas of the company as well. However, despite this observation, little work has been done to address the issue of the shop floor's information system or how the system may act as an element of performance evaluation. In addition, there is very limited work detailing the areas to which the shop floor could or should be integrated or, more importantly, *how that integration could be made*. Without even a recognition of the importance of other areas, little progress could be made in integrating their performance with that of the shop floor.

In one work, however, Hax, while supporting the call for more integrative OM research (1981), went on to identify the specific areas of the firm that should be of interest to the shop floor manager (and vice versa) and established a framework to create the linkages between them. The areas he identified were (1) Planning System, (2) Management Control System, (3) Organizational Structure, (4) Evaluation and Reward System and (5) Communication and Information System. Hax's specific inclusion of the information system was significant as was his description of the system as one that should "provide information with varying degrees of detail to all those managers..." (p. 576). Hence, he noted the key importance of the information system as an integrating tool and as one that could provide various views and presentations of generated data, depending on the user's needs.

A survey conducted by Gupta (1994) also pointed out the importance of an integrative shop floor information system, while discussing some reasons for its lack of implementation. He concluded that the primary reason for ineffective manufacturing information management was the lack of coordination among different departments– a point in general agreement with previous researchers' views (Hax, 1981). One reason for this, Gupta felt, is that in many organizations the information systems are viewed strictly as operational or data processing tools and not as strategic weapons. The MIS department was felt to spend most of its time in an accounting mode and, despite the technology at its disposal, did not u

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disposal, did not understand manufacturing or the shop floor. In an earlier work, Groff and Clark (1981) also addressed the issue of the firm's technology and concluded that it was not so much the lack of technology that was impeding the implementation of manufacturing information systems, but rather the lack of a theoretical framework. Although data retrieval may be quite advanced, OM researchers and practitioners need to know how to *transform* data into information so that it can support the problems being considered. This distinction between data and information was further made by way of different definitions of information as "biased data". (Hill, Koelling and Kurstedt, 1993, p. 380) and as "data that has meaning to the receiver– the information customer" (Hollander, Denna and Cherrington, 1995, p. 10). Thus, researchers have recognized that data for data's sake is not necessarily useful; it must have some organization or structure *and* be processed before meaningful information can be derived.

2.3.1 Data Structure, Management and Processing

The specific issue of shop floor data structure as it relates to information retrieval has been discussed only sparingly in the OM literature. Bhimani and Bromwich (1991) suggested that for Just In Time (JIT) systems, a more comprehensive means of data collection is needed, one which they denoted as "non-cumulative" data storage. Their argument was that it is important to collect data on *all* events and activities, both value and non-value added, thus allowing the calculation of total manufacturing costs. However, no suggestions were made as to how exactly to structure this "non-cumulative" information system. Son (1990) presented something similar by recognizing that there are many more contributors to manufacturing cost than just labor productivity and that these various cost categories must be separated out. The use of a computerized database was recommended as a means of capturing all of the disparate data categories. Although both of these works hinted at a different means of managing manufacturing information, they suggested no specific structure for the data nor did they provide a theoretical framework to do so.

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While only limited research on shop floor or manufacturing data structure exists, this is not to say that typical simulated job shop data have no structure. Their structure is just relatively aggregate in nature and designed around certain pre-specified performance measures that in turn restrict data collection. On the one hand, this limited approach to data collection was supported by Anderson, Chervany and Narasimhan (1979) who maintained that "you should not collect data if you do not know what you should be measuring" (p. 54). This is a caution against collecting data in other than a pre-specified manner to support certain measures. However, Melnyk *et al.* (1985) commented that a proper shop floor information system should be an objective record of events, without interpretation. This is somewhat at odds with the practice of collecting data only according to pre-specified measures. Such targeted collection implies an interpretative bias, i.e., raw data begins to resemble information (Hill, Koelling and Kurstedt, 1993).

Thus the issue of an exploitable yet objective and useful data structure, while mentioned in the literature, seems to be repeatedly skirted. Research has looked at the various uses of shop floor data, either directly or indirectly, but has not addressed their specific structure or organization.

2.4 Data Management in the Systems/Accounting Field

While data and information structure have not received much attention in the OM literature, they have been treated in IS theory and research. Much of this work has come from the accounting field as accountants have generally been considered the custodians of an organization's information store (Johnson and Kaplan, 1987). This work forms the basis for much of the study of information in the operations field, and thus is discussed in this review.

Goetz (1939) first proposed the idea of maintaining enterprise information in what he dubbed the "Basic Historical Record," which was to be an uncontaminated record of occurrences or transactions indicating what the enterprise obtained and surrendered.

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Goetz's goal was a flexible system that stored data in their most *primitive and disaggregated* form so that they could be reclassified or reaggregated into the form most convenient to the user. He states that "problem after problem may require special combinations of data" (p. 154), which is a very accurate depiction of a modern computerized database compiling data on demand for various users. This is very similar to the concept of a non-interpretive database of information as discussed by Melnyk *et al.* (1985) and as one that can provide information with varying degrees of detail (i.e. in different forms) to different managers (Hax, 1981). Each record stored would correspond to a separate transaction or event. This work was the first reported instance of a researcher suggesting that the actual structure or method of storage of the data merits study by itself.

Colantoni, Manes and Whinston (1971) extended the idea of a disaggregated events or record-based data store a step further by laying out a method of capturing event information in a functioning database. They suggested a means of coding the data so that each event or transaction could be identified as a binary record. Further, they presented a means of search and retrieval for the data that could be implemented in a computerized database. Each record would have various characteristics, such as name, date and hours spent for an operation. The database they suggested was hierarchical or tree-like in nature. Thus, the data structure proposed by Goetz (1939) was becoming somewhat more refined.

Perhaps the most significant contribution to the idea of events-based disaggregated data storage was made by Codd (1970) with his development of the relational database (RDB). Codd envisioned the RDB as a means of sharing information in very large organizations or across large data banks. The RDB concept differed from previous databases in that it stressed the independence of the stored data from any applications thereof. Moreover, data were broken down into separate tables in the RDB, each representing a different entity (an event, resource, person, etc.) with very specific local information. The database became very segmented. And, by basing RDB logic on set theory, Codd provided a sound theoretical basis for the idea of data disaggregation. In essence, he provide

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essence, he provided a justification for and the means of highly disaggregated data storage that could be accessed by multiple users in an organization. This was a realization of both Goetz's (1939) and Colantoni, Manes and Whinston's (1971) goal that in an "events" information system the user determines the level of aggregation of the data. Moreover, this approach to data management is very much in line with the perspectives of Melnyk *et al.* (1985) for an objective recording of shop information and Groff and Clark (1981) as providing a needed theoretical basis for manufacturing information management. The storage and use of disaggregated data has been called the "database approach" to information management (Dunn and McCarthy, 1997). Codd's RDB design, by storing data in separate and independent relations, laid the foundation for this approach and provided the tools by which the data could be exploited.

2.5 Semantic Data Models

The concepts of disaggregated data and the RDB provided valuable techniques by which data could be structured, manipulated and exploited. However, with these new tools came a need to model and depict actual situations so that the data associated with them could be compiled and used in a "database" manner. For this, the IS field has turned to a concept known as data modeling. A data model has been described by Navathe as "a set of concepts that can be used to describe the structure of and operations on a database" (1992, p. 112). Thus, a data model provides the structure by which disaggregated data on the phenomenon of interest can be captured, stored, interrelated and manipulated. Often, building a data model is a precursor to an RDB implementation (Batini, Ceri and Navathe, 1992).

A *semantic* data model enhances the structure of the stored data with the additional characteristics of (1) expressiveness– the various data and relationships describe the phenomena of interest and can be distinguished from each other; (2) simplicity– the user can readily understand it; (3) realism– objects in the model closely correspond to real-world phenomena and (4) r

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phenomena and (4) relevance– the actual value added activities or processes are modeled (Navathe, 1992; Dunn and McCarthy, 1997). Semantic modeling extends data modeling by attempting to capture reality more accurately. For example, in the case of a job shop, all related events and resources, such as order releases, employees' involvement, vendors and inventory orders would be included along with normal machining operations.

The most commonly cited technique to depict data models has been Chen's Entity-Relationship (ER) modeling (1976). ER modeling has a very semantic basis in that it can capture real world entities and their interrelationships. Chen essentially viewed the world as a set of entities that were interrelated. The methodology allows models to be built while remaining entirely within the relational framework. Additionally, such models are very visually appealing and clear and relatively easy to understand with only a few key basic concepts (Brodie, 1984).

McCarthy (1979) extended semantic modeling into the accounting field with his development of an enterprise model using ER techniques. Within his model, he first identified very clearly all entities and relationships of interest in an enterprise. By capturing all events or transactions, he demonstrated how "standard" accounting reports could be generated from a disaggregate dataset. This work was expanded by McCarthy (1982) with his development of the REA framework (Resource-Event-Agent). This framework recognizes that each transaction (Event) has two other related entities- a Resource, which is added to or subtracted from, and an Agent, the facilitator of the event. Thus he provided a more explicit categorization of an enterprise's total entities and relationships and was able to model and capture all value adding and their related paying events.

2.5.1 Manufacturing Information Systems and Semantic Modeling

There is a limited amount of work describing semantic modeling and the database approach to information management in the manufacturing field, most of it in the production planning area. Lee and Fu (1985) modeled a production planning process wherein they decomposed a machining environment by establishing interrelationships

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between parts and processes or operations. Moreover, the parts and processes were further broken down by types so that specific parts could be linked to specific operation types. Wang and Walker (1989) also developed a model where the relationship between parts and processes is clearly specified. They extended the model to include sequence dependent routing among various processes or operations. Through semantic modeling, they disaggregated the operational data to establish a three way linkage between machines, tools and parts to identify a unique instance of an operational event. Shooshtarian *et al.* (1993) disaggregated operational data on tools and machines into several types and subtypes using a process similar to Smith and Smith's (1977) generalization hierarchy. At the disaggregated level, they were able to show a strong semantic link between tools and processes or tools and workpieces, even going so far as to indicate cardinalities (Batini, Ceri and Navathe, 1992). Shooshtarian *et al.* alluded to a RDB implementation of this model, but provided no details.

Nandakumar (1990) extended semantic modeling into the Bill of Materials (BOM) environment. He suggested that basic part data storage can be done within one entity that has a *relationship with itself* within the database to represent parent-component relationships. He combined an RDB containing this disaggregated data with a FORTRAN BOM processor to perform MRP calculations. Marsh and Vickery (1995) extended this work by incorporating the time varying aspects of MRP within a semantic model. This allowed the complete implementation of the MRP environment within an RDB, as opposed to relying on a companion third generation language processor. In addition, their semantic model explored the inclusion of other functional areas in the MRP implementation, such as vendors/suppliers and customers. It was found that by modeling the MRP planning system semantically and in such a disaggregated manner, linking, for example, parts or subassemblies to vendors could be done in a relatively straightforward manner.

McCarthy's REA framework (1982), as discussed earlier, established a conceptual data modeling approach to a value added chain of activities, a concept which was later

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extended more explicitly by Geerts and McCarthy (1995). In the latter work, a semantic model of a manufacturing organization was proposed that allowed for the capture of all value adding events associated with production. Grabski and Marsh (1994) further advanced this concept to a "discretized" continuous manufacturing process and showed that individual activities within a complete process chain can be separately modeled as value added activities. They semantically modeled each stage of the continuous process within the REA framework. This "micro" approach to data modeling was shown to be an effective way of allowing for the collection of a detailed and disaggregated dataset representing manufacturing information. From this database, non-manufacturing or "enterprise" level information, such as cost summaries, exception reports and operational histories was reconstructed. Although relatively simple information was made available, Grabski and Marsh (1994) showed that it was the semantic structure of the model and process that allowed for this presentation.

Maybury (1995) discussed the usefulness of semantic and relational linkages among events-based data in producing meaningful summary information. He also presented specific methods of events summarization including aggregation– the combining of several similar events into one. Also emphasized was the distinction between events' frequency distribution and their distribution or occurences over time. These distinctions could be made more effectively, he felt, by proper modeling of events' datasets. Basta (1995) discussed the use of very large and very disaggregated datasets in presenting managerial information, although more from an application standpoint. He maintained the importance of properly structuring the resulting database to allow for useful information summarization.

2.5.2 Database Modeling in Simulation

Although some of the previous work in manufacturing data modeling has dealt with actual or simulated processes (notably Shooshtarian *et al.*, 1992; Grabski and Marsh, 1994), most has been on the conceptual or exploratory level, with very little work done in terms of implementat

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Yancey (1987) was perhaps the first to report on the advantages of using databases to manage data created by simulation. He maintained that a database that was closely integrated and designed with a simulation model would provide for detailed data storage and subsequent reporting of various types of information, including discrete or continuously time persistent data or the tracking of events over time. More importantly, he felt that such comprehensive storage of the vast amounts of data created by a simulation model could provide insights into why certain behaviors happen within a modeled environment.

Hitz, Werthner and Oren (1993) suggested a broader use of the database within simulation– to store entire models to enhance their reusability. If many different models' parameters and characteristics as well as their semantic relationships could be stored, they felt, it would facilitate researchers' selection of models for future research. While this approach may have some merit, most of the previous research regarding databases and simulation dealt with the database as a repository of generated data for a specific model.

Centeno and Standridge (1993) developed a general framework for the use of a database to help define a simulated environment. They suggested that the database can be an efficient enabling technology for the design of the simulation model, much as is being proposed in this research. The relational database model was cited in particular as being a very effective data storage and manipulation medium.

A work that perhaps extended database and semantic modeling the furthest into the field of simulation was that of Roberts (1991). He suggested that a semantically based ER model could act essentially as a template for an RDB that could receive data generated by a simulation model. The database then could respond to virtually any query regarding the model's historical operation. He compared the calculation of mean and variance, which are relatively simple to

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relatively simple to compute during a model run, with what may be available from a complete dataset, such as correlations, plots, histograms and the like. His work is significant in that he specifically encouraged the use of semantics to better design the simulation model and the resulting collecting database. Roberts presented a simple queuing example and described how it could be semantically (ER) modeled and what the resulting datasets would look like, however, no actual implementation was done. A later work by Koh, de Souza and Ho (1995) implemented a method dubbed "direct database simulation" which used an RDB in conjunction with a simulation model. An experiment was performed in which a simulation model was linked to an RDB that acted as the repository of shop floor parameters such as work center and part family information. The simulation model then had access to certain database information during operation. They found that performance could be improved by making this dataset available. However, no explicit mention was made of the database modeling technique (i.e., semantics or otherwise) and the collected data was not used for performance evaluation.

2.5.3 Semantic Data Modeling Summary

The IS field has produced some useful tools for compiling and analyzing data and information, with semantics and RDBs forming the core of this methodology. Manufacturing researchers recently have come to realize the benefits of semantic modeling and, while there are instances of some practical implementations, particularly of RDBs (Knight, 1994), there is little conceptual or theoretical work reported in the literature. What research there is has predominantly been in the simulation literature, where the notion of semantic modeling has been introduced, but no implemented models are discussed.

Prior to examining how simulation and database theory can be combined, it is necessary to first survey issues commonly studied using simulation in the past job shop literature.

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2.6 Simulated Shop Floor Operational Factors

Traditionally, simulation modeling has been used to evaluate the performance of a shop floor with the introduction of various experimental factors. These factors have been deemed by researchers and/or practitioners in the past to be relevant issues to explore. Some of those issues and factors, particularly as they relate to the proposed research, are discussed in the following sections.

2.6.1 Bottleneck Resources

A bottleneck resource is one that restricts the overall flow through the shop floor. Such a resource may be machines and/or labor (Trelevan, 1987; 1989) or tools (Melnyk, Ghosh and Ragatz, 1989; Ghosh, Melnyk and Ragatz, 1992). In the proposed research, the machine constraint will be studied. Studies of bottlenecks have appeared in both the academic and practitioner literature and are recognized as a relevant problem for production schedulers. There are two primary types of bottlenecks or constrained machine resources– the stationary bottleneck and the moving bottleneck.

The first type, the stationary bottleneck, is the simplest to describe, consisting of a machine that constrains the overall flow through the shop. The aggregate demand or flow through the shop is greater than the bottleneck resource can accommodate. A stationary bottleneck does not move, that is, a set machine remains the overriding constraint in the shop.

A shop experiencing a moving bottleneck always has one machine at a time that is acting as a brake on aggregate throughput, but the problem machine is not the same all the time. One work center will be the bottleneck initially, and another will be at a later time. This may be caused by the nature of the jobs in the shop over the course of a certain time period such as a month, or it may be caused by rotating maintenance schedules.

Resource constraints have been researched quite extensively in the OM literature. One of the first works in this area was by Harty (1969) in which he established that it was critical to identify bottlenecks and to schedule the shop so as not to overload them. He

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maintained that bottleneck resources must be kept free so that they would always be available to work on incoming jobs. Roy and Meikle (1995) also discussed the importance of scheduling around the bottleneck, but rather than emphasize keeping the bottlenecks underloaded, they maintained that it was important to keep them fully loaded with a high utilization and to assure that they are not starved for jobs. This approach differed from Harty's but is one that was to become increasingly prevalent. Roy and Meikle also discussed the idea of a resource based model, in which the work centers were ranked according to the severity of their constraint or by how much they were acting as a bottleneck, thus explicitly recognizing the bottleneck as a key element of the shop floor.

Lingayat *et. al.* (1995) investigated the presence of bottleneck resources in simulated shop floor settings. They based their models on actual systems studied empirically, in order to gain useful insights of a practical nature. They found that order release mechansims based on maintaining a high load through a shop's bottleneck resource were most effective in scheduling jobs in the shop.

Bottleneck management came more into the public eye with the publication of works by Goldratt (1990; 1992), extolling his belief that all policies on the shop floor must be subordinated to the bottlenecks. There were, he felt, two major areas of the shop floor- the constraints and everything else. The non-constrained portion of the shop cannot and should not produce more than the constraint can handle. Although Goldratt maintained that identification of the bottleneck is the first step in evaluating a shop floor's performance, he emphasized that this may not be an easy task. To demonstrate this, he provided the example of his fictitious characters in *The Goal* (1992) laboriously sifting through their information system before the bottleneck constraint was found.

Plenert (1993) also emphasized the importance of finding and utilizing the bottlenecks in a manufacturing environment and, more significantly, discussed how they may not always be stationary, referring to a moving bottleneck in which the constraint shifts through the plant. Certain analytical methods of dealing with stationary bottlenecks become immediately

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become immediately more complex when the bottleneck is found to be moving through the shop, for whatever the reason. This, he maintained, is much more prevalent in actual shops than is evident by the literature.

In a study of an actual job shop on which the simulation model in this research is based, management was often dealing with resource constraints, or bottlenecks (Marsh and Melnyk, 1994; 1995). One work center in particular was on the routing for a great many jobs and thus became a bottleneck. Even three shifts per day of operation could not satisfy all demand for the resource. Thus, schedulers had to be aware of this work center and base their due dates on the presence of a substantial queue in front of it.

2.6.2 Irregular order or job releases

Job releases to the shop floor is an area that has received a great deal of attention in the literature with a significant portion of this work being determining the way in which to introduce jobs so that overall shop performance is maximized (Law, McComas and Vincent, 1994). Law and Kelton devote an entire chapter (1991, p. 325-419) to prescribing how to develop input distributions for jobs entering a simulated shop. Although mention is made of empirically based input distributions, most often it is proposed that jobs' arrivals be modeled with theoretical distributions. Some researchers have developed algorithms and software packages that will approximate an empirical distribution with a theoretical one (Law and Vincent, 1993), aimed at establishing more accurate input interarrival times.

More recently, research has attempted to decouple jobs' entrance to the manufacturing facility and their subsequent release to the shop floor by the use of order release mechanisms. This entailed the creation of an additional area of the shop floor- the order review and release pool (Melnyk and Ragatz, 1989). As jobs are planned and generated, they first flow to this pool before being released onto the shop floor. The way orders are ultimately released to the shop floor has been the primary focus of the research in this area.

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Wisner (1992) identified several broad areas in the order release literature: (1) case studies and descriptive work; (2) analytical studies; and (3) simulation based studies. In essentially all of this work, the key element of order release is identified as that of separating job generation from job introduction to the shop floor. That is, order release mechanisms provide a buffer between customer orders and the rate at which those orders are released to the floor. In fact, in a recent empirically based work (Marsh and Melnyk, 1995), it was reported that shop floor management and personnel are concerned *just* with releases to the shop floor and not really at all with the actual generation of jobs. Jobs are generated and are first processed by different departments, such as engineering and estimating, before they are given to the shop floor. Thus the order release pool is present and, as far as shop floor management is concerned, is *the* source of jobs.

Order release's practical importance may have been overlooked in recent research in favor of other more popular operational factors. In a survey of practitioners Melnyk *et. al.* (1986) reported that managers felt that academic research overemphasized dispatching rules while ignoring order release mechanisms, which, according to the managers, have a much more substantial impact on shop floor operations. It was felt that, at a minimum, the two should be studied together. Other work examined the interplay between order releases and dispatching and found that not only was there a significant interaction between the two factors, but that the proper choice of an order release mechanism could greatly simplify the choice of dispatching rule (Ragatz and Mabert, 1988). Melnyk and Ragatz (1989) also reviewed order release mechanisms and similarly concluded that, used properly, they can reduce total shop work load, balance the work load across the various work centers and can have a significant impact on a job's total time in system, although such impact may not always be beneficial.

In two empirically based works by Marsh and Melnyk (1994; 1995) orders in a simulated shop floor were released to the shop floor according to policy set by shop floor management. Depending on the type of job, order release varies by shift and can be relatively smooth and

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2.6.3 Due Date Assignment

In the literature, one recurring measurement of simulated shop floor performance has been due date performance, normally represented by mean job lateness or tardiness (Blackstone *et. al.*, 1982). Coupled with this focus on due date *performance*, however, has been a large body of research dealing with actual due date *management*. The primary emphasis of due date management has been the assignment of due dates to jobs (Ragatz and Mabert, 1984), that is, how best can due dates be assigned to assure realistic operation. In establishing a framework for the study of due date related problems, Cheng and Gupta (1989) partioned the literature into three areas: (1) exogenous versus endogenous due date assignment– the due dates are assigned externally to and out of the control of the shop *versus* being set internally; (2) static versus dynamic due date assignment (Ragatz and Mabert, 1984)– due dates are fixed upon job introduction *versus* being allowed to vary with changing shop conditions; and (3) analytical *versus* simulation based research– an optimized algorithmic method versus significance testing of several different experimental factors.

One particular stream of due date research that spans both analytical and simulation based work related to this research is that of managing jobs in an assembly shop. Ragatz and Mabert (1984) discussed the difficulty of coordinating the due dates of various components in an assembly shop. This problem was also discussed and analyzed by Bagchi *et. al.* (1994) in an analytical examination of a single machine shop that explicitly studied multi-job customer orders. Two different due date assignment methods were studied- a common due date was given to all jobs in a single customer order, and separate due dates were assigned to each job. An optimal solution was developed for the case of the common due date when each order's jobs were processed contiguously. However, Bagchi *et. al.* called for more

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et. al. called for more research in the case of the individual due dates as that problem proved too difficult for an analytical solution.

Cheng (1988; 1989) looked at the problem of assigning common due dates to a batch of *n* jobs in a shop with *m* parallel machines. It was possible to develop an optimal solution, but it had limited application due to the shop's relatively simple structure. Goodwin and Goodwin (1982) also performed a study of due date assignment in an assembly shop but with a much more explicit examination of different products and product structures. In their model there were 14 different product structures with four different assembly levels with ***assembly dependency***, that is, sub-assemblies could not be made and shipped to the next level until all of their components were completed. A common due date for all components was set, although it was not entirely clear exactly how this was done. It was determined that not all results of a traditional job shop generalized to an assembly shop. For example, due date based dispatching rules outperformed SPT on most dimensions. Goodwin and Goodwin called for more research in the multi-level assembly shop to help ascertain why such results were not generalizable, with the suggestion that more detailed data, such as that of a distributional nature, be examined.

Adam *et. al.* (1993) also studied a multi-level assembly shop in which jobs were divided into "segments" which have to be assembled together after processing is complete. A segment is represented by a series of operations. The same assembly dependency as proposed by Goodwin and Goodwin (1982) was used in this study. Three different methods of internally (endogenously) assigning due dates were used, both traditional and dynamic, with the dynamic methods relying on things such as job characteristics and the state of the shop at the time of assignment. Jobs introduced were of various types, some with segments, some with sub-assemblies and some with sub-sub-assemblies. Nine different job structures were studied. Adam *et. al.* found that there were significant differences between the performance of the different due date assignment methods and that these differences wer

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2.6.4 Different Job Types

Since the concept of a job type can, if only by its generic name, be almost anything to anyone, some more precision is warranted to further define a job type in both this and past research.

In the literature, jobs have been segregated into types based on various criteria. One way they have been so separated is by the nature of their routing and operations. Elvers and Treleven (1982) performed a simulation study comparing the performance of a shop that had varying mixes of jobs of different types. One type, job-shop jobs, were assigned random routing among between two and six work centers. The other type, flow-shop jobs, each had four operations, all in the same sequence. They found significant differences between the two types when they were mixed, with the flow-shop jobs in general having superior performance. In fact, of three different job type mixes, the one that emphasized flow-shop jobs, while retaining some job-shop jobs, was the best performer.

Jobs also can be typed by different priorities, as has been done in the literature. Ashby and Uzsoy (1995) developed a study based on the assumption that different jobs have different customers and, hence, potentially different priorities. Different order release mechanisms were used based on jobs' different priorities. In this study, four main job types were introduced- standard, non-standard, priority and rush. The mix of jobs was varied in the study. It was found that the choice of order release mechanism had a significant effect on shop performance, with the due date (hence priority) based release methods having the best performance. This line of study was also pursued by Malhotra *et. al.* (1994) who stated that "not all jobs on the shop floor are of equal strategic importance to the firm" (p. 713). They also recognized that different customers have different priorities that are usually *dictated by the customer*. Thus it became necessary to deal with a multi-class priority system within a job shop. Like Ashby and Uzsoy (1995) this study included

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Perhaps the most explicit treatment found of different job types was developed by Huq and Huq (1995). The model in this study was a hybrid shop, with a job shop being followed by a flow shop; followed in the sense that jobs were first routed through the job shop and then to the flow shop. Job types were defined by their routing, which was fixed by each type. Also, different job types were assigned different processing times at each work center. That is, it was assumed that jobs of different types had different machining requirements at the same work centers. Despite such explicit treatment of types, the mix of types was not an experimental factor in the study nor are any results broken out by job type.

2.6.5 Dispatch Rules

Dispatch rules are perhaps the most heavily researched area in the OM literature. In a relatively early work, Gere (1966) made an attempt to distinguish between what he termed priority or dispatch rules, scheduling rules, and heuristics. He defined priority or dispatch rules as those that simply assign values to jobs in a queue and which in turn determine the order in which the jobs leave the queue. Scheduling rules were seen as combinations of one or more priority rules while heuristics were rules of thumb. In one review, Panwalkar and Iskander (1977) proposed a further classification of scheduling rules into simple priority rules, combinations of priority rules, weighted priority indexes and heuristics and other rules. In their review they list and describe 35 simple priority rules as well as over 60 other types. Their resulting literature review included approximately 36 works that referenced use of one or more scheduling rules. Among those figured prominently were SI (shortest imminent operation, also known as SPT), DD (earliest due date), FIFO (first in first out) and S-2 or S-1/OP (variants on least slack or ratio of slack).

Blackstone *et. al.* (1982) performed an equally exhaustive review of dispatching rules, primarily as used in simulated environments. Throughout the review, some common dispatching rules em

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dispatching rules emerged as not only the most researched, but as the most effective in improving shop floor performance. Among those listed as the overall best performers included SI, DD, least slack and least slack per operation, critical ratio and FIFO. Blackstone *et. al.* evaulated performance based on the traditional aggregate measures of mean time in system, mean tardiness and mean lateness.

There has been additional work dealing with dispatching rules in the past 17 years. However, the conclusions that have been reached are startlingly similar to those of Blackstone *et. al.* (1982). SI or SPT continues to be the overall best performer when judged on the measure of mean time in system. It does, however, result in considerable variance in this measure due to its tendency to hold onto very long process time jobs. Earliest due date tends to outperform other rules when judged by mean job tardiness or lateness. And, slack based rules (including critical ratio) are also strong contenders.

2.6.6 Operational Factors Summary

There exists a substantial body of literature discussing the commonly studied areas of shop floor control. As has been seen, the predominant method of study has been simulation modeling with the various problems and conditions being the factors of structured experiments. Throughout this work, with few exceptions, the research methodology has been relatively traditional and the performance measures aggregate and tactical in nature.

2.7 Performance Evaluation of the Shop Floor

The most common performance measures for simulated shop floor studies have traditionally been very local and very tactically oriented. In Blackstone *et. al.*'s survey work (1982), they restricted themselves to reporting on the results of only three main measures– time in system, lateness and tardiness. These measures do not require a great deal of data collection nor do they require data from areas outside of the traditional shop floor. While other measures have been reported, the majority are very local and aggregate.

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Another survey piece (Panwalker and Iskander, 1977) reported on a great number of scheduling rules and numerous performance measures. However, those measures were made up predominantly of such aggregate tactical measure as time in system and lateness.

A review of several other survey articles dealing with the dual resource contrained literature (Trelevan, 1989) and order review/release works (Wisner, 1992), revealed that mean flow time and mean lateness were the most commonly used measures, appearing in, respectively, 42% and 33% of the studies. Variance of flow time and percent of jobs late were the next most common, being reported 28% and 25% of the time, respectively. A limited review of the scheduling literature revealed a very similar trend, with mean flow time and mean lateness being reported in 44% and 78% of the articles surveyed, respectively.

2.7.1 Shop Floor Financial Performance Measurement

Although tactical and operational measures are by far the most common, there are instances of utilizing financial or cost based performance measurements in shop floor simulation studies. Despite the inclusion of costs, however, most such measures remain relatively local and aggregate in nature.

One of the original works (Rowe, 1960) used work in process (WIP) values for both dispatching decisions and measuring performance. Rowe found that by dispatching jobs according to their WIP value, it was possible to reduce overall inventory costs. This dispatching technique was similar to other local methods in that it looked only at jobs in individual queues. Another work (Hershauer and Ebert, 1973) denoted a response variable to be minimized as the weighted sum of various traditionally non-cost (i.e., aggregate and tactical) peformance measures. Each such measure was assigned a weighting coefficient so that the resulting sum could be represented in cost (dollars). The authors readily admitted that the choice of coiefficients was difficult and somewhat arbitrary and provided little rationale for their choices thereof. In both of these works, the ultimate measure of performance was co

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Other work (Hoffman and Scudder, 1983; Scudder and Hoffman, 1987) has evaluated a fairly standard job shop using cost based performance measures, primarily WIP value. In general it was found that WIP value acted as a more accurate indicator of overall shop performance than traditional measures, particularly when value based dispatching rules were employed. In both of these related works, WIP was calculated in the aggregate, based on the value added to each job as it was processed in the shop, with value being primarily that of the labor added.

Other researchers have explored the idea of value based dispatching in conjunction with cost performance measures. Srivastava and Prabhu (1993) and Wilson and Mardis (1983) discussed the same value-based variant of SPT dispatching, denoted VSPT by Srivastava and Prabhu, who dispatched jobs according to the ratio of job value to imminent process time, with higher value and shorter jobs having the higher priorities. Wilson and Mardis used the reverse ratio, that is, imminent process time to job value, and dispatched jobs first with the lowest ratios. Both studies' models tracked WIP value by the following formulation:

$$WIP = Flowtime \times Job\ \ Value \times Carry\ \ Rate\ (\%)$$

Jobs' WIP values are accumulated as the model runs and reported at the conclusion of the run. Both authors discussed the importance of properly valuing each job, but provide little guidance as to how it was done in their studies. In both cases, WIP is measuring aggregate shop performance.

A different approach to the problem of evaluating a shop financially was suggested by Scudder and Smith-Daniels (1991). In this work, they incorporated a method to calculate each job's Net Present Value (NPV). It was found that NPV was a better indicator of shop performance than simply mean WIP value, particularly when value based dispatching rule

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dispatching rules are utilized. However, with short run simulation models (less than one or two years), it is questionable how applicable NPV is as a measure.

While financial measurements have been used in conjunction with simulation models, they have still been based on, for the most part, aggregate data collection and reporting. There have been very few if any attempts to collect financial or cost data in a disaggregate or events-based manner.

2.7.2 Non-Aggregate Data Collection and Reporting

While there is a strong tradition of reporting aggregate tactical and, to a lesser degree, financial measures in simulation, some researchers have presented arguments that such aggregate mean or variance measures may not be as insightful as others. For example, Melnyk *et. al*. (1995) used the method of survival analysis to analyze and report on the results of a simulation study of a service operation (i.e., a Red Cross blood donation process). They employed survival analysis to study of the distribution of simulation data, rather than simply batch means and variances. Thus, differences in distributions of data between various conditions were presented and studied. This was found to be particularly useful when the data were not normally distributed, as required by more traditional mean analyses (i.e., ANOVA).

2.8 Summary

Although past OM researchers have discussed the importance of information and data management, there has been little work done on its explicit treatment in the manufacturing field. As has been shown, the information systems field has produced some meaningful and efficient methods of modeling and implementing data management systems (i.e., semantics, ER models and the RDB) that have been carried over into the OM field somewhat, but not to a large degree.

Recent work in the simulation, engineering and information systems literature indicates a strong interest in semantic modeling to aid in simulation design, information presentation and perf

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presentation and performance evaluation. However, very few implementations of actual working systems are reported and none deal explicitly with enhancing performance evaluation. Consequently, this lack of implementations has also meant that actual users of information have not been given the opportunity, in a research setting, to test different types of shop floor information and to evaluate their relative utility. That is, information users have never been evaluated based on their identification of shop floor problems or conditions.

There are certain areas of information management within manufacturing environments that require additional research to be fully incorporated into the current body of OM and IS literature. As shown in figures 2 and 3, this research proposes to address some of these specific issues not explored before. Among those that will be presented in the following chapters are:

- The explicit use of a relational database to manage simulated shop floor information, including an actual implementation;
- The materialization of shop floor information and performance measures from actual (simulated) disaggregated data in a relational database. These measures will then be used for actual managerial decision making;
- The development and use of disaggregate-based shop floor performance measures, such as time series and distributional data.
- The evaluation, in a lab setting, of information users' performance in evaluating shop floor performance and operation based on the type of information provided to them.

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Disaggregated Storage	X
Data manipulate, storage	X
Database	X
Conceptual Examples	
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	Goetz 1939	Colantoni et. al. 1971	Codd 1970	Chen 1976	McCarthy 1979,1982	Lee & Fu 1985	Wang & Walker 1989	Shoosh. et. al. 1991
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Figure 2: Database Modeling Literature Summary

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Semantic
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PM Evaluation

	Nandakumar 1989, 1990	Marsh & Vickery 1995	Yancey 1987	Roberts 1991	K,S& Ho 1995	*This Work*
Disaggregated Storage						X
Data manipulate, storage						X
Database						X
Conceptual Examples						
Accounting						
Value Chain						
OM	X	X			X	X
Implementation	X	X			X	X
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Semantic	X	X	X	X		X
Data Collection & storage						X
Use for PM			X			X
PM Materialization						X
PM Evaluation						X

Figure 2 (cont'd)

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Graphical Presentation
Distributional
Simulation based testing
Lab Experiment

Figure 3: Informati

	Amitage& Atkinson 1990	Howell & Stoucy 1988	Azzione *et.al.* 1991	Bruns & McKinnon 1992	Bhimani & Bromwich 1991	Son 1990
Aggregate versus Disaggregate Info	X		X			X
Define "useful" performance measure	X			X		
Operational vs. Financial	X	X				
JIT, flexible manufacturing					X	X
Graphical Presentation						
Distributional						
Simulation based testing						
Lab Experiment						

Figure 3: Information Managment and Performance Measurement Literature Summary

Aggregate ve[...] Disaggregate [...]
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Operational vs Financial
JIT, flexible manufacturing
Graphical Presentation
Distributional
Simulation bas[...] testing
Lab Experimen[...]

	Anderson, *et. al.* 1979	Melnyk *et. al.* 1985	Tufte 1983	Melnyk *et. al.* 1995	*This Work*
Aggregate versus Disaggregate Info	X	X			X
Define "useful" performance measure					X
Operational vs. Financial					
JIT, flexible manufacturing					
Graphical Presentation			X		X
Distributional				X	X
Simulation based testing					X
Lab Experiment					X

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3.0 Research Questions and Design Overview

3.1 Chapter Overview

As shown in the preceding literature review, data and information structure, while explored theoretically in the IS field, has had limited treatment in the OM field. Although some instances were identified in the literature, the use of data and information modeling techniques has not been explored and implemented extensively in a manufacturing or shop floor setting.

One of the purposes of this research is to determine whether IS based data and information management techniques can be applied to a simulated shop floor setting. Specifically, can a semantic data model for the shop floor be developed and act as the basis for developing an enhanced simulation model?

Another issue discussed at some length in the IS literature, and one examined in this work, is the "materialization" of performance measures and information. Is it possible to derive desired measures from a disaggregated database and are such measures more descriptive? Such claims have been made by McCarthy (1982), but have not been specifically evaluated in the OM field.

While some topics being explored in this work have been studied by past researchers (see figures 2 and 3), they have not been brought together as a whole in any single work. While relational databases have been proposed for an enterprise's disaggregated data storage vehicle, their specific conceptual modeling for a simulation setting has not been discussed extensively. Moreover, no such implementations have been reported. Further, the concept of disaggregate versus aggregate information and measures has been discussed in both the IS and OM literature, as has the use of more descriptive measurements, but, again, in isolation from each other and without any reported implementations. Finally, the actual evaluation by information users of such measures, whether materialized

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whether materialized from actual operations or from a simulation model, has not been studied before, particularly in a laboratory setting.

3.2 Research Questions and Hypotheses

To evaluate the issues discussed in the previous section, the following research questions are proposed.

1) Can an events-based model of a shop floor completely and accurately capture disaggregated shop floor data in a manner that allows for the efficient transfer of that data into an events-based database for information storage and presentation?

2) To what extent can a database populated with disaggregated data be more useful in completely describing shop floor performance and in identifying operational problems that may not be detectable with traditional aggregate measurements?

3.2.1 Discussion of Research Questions

Research Question #1 proposes a non-conventional conceptual approach to shop floor data capturing and reporting. Specifically, it is asking if a structured data model based on disaggregated entities can be superimposed on a simulation model to produce a meaningful dataset. Also, it asks whether these data can be efficiently transferred to a database that can in turn present the data as usable information. In evaluating this question, several factors will be specifically examined and tested. One overall issue to be explored is the technical feasibility of linking two such models. Can a data model be developed that can be meaningfully translated into or superimposed upon a simulation model? One way of evaluating this specific issue is to determine if useful measures can be derived from a dataset generated by a database enhanced simulation model. Another issue is the consistency of measures materialized from a disaggregate dataset and those derived in a conventional manner in a simulation model. In other words, when considering the same performance measu

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performance measures, such as time in system, do the two methods produce similar results? These specific issues are addressed by the hypotheses and propositions in the following section.

Research Question #2 looks at the issue of usefulness. Once collected and reported, does the information available from the proposed disaggregated data collection serve a useful purpose? That is, can it help users of the information identify why performance is either superior or inferior? Can information be generated that is more insightful in terms of its ability to explain and identify the underlying operational problems and behaviors that may be leading to inferior performance? This question will attempt to address whether or not such information is relevant for users of the data. The results of a controlled laboratory experiment in which users are given disaggregate or aggregate based measures and information will be used to evaluate this question.

3.2.2 Theoretical Basis for Questions

The research problem being explored is the lack of descriptive and insightful performance measures and information from current simulation models. The asserted lack of such information restricts simulation's uses to research without making it widely available as a managerial decision tool.

This research is based on the theoretical assertion that *more descriptive and more comprehensive* performance information will lead to better shop floor performance evaluation. Specifically, the effectiveness and efficiency of users' evaluation of the causes of shop floor performance problems will be tested based on the information they have available. In general, the comparative types of information users will have available in this research are:

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Those users who have the alternate, more descriptive information should, according to the theory being proposed, be able to more efficiently and effectively evaluate shop floor performance and correctly identify the underlying causes of any performance degradation.

The semantic database approach to information collection and generation is offered as the means by which to provide better performance measurement. Thus, this research will be testing this theory according to the hypotheses and propositions in the following section.

3.3 Hypotheses and Propositions

Some of the research questions of this study do not lend themselves to formal statistical analysis, while others do. For this reason, both hypotheses and propositions are being presented, the former being more suitable for testing. Propositions are expected directions of the research, but will only be evaluated and discussed, not formally or statistically tested. Hypotheses, on the other hand, will be tested statistically for significance.

3.3.1 Proposition #1

> PRP-1: The means of conventionally (non-semantically) derived performance measures are comparable to the means of the same measures that have been derived from a semantically based disaggregated dataset.

This proposition addresses one of the issues raised by research question #1, that of the compatibility of the proposed enhanced approach to simulation modeling and the conventional approach. It will examine the ability of an enhanced or expanded simulation model to report traditional tactical measures that are consistent with those derived by conventional means, i.e., through built-in functions of the simulation software. It is a validation and proof of concept of the method of measurement materialization and a means of assessing its accuracy.

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This issue of consistency of two differently derived measurement sets has not been previously explored in the literature, thus there is no past basis for making *a priori* expectations of the findings for this particular proposition. Researchers have generally pointed to disaggregate data storage as producing more descriptive information than traditional measures, rather than simply providing an alternate method of deriving traditional measures (Centeno and Standridge, 1993; Yancy, 1987; Roberts, 1991). Although the materialization process within an RDB may be quite complex, since the disaggregate data and the aggregate measures will be of the same simulation run, it is very reasonable to assume that the results will be very similar, if not nearly identical.

Support for the proposition would indicate that the proposed methodology is compatible, at least in this instance, with that already being done within conventional simulation software and models. Lack of support for the proposition could indicate that the proposed method of data management may not provide a means of creating usable performance measures, or that the conventional method of measurement derivation, directly within the simulation software, is inaccurate.

3.3.2 Proposition #2

> PRP-2: It is possible to materialize useful measures through the use of a database enhanced simulation model and its resulting disaggregated dataset.

This proposition is evaluating, in qualitative terms only, the question of the overall feasibility of the approach suggested by research question #1. It addresses the actual "materializability" of useful performance measures. The manner in which such measures are determined to be useful involves several interviews and questionnaires and is discussed in the next chapter. The proposition supports the position that a disaggregated dataset from a semantically enhanced model can provide a means of producing useful measures that are not obtainable by conventional means. Based on work such as that of Yancey (1987), who first discussed designing semantic data models in conjunction with simulation models, and

Roberts (1991), who introduced the idea of using a database of simulated data to materialize useful measures, a reasonable *a priori* expectation is that it is feasible to materialize useful measures from a disaggregate dataset. In fact, Roberts suggested some specific types of enhanced measures, such as time series plots and histograms, that will be utilized in this research. Thus, expectations are such that this proposition will be supported. Lack of support for this proposition, as with proposition #1, would indicate that the proposed method of data management may not provide a means of creating usable alternate performance measures.

3.3.3 Hypothesis #1

> H_{o}-1 Information and measures materialized from a semantically based historical dataset do not result in significantly different performance by users in identifying and describing shop floor operational problems and conditions, as opposed to using traditional aggregate tactical measures.

This hypothesis provides a direct means of evaluating research question #2. In testing this hypothesis, the issue of the usefulness of the proposed measures and information outputs will be examined. Participants in a lab experiment will be given the opportunity to use the actual outputs- either traditional aggregate tactical measures or the information and measures derived from a disaggregate dataset. The success of the various groups in identifying and describing the underlying operational conditions will be evaluated statistically to determine if access to either set of measures results in significantly different (greater or lesser) success.

The null hypothesis holds that there will be no difference in performance between groups using two different types of measures. It is expected that this null will be rejected. In fact, the specific theory being tested in this research, that a disaggregate, semantic-based approach to modeling yields more useful information, postulates that the performance of the group with the disaggregate-based measures will be significantly superior. Works cited previously in this s

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previously in this section (Yancey, 1987; Roberts, 1991) along with others in the IS field, such as McCarthy (1982) and Maybury (1995) point to the expectation that measures based on a disaggregate dataset are both more useful and more descriptive. Thus, such measures can be reasonably expected, *a priori*, to improve the performance of those using them, leading to a rejection of the null.

3.4 Discussion of the Research Methodology

Several different methodologies are employed throughout this research and each is discussed in more detail in the following chapters. However, an overview is presented at this time.

3.4.1 Development of Useful Performance Measures

Proposition #2 makes reference to "useful" information and the ensuing discussion briefly describes how such usefulness is determined. In the first phase of the research, two shop floor experts are contacted and interviewed as to their opinions of various measures, both traditional aggregate and disaggregate. In addition, a questionnaire is provided to further capture their opinions. These opinions, in conjunction with a literature review, form the basis for developing a list of measures for future evaluation. No statistical analysis of the experts' responses is made.

3.4.2 Semantic and Simulation Modeling

Research Question #1 asks whether a semantic data model and a simulation model can coexist, so to speak, to allow for the generation of data that can be utilized in a relational database and whether the database can be used to materialize performance measures. To begin addressing this issue, first, using Entity Relationship (ER) drawings, a detailed data model of the shop floor was developed. This formed the basis of the relational database that stored the inforamtion and also dictated, to a certain extent, the design of the simulation model. Next, the actual simulation model was developed, incorporating many traditional features but also some additional ones to allow for the collection of a larg

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collection of a large disaggregate dataset. To evaluate the models' output and address research question #1, a comparison of the means of conventionally and non-conventionally (with a database) derived measures was made.

3.4.3 Usefulness of Aggregate versus Disaggregate Measures

A laboratory experiment was performed in which two independent groups of participants were given different measurement types and asked to identify the underlying shop floor problems and conditions. Since each participant was asked to evaluate five different conditions, a repeated measures Analysis of Covariance (ANCOVA) was the primary analysis tool to test the *a priori* hypothesis (Hypothesis #1). This analysis allowed the inclusion of covariates while comparing the mean performance of the two independent groups. Chi Square and Kolmogorov-Smirnov tests are used as *post hoc* analysis tools to further analyze the nature of the lab participants' responses. In addition to testing the results of the lab experiment, the participants' judgement of the various measures' usefulness was also evaluated, although not statistically. The measures that each group found most useful were identified and compared with expectations.

This is the only section of the research in which independent and dependent variables were defined. The dependent variable is the performance of the two groups of participants. As will be discussed in the next chapter, this performance was judged on several dimensions, such as accuracy, efficiency and confidence. The independent variable is the type of information and measures being used, specifically aggregate and disaggregate. In addition, several demographic covariates were also analyzed.

3.4.4 Clarity of Information Presented

The final phase of analysis involves the evaluation of the lab participants' opinion of the clarity of the information presented. This is done to determine if there is a significant difference between the two groups' feelings regarding the clarity, adequacy and usefulness of the information given to them and the manner in which they were trained to use the information. Anal

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3.5 Conclusion

The initial research problem was addressed by two research questions, one dealing with IS and OM data management techniques and the other with the actual utility and effectiveness of different types of performance information. The first question deals primarily with qualitative and conceptual issues, hence its related propositions are not evaluated in a rigorous statistical sense. Rather general evaluations are made and compared with expected results. Research question #2 goes more to the heart of the research and lends itself to more in depth quantitative analysis. Its accompanying hypothesis, #1, asks specifically if using either of two types of measures allows users to more effectively or efficiently evaluate shop floor conditions and is tested much more rigorously.

Additional analyses address the users' (lab participants') perceptions and opinions of both the different measures' relative usefulness and the manner in which they were presented. This allows us to evaluate if those measures expected to be helpful actually were and if either group felt that the information could have been presented differently or better, thus allowing some insights into the structure of the experiment itself.

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4.0 Research Methodology and Design

4.1 Chapter Overview

This chapter outlines the four main phases of the research design. The first section covers how certain experts in the field of OM and shop floor control were contacted and polled as to which performance measures and information they thought were useful. These measures are used in a later phase of the research. Next, the model building process is described. This includes a discussion of information systems methodology and how, in this case, it augments traditional simulation modeling. Also covered is the development of a shop floor's semantic data model and resulting relational database that forms the basis for generating and collecting data from the simulation model. Next, the shop being modeled is discussed, including the various parameters and experimental conditions that are explored. The remaining sections of this chapter discuss the development, validation and use of an experimental instrument within the laboratory setting. This includes a discussion of the experimental conditions that will be evaluated, the design of the lab sessions themselves, the questions being addressed by the instrument and the method by which the lab participants' performance will be judged.

There are four primary phases to this research, as outlined in figure 4 and discussed in the following sections, which numbers are indicated in the figure.

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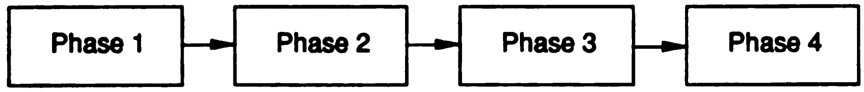

Phase 1	Literature review; poll shop floor and Operations Management experts; obtain opinions on "useful" measures.
Phase 2	Design and build a semantically based data model and accompanying relational database for the shop floor; develop a discrete events simulation model of the floor as well.
Phase 3	Validate, verify the simulation model; run it to generate and collect aggregate and disaggregate datasets; populate relational database.
Phase 4	Conduct controlled laboratory experiment allowing participants to judge effectiveness, efficiency, usefulness of various measure types.

Figure 4: Phases of Proposed Research

4.2 Determination of Performance Measures and Information

The performance information was developed for this research with a combination of empirical and literature research, with the assistance of OM experts, as described in figure 5.

Figure 5: Determination of Performance Measures and Information (Phase 1)

The goal of this research phase was to provide a reasonable basis for the measures to be used in later phases, specifically those to be presented to laboratory experiment participants in Phase 4. To that end, traditional simulation performance measures, as identified in the literature, were augmented by additional measures obtainable from disaggregated data storage. All measures were then reviewed by two OM experts prior to final compilation and presentation in the lab setting. This was done principally for added insights to

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insights to the literature review and to provide some additional relevance to the initial literature-based performance list.

4.2.1 Initial List

A list of traditionally used aggregate and financial shop floor performance measures, as identified in section 2.7, was compiled. To the list were added other operational measures that could be materialized from a disaggregated shop floor dataset. These included measures and information such as distribution of time in system, as opposed to the aggregate measure of mean time in system, and time series of queue length, as opposed to mean queue length.

4.2.2 Expert Opinion

After the initial list of measures and information was drawn up, two experts in the fields of OM and Shop Floor Control were contacted and asked to respond to the listed measures.

Only two persons were interviewed and surveyed, for several reasons. First, it was necessary to have several in depth discussions of the project and the data management techniques with those persons prior to their completing the survey. In addition, it was important to have persons who were indeed expert and who had a wide array of experience in manufacturing environments. In limiting the sample to those in this category, only two persons were chosen. This allowed an examination of the results of the survey in some depth, although not as much breadth as is traditionally done. The limited size of the sample did, however, effectively eliminate any statistical power, making formal analysis of the survey results impossible.

4.2.2.1 Interview Structure

The two experts were interviewed, one in person, the other on the telephone. The beginning portion of the interview was devoted to discussing the research in general terms. Both aggregate and disaggregate data and measures were discussed along with the possible advanta

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advantages and disadvantages of each. Care was taken to keep the discussions focused on the uses of the information and why some types were felt to be more useful than others. The structure of the interview was patterned closely on the survey instrument, which was left with them after the discussion. This enabled the interview to proceed in an orderly and consistent manner.

The primary researcher was the only interviewer with both subjects and spent between 40 and 60 minutes with each person. During this time, notes were taken regarding the subject's comments and suggestions as to what constituted a "useful" measure. Also, the survey instrument was discussed so that it was clear what was required of the subjects. At the end of the interview, the subjects were requested to fill out the survey form and return it to the researcher. In the case of the telephone interview, the survey form had been faxed to him prior to the conversation. The survey form consisted of ranking various measures and information sets in terms of their managerial usefulness. See Appendix B for a complete copy of the survey form.

4.3 Model Building

The second phase of this research involved developing the simulation model and the accompanying relational database and then linking the two within the simulation model. The steps entailed are as shown in figure 6.

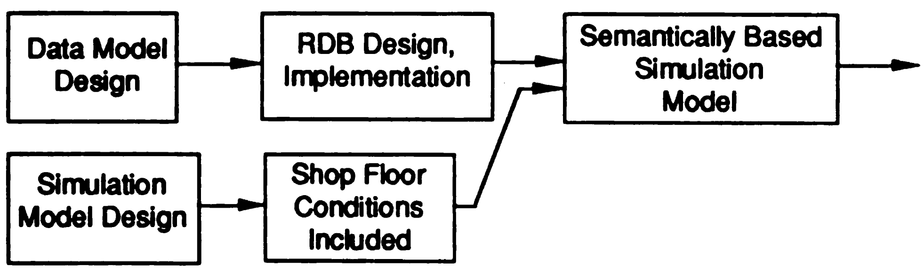

Figure 6: Model and Database Development (Phase 2)

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The simulation model and database were designed concurrently based on a semantic data model of the shop floor and on the actual workings and design of a shop floor previously studied (Marsh and Melnyk, 1995). In doing so, the methodology suggested by McCarthy (1979) and shown in figure 7 was used. It is important to note that the two models are not only built concurrently, but are also used in conjunction with each other. And, while the simulation model is in many ways fairly traditional, it has been altered to generate the necessary information for evaluation, as will be discussed in section 4.4.1.

It was found that McCarthy's work (1979) provided a reasonable framework due to its top-down approach to system modeling and its focus on a conceptual and visual model. Also, his framework described the various levels of model building in general terms, allowing the modeler to define each as his/her needs dictate. Like Chen's (1976), McCarthy's framework in this work used ER drawings to help visualize a system. Further work has substantiated this approach, as discussed in section 2.4, particularly that of Denna *et. al.* (1993), in which several successful implementations of this approach are discussed. Additional work by Marsh (1995) and Grabski and Marsh (1994) have extended McCarthy's methodology and shown its applicability to the OM field, as discussed in the literature review sections 2.5.1-2.5.3.

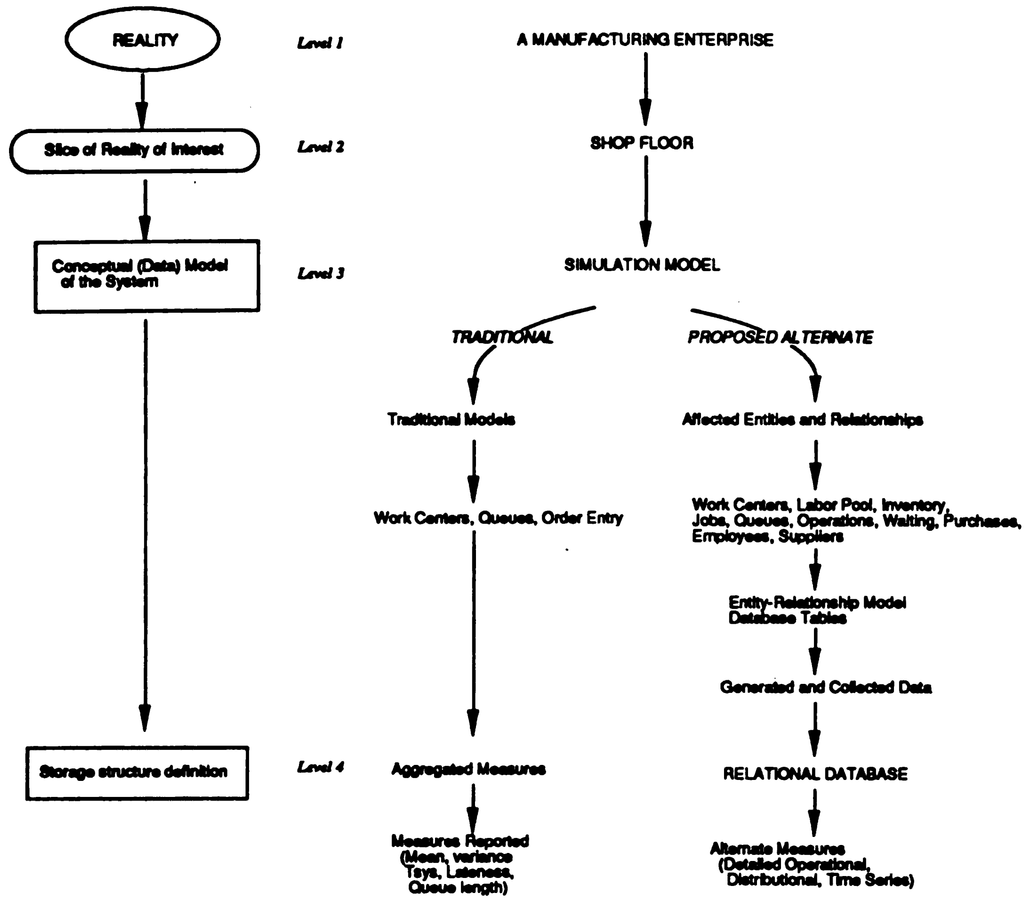

Figure 7: Database Development Process (adapted from McCarthy, 1979)

4.3.1 Levels 1 and 2

The first step in the implementation of the proposed shop floor information system, described by Levels 1 and 2 in figure 7, was considering the specific environment to be studied. In this research, the general aspect of reality of interest is the manufacturing enterprise, with an in-depth look at the shop floor.

4.3.2 Level 3

Once the environment had been identified, the next step was to build a conceptual and operational model of the system. This step actually entailed the building of two separate models– the semantic data model and the discrete events simulation model. As it was important to capture the operational and tactical features of the shop floor environment, the first part

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the first part of this step was to build a relatively traditional simulation model. This model was augmented with the ability to generate and capture disaggregate historical data during operation, as discussed in more detail in section 4.4.1. It is this generated data that will be analyzed and evaluated in the further phases of the research. The simulation model will be presented in general terms in the following sections, with a more in-depth discussion of its parameters and operation in Appendix A, sections A.1 - A.3.

4.3.2.1 General Shop Description

While the simulation model is that of a hypothetical shop floor, it is strongly patterned after an actual environment previously studied– the machine/support tool room for a major automobile manufacturer (Marsh and Melnyk, 1995). The actual shop consists of 27 different work centers (lathe, boring mill, welding, heat treating, etc.) with most centers containing from three to ten machines. For this research, however, the shop will be simplified to six work centers, comprising those that are the most frequented. The shop is operated three shifts everyday, although staffing levels are lower during the afternoon and midnight shifts and on weekends. There is a centralized customer service area that serves three purposes: (1) to provide an entry to the shop for those jobs being carried in by customers; (2) to provide a central inter-operation queue area; and (3) to provide final inspection prior to the jobs' exit from the shop. All jobs, once done at a work center, are taken to this area for inspection and holding until an operator is available at the next work center. The customer service area is also where material orders are placed and received.

Of the six work centers, four are conventional in that they process jobs according to preset process times and have an accompanying queue that can be measured. The fifth work center is a batch heat treating station that does not have a queue *per se*, but does handle jobs that flow through it according to preset processing times. Various machines in the center have queues in which jobs wait until a batch load accumulates, however, the lengths of these queues are not reported. The sixth work center is simply final inspection and is the last

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and is the last station for all jobs in the shop. There is never any waiting for this work center and entry to the center is equivalent to leaving the shop. This center has a zero processing time.

4.3.2.2 Model Validation and Verification

To validate the simulation model, it was discussed with the actual shop floor management during its original construction. Interarrival times, routings and employee scheduling were confirmed with management as they were built into the model. In addition, as the model was run, its output was compared with that of the actual shop in terms of number and type of jobs and overall shop load. It compared favorably with many features of the actual shop. Moreover, many general features of the shop, such as multi-machine work centers, queues and order release pools, are similar to those seen in the literature.

To aid in verification, the model was built in modules, such as the order/release pool and mechanism, work centers, assembly and inventory areas. Each module was tested and verified individually with numerous traces to assure its proper operation. As the modules were assembled into the final model, additional testing was done to assure that all the components operated well together.

4.3.2.3 Shop Floor Conditions

Ultimately, this research evaluates the impact of various types of information on shop floor decision making and problem identification by examining the effect of the type of information on users' assessment and identification of problems. To this end, a series of shop floor problems and conditions as identified in the literature (section 2.6) and substantiated by experts (section 4.2) were developed and operationalized in the simulation model. The conditions are discussed more thoroughly with the detailed shop and model description in Appendix A, but are summarized in the next section.

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4.3.2.4 Conditions Summary

The six conditions being introduced to the model in this research are as follows:

1. Varying dispatch rules
2. Varying due date assignment rules
3. Irregular job or order release
4. Stationary bottleneck
5. Moving bottleneck

These conditions were deliberately inserted into the simulation model one at a time, to prevent interactive effects. It was felt that more than one condition at a time would create interactions that would excessively complicate the identification for the experimental participants. This approach also allowed the analysis of the performance data in a more straightforward manner, as discussed in section 4.6.1. Since the objective of the research was to test the identifiability of such conditions, depending on the type of information presented, such conditions were not tested as experimental factors in the traditional sense. That is, the actual performance of the shop floor was not evaluated with one or more factors being determined as the "best." Rather, performance results of the model were presented to lab experiment participants so that they could attempt to identify the conditions.

These conditions do not constitute an exhaustive list, but are illustrative of the general category of problems seen by shop floor managers, who would be the main users of the performance information being evaluated in this research.

4.3.2.5 Base Case Operational Parameters

A base case was established that represented no conditions being inserted into the model. The following summarizes the operational parameters for the model's base case:

1. No stationary or moving bottlenecks
2. Smooth job release to the floor

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3. Individual due date assignment for projects' jobs
4. "Historical" mix of job types (more projects)
5. First come first served (FCFS) dispatch rule
6. Job routing established at outset; 10 work centers maximum; repeats allowed
7. No job preempting (although priorities varied)
8. Capacity utilization range: 87–89%

4.3.3 Data Model Design

Concurrent with the development of the simulation model, a semantic data model of the shop floor was designed. During this process, all of the relevant Resources, Events and Agents (REA) involved in the shop floor were identified, as were their key interrelationships. This is in accordance with McCarthy's (1979) proposed methodology shown in figure 7 and discussed in a subsequent work (McCarthy, 1982). Figure 8 summarizes the various entities of the shop floor.

Resources	Events	Agents
WORK CENTERS	OPERATION	EMPLOYEE
JOBS	RAW MAT'L RECEIPT	RAW MAT'L SOURCE
RAW MAT'L		RAW MAT'L ORDER
MULTI-JOB ORDER		

Figure 8: Shop Floor Resources, Events and Agents

Resources are those entities that represent assets and that may be altered during the operation of the system. For example, JOBS represents an asset to which value is added as it is routed through the shop. Similarly, RAW MATERIAL represents a store that may be decremented (inventory). Events represent specific instances or occurrences in the system. OPERATION refers to the actual work being done to a particular job at a particular work center. Each operation is a different event. RAW MATERIAL RECEIPT represents the event of actually

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event of actually receiving a shipment of a specific order. Agents are those responsible for implementing the events. The primary agent- the EMPLOYEE- is responsible for the OPERATION event that adds value to JOBS.

In a traditional REA model, each Event is related to an incremented and decremented resource. In the case of this shop, an OPERATION will increment the JOBS resource and decrement the Employee labor-hours pool. Thus one resource pays for the enhancement of another. It should be noted that, while the entities in this model were identified as either Resources, Events or Agents, the data model was not developed in strict accordance with the REA framework (McCarthy, 1982), as will be apparent.

After identification of the various entities in figure 8, their key interrelationships were noted. The shop floor's data model was then developed using Chen's ER methodology (1976). Developing such a model allowed the creation of a system of data tables modeling the shop floor and avoided the prespecification of which data or information to accumulate. This is in keeping with events based accounting theorists such as Colantoni, Manes and Whinston (1971) and McCarthy (1979). The ER model for the shop being modeled is shown in figure 9.

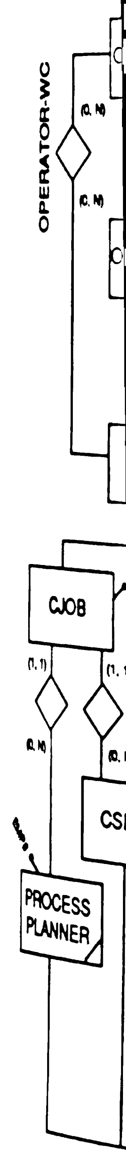

Figure 9:

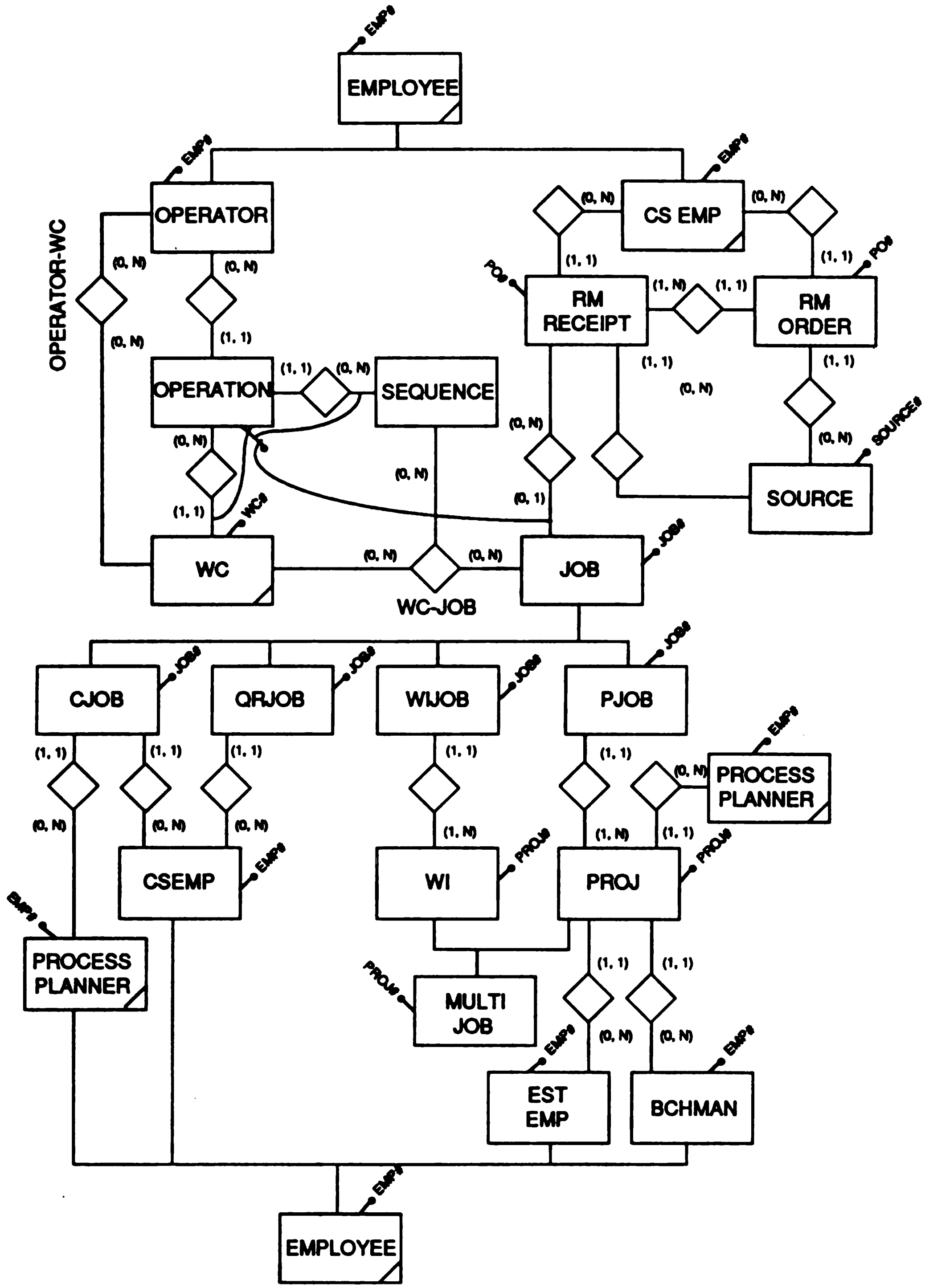

Figure 9: Data Model of Simulated Shop Floor (Primary Keys Noted)

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4.3.2.8 Entity Types

Within several of the entities listed in figure 8 and shown in figure 9, different types were identified, as shown in figure 10.

Resource	Types
JOB	PROJECT WALK-IN CRIB QUICK RESPONSE
MULTI-JOB ORDER	PROJECT WALK-IN
EMPLOYEES	OPERATOR CUSTOMER SERVICE CLERK (CSEMP) PROCESS PLANNER BENCHMAN (BCHMAN) ESTIMATOR (EST EMP)

Figure 10: Shop Floor Entity Types

These various types are represented by generalization hierarchies (Smith and Smith, 1977) in figure 9. For example, Jobs consists of four different types, as shown more clearly in figure 11.

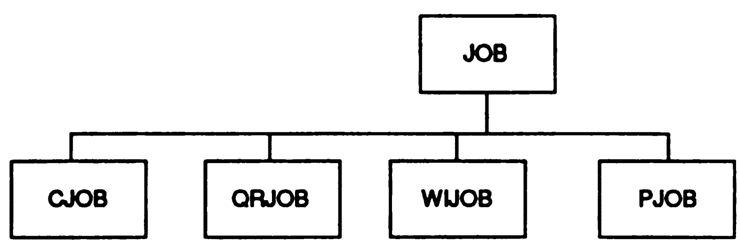

Figure 11: JOB Generalization Hierarchy

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Also note that, although Employee shows five different types (CUSTOMER SERVICE, OPERATOR, BENCHMAN, PROCESS PLANNER and ESTIMATOR), only one- OPERATOR- is used in any meaningful way in this research. This will become apparent with the discussion of the experimental results and was done to keep the presentation and analysis of information manageable.

4.3.4 Level 4

Level 4 is the outcome reporting portion of the modeling process. Traditionally built simulation models report various aggregate and primarily tactical measures, which comprise essentially all of the data captured by the model. The approach proposed in this research however, has available the more complete detailed data represented by the ER tables in Level 3. In his original methodology, McCarthy (1979) did not specify a method of data storage but rather left that to the reader's choice of database systems. In this research, a relational database was chosen as the means of data storage and processing. It is within the database that *all* shop floor data from the simulation model runs were transferred and where both traditional measures and more enhanced and descriptive measures and information were derived. The ER model in figure 9 formed the basis of the relational database implementation. Figure 13 shows the complete relational database tables of the model.

It should be noted that the tables shown in figure 13 do not include all relevant posted foreign keys as would normally be expected for one-to-many relationships. Only in several tables (OPERATION, PJOB, WIJOB) are foreign keys shown (Emp#, Proj#, Proj#, respectively). This is done so that the tables more closely resemble those actually derived from the simulation model. Also noteworthy is the presence of the table SEQUENCE and the use of its key, Seq#, in the OPERATION and JOB-WC tables. This entity is somewhat non-operational in nature, but necessary to distinguish those records in OPERATION or JOB-WC that repeat work centers, since such repeats are allowed. Thus, if Job #101 pr

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if Job #101 proceeds to WC #2 as its first step and later again as its third step, these two records would be identified in OPERATION as shown in the first and third row of figure 12.

Job#	WC#	Seq#	PT	Emp#	Time_in	Count
101	2	1	--	--	--	--
101	3	2	--	--	--	--
101	2	3	--	--	--	--

Figure 12: Sample OPERATION Records

Thus, the triple key Job#-WC#-Seq# is the primary key for each record.

Figure 14 shows the key database tables that were used in the research with some actual data from the simulation runs. The method of data collection and table population will be discussed in the next section.

4.3.4 Phase 2 Outcome

This phase of the research builds upon the first, the development of a list of useful and meaningful measures, and develops the models by which such measures can be formulated and created. The exercise of developing the semantic data model allowed for the unambiguous definition of each relevant entity of the shop floor and, as a result, the building of an accurate simulation model and one that will be able to generate the disaggregate dataset that will be required in further phases of this research.

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JOB (Job#, Job_Type, Job_DueDate, Total_PT, Time_in)

CJOB (Job#)

PJOB (Job#, Proj#*)

WIJOB (Job#, Proj#*)

QRJOB (Job#)

MULTI JOB (Proj#, Num_Jobs, PTtotal, Time_In, Emp#*)

PROJECT (Proj#, Num_Jobs)

WI (Proj#, Num_Jobs)

WC (WC#, Name, Num_machines)

OPERATOR-WC (Emp#, WC#)

SEQUENCE (Seq#)

JOB-WC (Job#, WC#, Seq#, Time_Into_Queue)

OPERATION (Job#, WC#, Seq#, Process_Time, Emp#*, Time_in)

SOURCE (Source#, Name, Address)

RM ORDER (PO#, Source#, Job#, Time)

RM RECEIPT (PO#, Time)

EMPLOYEE (Emp#, Name, Address, SSN, PayRate)

CS EMP (Emp#)

OPERATOR (Emp#)

PROCESS PLANNER (Emp#)

EST EMP (Emp#)

BCHMAN (Emp#)

Figure 13: Relational Database Tables

JOBS

Job#	Job_Type	Job_DD	Total_PT	Time_in
1	2	1335.39	338.50	0.00
2	4	25.28	500.50	1.28
3	3	722.00	320.00	2.00
4	2	1393.66	812.50	2.56
5	3	1082.94	516.50	2.94
6	2	335.10	327.00	3.84
7	4	101.12	163.50	5.12
8	4	30.40	182.00	6.40
9	3	726.72	499.50	6.72

MULTIJOB

Proj#	Num_Jobs	PT_Total	Time_in
1	1	123.56	0.00
2	1	356.55	2.56
3	1	1256.30	3.84
4	1	23.56	7.68
5	1	1256.35	8.96
6	1	2567.30	11.28
7	1	768.50	12.54
8	1	673.50	20.18

CJOB

Job#
3
5
9
12
18
20
59
61

PJOB

Job#	Proj#
114	33
115	33
116	33
117	33
118	33
119	33
120	33
121	33

PROJECT

Proj#	Num_Jobs
11	16
11	16
11	16
33	10
53	76
79	113
79	113
122	15

OPERATION

Job#	WC#	Seq#	Process_Time	Emp#	Time in
1	6	1	6.0	601	17.09
10	6	1	3.0	602	17.09
13	6	1	30.0	603	17.14
14	5	1	1.0	501	17.19
11	6	1	3.0	604	17.21
14	4	2	1.5	401	18.19
14	5	3	2.5	502	19.69

JOB-WC

Job#	WC#	Seq#	Time_ into_Q
1	6	1	17.09
10	6	1	17.09
13	6	1	17.14
14	5	1	17.19
11	6	1	17.21
14	4	2	18.19
14	5	3	19.69

Figure 14: Sample Database Tables

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4.4 Simulation Model Operation and Data Collection (Phase 3)

The third phase of the research uses the simulation model to generate the data that is later analyzed by the laboratory participants. The overall parts of this phase are shown in figure 15.

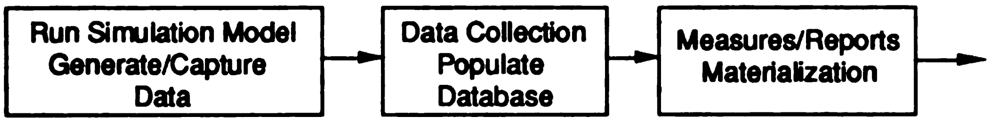

Figure 15: Data Generation and Capture (Phase 3)

4.4.1 Data Generation

Although the simulation model used in this research has many conventional features, its main purpose was to generate data for later analysis. The data shown in the relational database tables in figure 14 were obtained from the simulation model, which was specifically designed so that the data required by the semantic model could be captured. This was done primarily by attaching attributes to the various items, such as JOBS, within the simulation model and then reading the values of those attributes as the items move through the shop. For example, the attributes Job#, Job_Type, Job_DueDate, Total_PT, Time_in were assigned when the job was introduced to the shop, and make up the JOB record (figure 13). The work centers to which the job is routed also are assigned, but stored in an internal array until such time that they are needed and recorded (in JOB-WC). So while JOB-WC represents a routing table whose data are set at the beginning of a job's run, it is populated only during the run, so that other attributes such as Time_Into_Queue can be captured. Storing data initially in an array rather than as attributes avoided exceeding the simulation software's limitation of 15-20 attributes per item (Job).

When a job is processed at a work center, the job number (Job#) is read as is the process time for that specific work center (Process_Time), actual clock time (Time_in), work center number (WC#) and employee number (Emp#), among others. These data are recorded i

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recorded in the OPERATION record. This allows for a complete disaggregated record of all operations to be captured. Note the subtle distinction between JOB-WC and OPERATION: not all jobs that enter a work center's queue will be processed during the run of the model. Thus, JOB-WC captures all jobs routed to a particular work center, while OPERATION captures only those that leave the queue. This can be seen by the difference in the "time" attribute for each entity: JOB-WC captures Time_Into_Queue, while OPERATION is concerned with Time_In and Process_Time at the work center operation. Figure 16 is a schematic representation of the model showing the approximate data collection points.

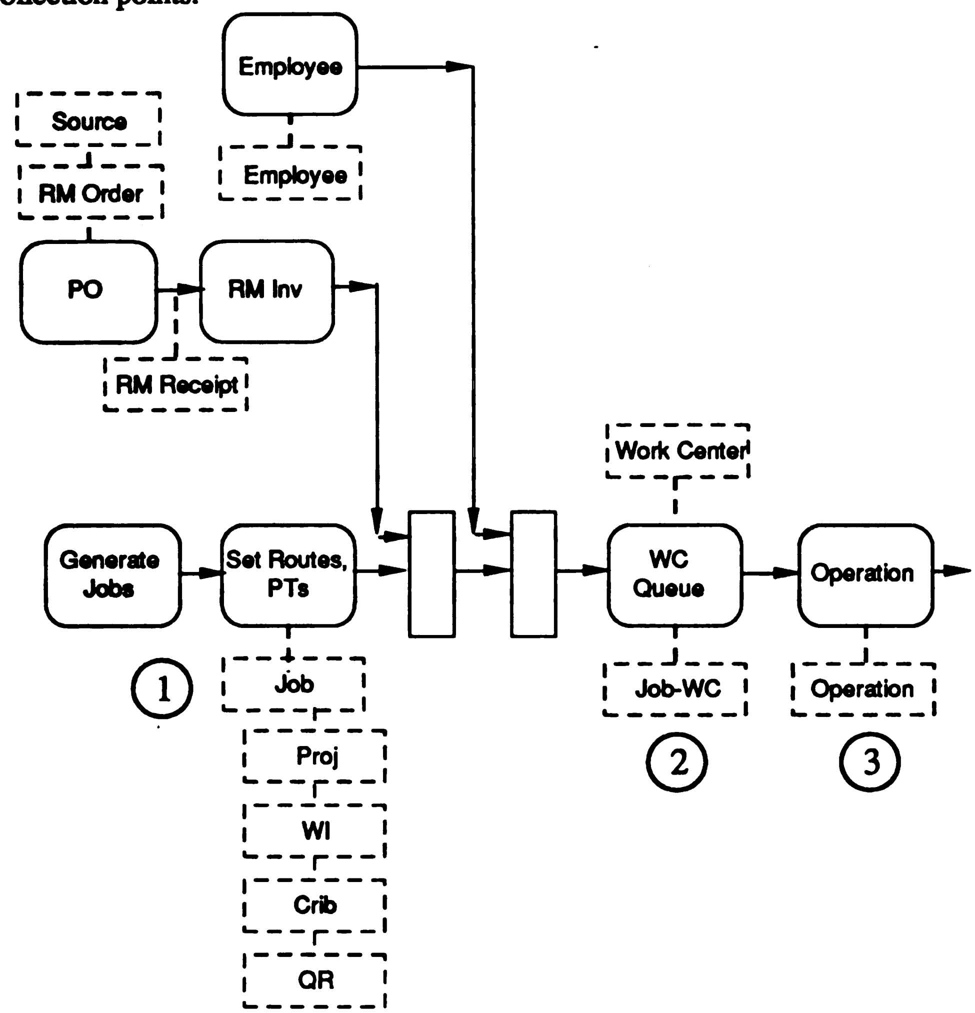

Figure 16: Simulated Shop Floor Model with Data Collection Points

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The information generated in the simulation model was stored internally in text file arrays that could be transferred to the relational database for further processing after the model's run. It is within the database that the chosen performance measures were materialized and reported. The simulation model was written in Extend™ (1995) simulation software, version 3.2 PPC, and was run on a 75 Mhz Power Macintosh 7200 computer equipped with 32 MB of RAM and 500 MB of hard drive space. Macintosh operating system 7.5.3 was used. The database software chosen in this research was Helix Express™ (1994), version 3.5, developed by Helix Technologies, Inc, running on the same hardware platform.

4.4.1.1 Simulation Operation

Because of the simulation model's primary role as a data generator, the experimental factors in the model were not analyzed *per se* in the traditional statistical sense. Some factors, specifically the moving bottleneck and the irregular order release mechanism, were, by design, non-stable in nature. In fact, one of the purposes of this research was to test the usefulness of disaggregate data in identifying conditions when non-steady state behavior may be more common. For this reason, steady state was not achieved in all cases nor was it a prerequisite for data collection. But, attainment of steady state was attempted to avoid introducing a potential confounding factor into the research.

To avoid start up conditions as much as possible, the model was allowed an initialization period after which data were collected for the equivalent of approximately 100 days of operation for each condition. This time period, which is approximately three months or one quarter of a year, was felt to be adequately representative of a period of operation a manager may review in an actual manufacturing setting. Only one run of the model per condition was made due to the nature of the measures being collected. Since large disaggregated datasets (long tables) were being generated in each run and those data were used to create not only point estimates (means, variances) but also distributional and time

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time series information and graphs, the concept of taking the means of multiple runs did not apply in this case. However, common random numbers were used to assure that the general shop parameters were unchanged across all of the conditions. This included the type and frequency of jobs generated, interarrival rates and process times.

4.4.2 Data Collection and Database Population

Although data were collected for most of the entities and tables shown in figures 9 and 13, the primary sources of data for analysis were just two entities and one relationship: JOBS, OPERATION and JOB-WC. The method by which these tables were populated within the simulation model for transfer to the database is outlined in figure 17. Note that the circled numbers 1, 2 and 3 in figure 17 refer also to the points in the model at which data were collected, as shown in figure 16.

As jobs enter the shop/model, data are generated and captured in the JOBS table, hence the 1 in figures 16 and 17. Also shown below the Job attributes in figure 17 is the Routing Array, which in addition to storing routing information, is used to calculate each Job's total process time (Total_PT).

As Jobs enter a work center's queue, data are again generated and captured in step 2 at JOB-WC. Since this is a relationship table, it uses the primary keys of other entities. As shown, the attribute Job# comes from the JOBS entity, while WC# comes from one of the other entities, WORK CENTER. The latter entity is unchanging for the purposes of this model, although additional work centers could be added to the database as needed in an actual situation. Seq# is the key of SEQUENCE, a non-operational entity whose purpose is to allow for repeat visits of Jobs, as discussed in the previous section. The only non-key attribute in JOB-WC is Time_into_Queue, which is generated by the model's internal clock.

The third primary entity involved in data collection, OPERATION, has the same triple key as JOB-WC, but captures different information at step 3. Process_Time is the actual time the Job spends at the particular work center and is obtained from the Job's

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Routing Array. Emp# (employee number) is also captured at this time from the other unchanging entity, EMPLOYEE. The Job "grabs" the first available employee (a unique Emp#), availability being determined both by shift and by employee idleness at the time. The employee pool in the simulation model is captured by the many-to-many relationship, OPERATOR-WC, in the data model.

Thus steps ①, ② and ③ indicate not only the progression of each Job through the shop (figure 16), but also the method by which data are created and captured, while maintaining their interrelatedness (figure 17), in accordance with the data model.

Figure 17

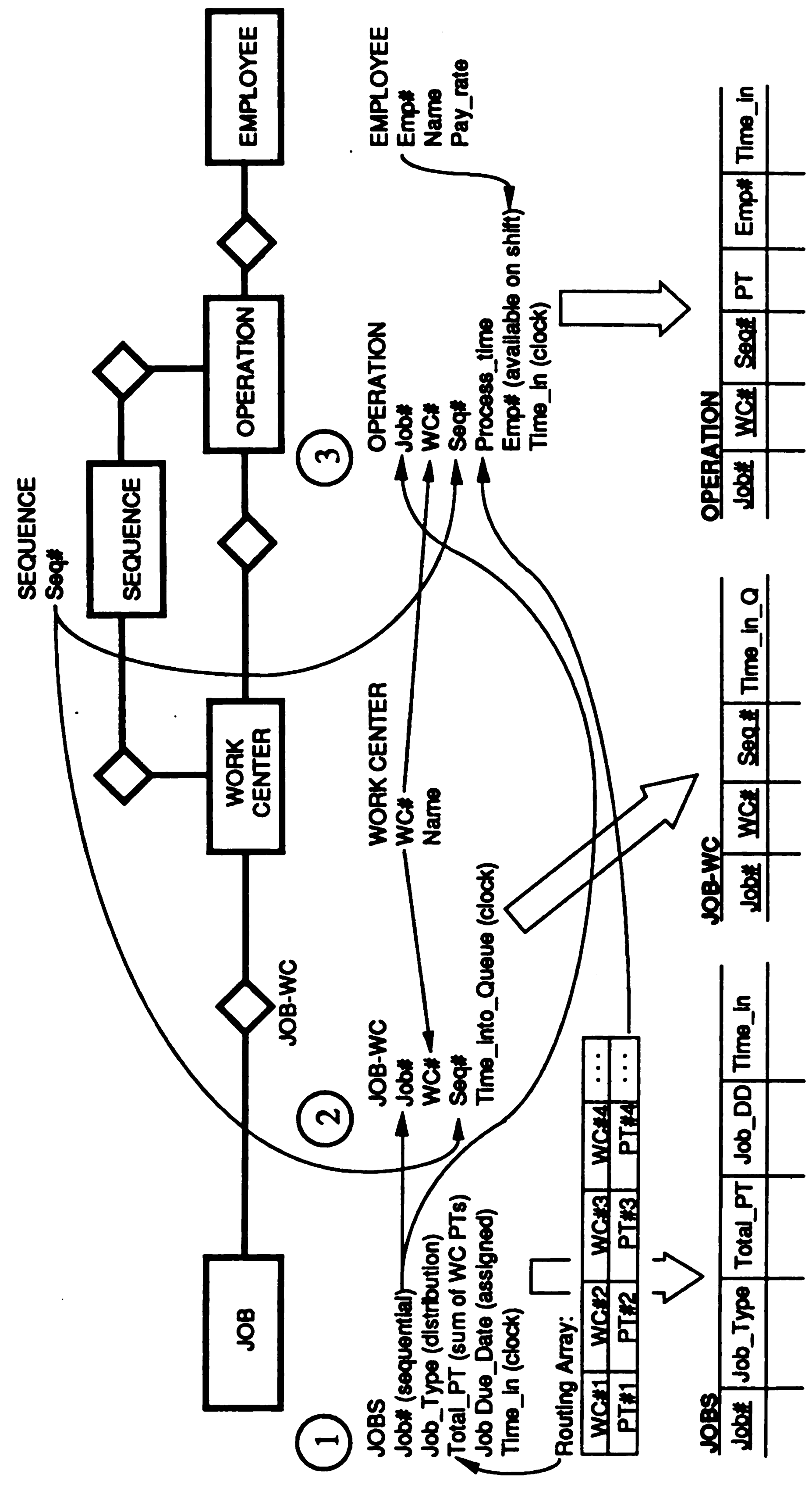

Figure 17: Creation of Main Entities' and Relationship's Data by Simulation Model

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4.4.3 Measurement Materialization

The disaggregate measures produced for the lab experiment were all distributional or graphic in nature. Deriving these measures/information sets required the use of both the relational database and a spreadsheet. Various entities were queried within the database to produce the values required. These values were then "dumped" from the database as a text file and reloaded into a spreadsheet, which was Excel version 5.0 for the Power Macintosh. This was done to take advantage of Excel's superior graphics and computational capabilities.

A summary of the measures that were materialized from the database and the attributes and entities necessary for them are shown in figure 18.

Measure	Attributes	Entity/Relationship
Time in system	Time_in Time_out	JOBS OPERATIONS
Lateness	Job_DueDate Time_out	JOBS OPERATIONS
Tardiness	Job_DueDate Time_out	JOBS OPERATIONS
DD Allowance	JobDD, Time_in	JOBS
Queue Length	Q_length	JOBS-WC
Jobs process/day	Time_in Time_out	JOBS-WC OPERATIONS

Figure 18: Measurement and Entity Summary

Due to the importance of the JOBS entity and the Time_out attribute in the management of the simulation data, as evidenced by their prominence in figure 18, their role will be discussed in general terms in the following section. For a more in-depth description of the method by which the Helix® database and Excel derived the disaggregate measures, please refer to Appendix A, sections A.9-A.11.

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4.4.3.1 JOBS Entity Measures Materialization

The JOBS table consists of the following attributes:

Job#	Job_Type	Job_DD	Total_PT	Time_in

In addition to these attributes, another value was calculated within the database, Time Completed, or Time_out. This was the time that the Job completed its last operation, and was derived by querying the OPERATION entity within the database.

As can be seen in figures 13 and 17, the OPERATION entity contains the attributes Time_in, which is the time at which the Job enters a work center, and Process_Time, indicating the elapsed time the Job will spend in the work center. Thus, to determine the time of completion of each operation, the following simple addition is required:

$$Time\_out = Time\_in + Process\_Time$$

Of interest is the Time_out of the final operation of the job, which indicates when the job is completed. To retrieve this value, OPERATION is queried for the *maximum* value of Time_out for each job. This corresponds to the time that Job is completed. The query for this value originates in the JOBS relation. Once this is done, the following attributes/values are available in the JOBS relation and are converted to a text file for transfer to Excel:

Job#	Job_Type	Job_DD	Total_PT	Time_in	Time_out

Note that Time_out is not a stored attribute of JOBS, but rather is procedurally derived, as just described

4.4.3.3 Additional Entities and Relationships

As discussed in Appendix A, there were some additional entities and relationships built into the database that did not appear in the data model of figure 9. These were put in the dat

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the database for ease of implementation and computation. These additional entities are RUN and DAYS and the relationship is DAYS-WC. Figure 19 shows the placement of these new items relative to the original data model with their names italicized.

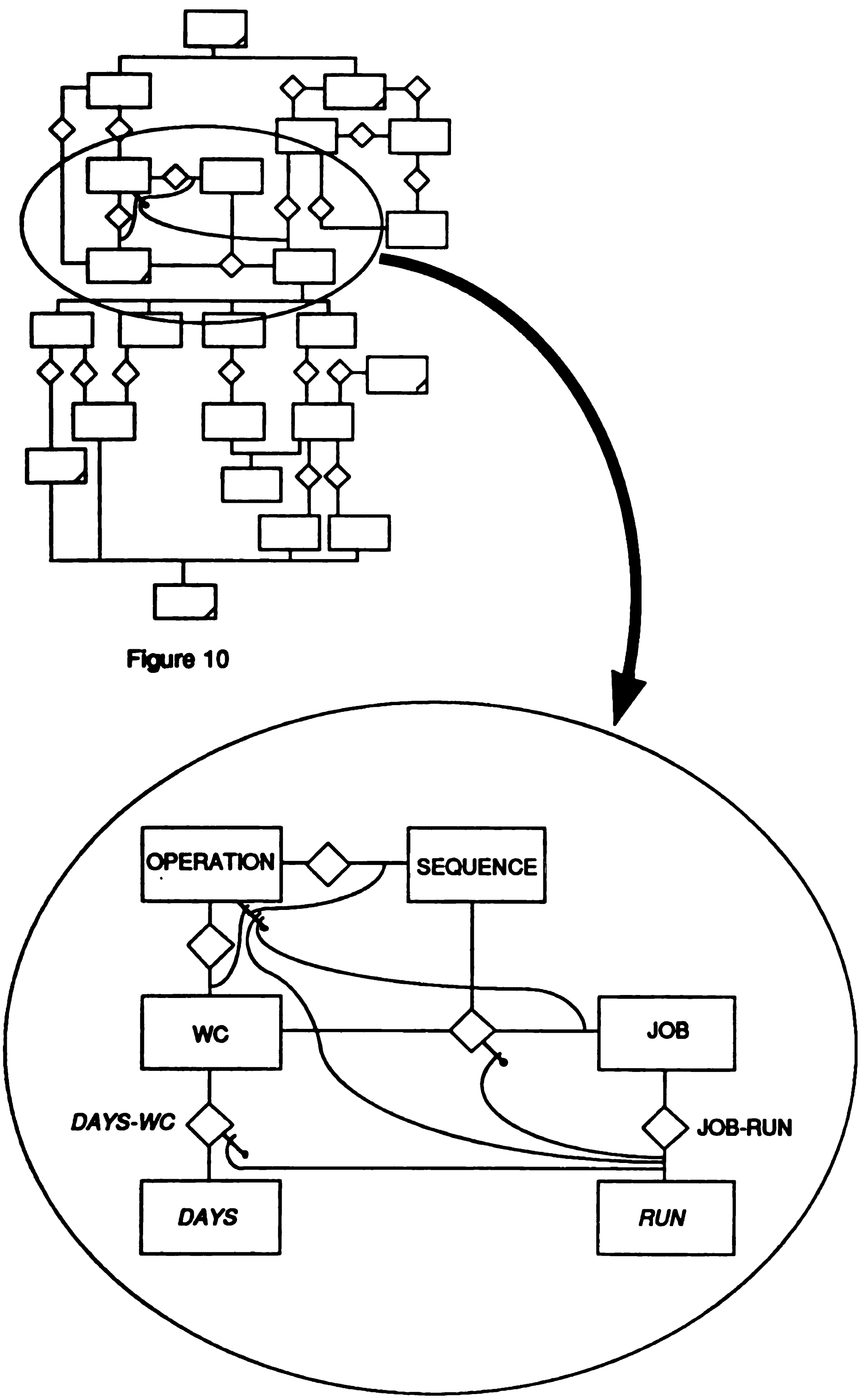

Figure 19: Data Model with Implementation Additions

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As can be observed from figure 19, the addition of the new entities and relationships changes the nature of the data model somewhat. OPERATION and JOB-WC now have quadruple keys, rather than merely triple keys. The new key for both of these tables is as shown below:

Job#	WC#	Seq#	Run#

Run# is necessary to track the proper data within the database, although it is not essential to the conceptual model of the shop floor system. Also note that, as a result of the RUN entity, there is a new relationship, JOB-RUN. This relationship is set up as a table within the database and it is within this relationship that all Job related information is actually stored. Thus, the Jobs record appears as the following:

Job#	Run#	Job_Type	Job_DD	Total_PT	Time_in

This allows querying and compiling of the correct Job data for the run (condition) in question. OPERATION and JOB-WC are similarly revised.

Another new relationship, DAYS-WC, due to the addition of the DAYS entity, is also shown in figure 19. This relationship also uses Run# as part of its key, for the same reason as those of the other entities. The use of this triple key can be seen in the query/calculation for average daily queue lengths in figure 67 of Appendix A. It is within this relationship that *per day data* regarding queue lengths and work center activity are compiled. Figure 20 shows the relational database tables for the new entities and relationships and those directly affected. Additional attributes to existing tables are shown in italics.

OPERATION (<u>Job#</u>, <u>WC#</u>, <u>Seq#</u>, <u>*Run#*</u>, Process_Time, Emp#*, Time_in)

JOB-WC (<u>Job#</u>, <u>WC#</u>, <u>Seq#</u>, <u>*Run#*</u>, Time_into_Queue)

DAYS (<u>Day#</u>)

RUN (<u>Run#</u>)

DAYS-WC (<u>Day#</u>, <u>WC#</u>, <u>Run#</u>)

JOB-*RUN*(<u>Job#</u>, <u>*Run#*</u>, Job_Type, Job_DueDate, Total_PT, Time_in)

Figure 20: Database Tables for Additional and Revised Entities and Relationships

4.4.4 Hypothesis and Proposition Evaluation

This portion (Phase 3) of the research considers proposition #1 and #2. Proposition #1 is evaluating the differences between two different sets of performance measures while Proposition #2 merely looks at the possibility of materializing certain measures "through the use of a database enhanced simulation model and its resulting disaggregated dataset." Given the nature of proposition #1 and the use of only one run of the simulation model to generate data, formal statistical testing was not done. Measures derived conventionally (aggregate measures from the simulation model) were compared to those derived from a disaggregate dataset, but their differences were not tested statistically. Similarly, for observational purposes, those measures deemed useful by the experts in Phase 1 were materialized from the database. This exercise endeavored to answer the question "Can the measures so desired be created for use?" The expected result of this question is represented by Proposition #2.

4.4.5 Phase 3 Outcome

Phase 3 exploits the semantic and simulation models developed in Phase 2 and implements them to produce the measures needed by the lab participants in the next phase. This phase includes the actual running of the simulation model and the generation of the disaggregate dataset. In addition, it includes the transfer of the data from the simulation model to

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model to the relational database and the materialization of the disaggregate measures in both the database and the spreadsheet. Certain implementation issues are resolved, such as the selection of the proper software environment in which to perform the materializations (database or spreadsheet) and the addition of several entities and relationships to the original semantic model.

4.5 Model and Performance Measurement Evaluation

This final portion of the research involved the use of laboratory participants to evaluate performance measures and information of both types (traditional, aggregate and disaggregate-based) to determine if one allows users to more readily identify shop floor problems and conditions. The overall steps are shown in figure 21:

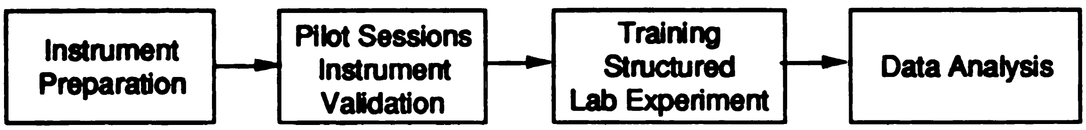

Figure 21: Performance Measures Evaluation (Phase 4)

The populated relational database was used to create reports with various information and measures to evaluate the simulated shop's performance. After the creation of the performance information, it was provided to participants in a controlled laboratory experiment for their evaluation. The results of this experiment were then used to analyze the quality of certain information in identifying the inserted shop floor conditions.

4.5.1 Lab Session Instrument

After data from all simulation runs was collected in the relational database, it was compiled into two general forms. Information presented in the traditional aggregate form was prepared as was information derived from the disaggregate dataset. The two instruments, copies of which are shown in Appendix D, were presented to the two groups of experimental participants. The following sections describe the various parts of the instrument- the conditions, measures and questions.

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4.5.1.1 Aggregate Group

Figure 22 summarizes the aggregate measures provided to this group of participants.

Measure	Provided
Time in System	Mean, standard deviation
Job Lateness	Mean, standard deviation
Job Tardiness	Mean, standard deviation
Due Date Allowance	Mean, standard deviation
Queue Lengths (by WC)	Mean, standard deviation
Machine Utilization	Mean percentage

Figure 22: Information Derived from Aggregate Dataset

The following describes how the above measures were defined and calculated:

Time in System: Measured as the difference between the time a job enters the shop floor, including the order release pool, to the time it exits its final inspection center. It includes work center queue waiting time, if any. Measured in hours.

Job Lateness: The amount of time a job varies from its assigned due date. Lateness may be negative for early jobs, or positive for jobs actually behind schedule. Measured in hours.

Job Tardiness: The amount of time a job is actually behind schedule. Jobs ahead of schedule are not counted in mean tardiness. Measured in hours.

Due Date Allowance: The amount of time a job is allowed to finish. This is assigned when the job enters the shop and represents the total time that job is expected to be on the shop floor, including queue time. The time a job enters the shop plus its due date allowance equals its due date. Measured in hours.

Queue Lengths: Measured by the number of jobs waiting. There is a separate value for each work center with a measurable queue.

Machine Utilization: Represents the proportion of time the work centers are busy with operations. Shown as percentage.

4.5.1.2 Disaggregate Group

Figure 23 summarizes the disaggregate measures provided to this group of participants.

Measure	Provided
Time in System	Distribution
Lateness, all jobs	Distribution
Lateness, project jobs	Distribution
Tardiness	Distribution
Due Date Allowance	Distribution
Queue Lengths (by WC)	Time series
Jobs Processed per day	Distribution

Figure 23: Information Derived from Disaggregate Dataset

Most measures above are derived in the same manner as those in the previous section, but their manner of presentation is different. Time in system, lateness (all jobs and project jobs), tardiness and due date allowance are presented as histograms so that the participants can see their actual distribution. Queue lengths are shown in a time series so that the participant may see the change in lengths over time for all work centers. The final measure, jobs processed per day, is also shown as a histogram and is a distribution of the number of jobs processed per day of operation. For an in-depth description of how these measures were created, please refer to Appendix A.

4.5.1.3 Condition Identification

Various questions were asked of the participants on the instruments, the first one, question 1, being the actual identification of the inserted condition. Six possible conditions were listed, plus the possibility of no condition having been inserted into the base case.

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The participants were asked to provide a ranking for each possible condition, with a "1" ranking indicating that which they felt was the most likely condition and "7" representing the least likely. Thus this question entailed assigning a rank to each possible condition.

Question 2 asked the participants to indicate their degree of confidence that the condition identified as most likely ("1" ranking in question 1) is correct. Reponses could vary from 0 to 100% confidence.

Question 3 asked the participants to indicate, through a rank ordering, which information sets were used in answering questions 1 and 2. The participants indicated a rank ordering of the measures, *for only those actually used.*

In addition to providing answers to these questions, the participant was to indicate the starting and ending time for identifying each condition. Starting time represented when he/she started to review the information and measures; ending time was after question 3 was answered.

Questions 1 and 2 above and the reported starting and ending times formed the basis for the lab sessions' performance measures, as described in greater detail in section 4.5.3.4

4.5.1.4 Identification Process

There were additional questions asked of the participants that attempted to determine why certain information was more useful, how the information was used and what additional information, if any, would have been useful in identifying the conditions. These questions and their answers, however, were not included in the analysis for this work but rather may form the basis for future research.

4.5.1.5 Clarity of Information Presentation and Training

Each participant was asked to provide answers to eight follow up questions after the experimental session ended. These questions were asked in part to determine if any difference in performance of the two groups was due to inadequate training or lack of understanding of the shop and its conditions. Also, the follow up questions addressed the issue of adequacy of the information and the nature of its presentation (tabular versus graphical). Answers were given as numbers on a scale from one to seven indicating strong agreement to strong disagreement with a given statement. Five of the questions dealt with how clear the information was presented and how useable it was. Three questions dealt with how descriptive the information was or how useful it was in understanding the nature of the shop floor and its conditions. The questions were the same for both information type groups, with one minor exception to be discussed later. Appendix D includes a complete copy of this questionaire.

4.5.2 Instrument Validation and Pilot Sessions

After preparation of the instruments, a validity check was performed using four Michigan State University Operations Management doctoral students. These students attended a training session in which the modeled shop floor was described and the performance measures and information were explained. The students were free to comment on the content and presentation of the experimental protocol. The purpose of this trial session was to check the training presentation for completeness and to obtain preliminary feedback prior to the actual sessions.

After the trial training session, one Ph.D. student worked through the actual condition identification exercises prepared for the experiment participants. The primary researcher was in the room at all times during this exercise to answer questions and clear up any confusion. The purpose of this session was to identify any ambiguity in the instruments and to determine if any conditions were undetectable. This session provided valuable feedback into the presentation of the material and also revealed several useful points of clarification within the instruments. After some discussion, it was agreed that none of the conditions were completely intractable and that the instrument could proceed to the next phase.

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4.5.3 Laboratory Experimental Sessions

Participants for the experimental sessions came from two different sources. Some were recruited from various classes in Michigan State University's (MSU) Eli Broad Graduate School of Management. Other participants were from an MBA level Management Information Systems class at Lake Superior State University (LSSU), where the primary researcher teaches. Participation of the MSU students was voluntary and had the potential of being rewarded according to a compensation scheme to be described the next section. Participants from LSSU were students in the researcher's class and took part in the experiment as an in-class assignment. Approximately 2/3 of the total participants were MSU students, while 1/3 were from LSSU.

4.5.3.1 Recruitment and Incentitives

Students at MSU were approached in their classes, with the permission of the instructor, and read the approximate text as shown in Appendix C. The voluntary nature of the experiment was stressed throughout the 5-10 minute presentation. Students were given the opportunity to ask questions of the experiment both during the presentation and afterward via Email or telephone with the researcher. Students from one MBA level class were informed by their instructor they would be awarded nominal participation points in the course in return for volunteering.

Participants in the experimental sessions were given the opportunity to win various prizes, based on performance. For two of the three performance measures for the sessions (Gap and Time, section 4.5.3.4), participants in each group were ranked separately. In other words, there was a different "curve" for each of the two groups. The top performers in each group were awarded 11 points and the bottom performers 5 points.

After the sessions were completed, each participant earned a number of tickets, or chances to win, equal to the number of points he/she earned. These tickets were placed in a bowl and three winners' names were drawn by a Marketing and Supply Chain Management department secretary. The first name drawn won a new "mountain" bicycle, worth approximately $600. The second, third and fourth names chosen won cash prizes of $200, $100 and $50, respectively. These prizes were fully explained to the students during the recruitment presentation. Thus, all participants had a chance to win the prizes, although those with better performance had a higher probability of winning.

Six separate experimental sessions were conducted- three with traditional aggregate measures (figure 22) and three with alternate, disaggregate-based information (figure 23). There were a total of 53 participants, roughly evenly divided between the two information/measure types. More details on the composition of the sample are given in section 5.4.1.

4.5.3.2 Lab Experiment Structure

Each experimental session, regardless of the information type, was conducted as outlined in figure 24.

1.	Introduction and presentation of objectives.
2.	Description of shop floor environment.
3.	Description of possible operational conditions.
	Total time (1-3), approximately 45 minutes
4.	Break
5.	Presentation of example condition identification with measures.
6.	Example of additional condition- participants solve. General discussion and presentation of correct answer afterwards.
	Total time (5-6), approximately 30 minutes
7.	Participants work on four conditions on their own. Randomly assigned order.
	Total time for entire session (1-7), 2 to 2.5 hours

Figure 24: Experimental Session Outline

The purpose of the training session and the first two condition identifications (steps 1-5) was to familiarize the participants not only with the environment, but also with the process of identification. Working through an example for them (step 5) and then discuss

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discussing their work after one task (Step 6) helped to introduce them to the problem solving techniques necessary for this task. By the time they moved to step 7, their own work and identification, they were all equally prepared.

4.5.3.3 Lab Sessions' Experimental Factors

The primary factor in this experiment is the type of information being presented. In considering Research Question #2 (section 3.2), the main point of interest is the extent to which one type of information is "more useful . . . in identifying operational problems." Thus, performance based on two levels of one factor– information type– will be compared.

In addition to the information type data, other facts, such as participants' age, sex, grade point average and previous manufacturing experience was also collected. This was done so that the effect, if any, of such demographic factors on the participants' performance could be evaluated. Figure 25 summarizes the main factors and covariates of the analysis.

Main effect: Information Type (Aggregate vs. Disaggregate- 2 levels)
Covariates: Age Sex Grade point average (GPA) Manufacturing experience Year in college

Figure 25: Analysis of Covariance Factors and Covariates

Age, sex, year in college and GPA were self reported. Year in college was given a value from one to five for the years freshman (1) through graduate (5). Since all graduate students were either in the first or second year of an MBA program, no further distinction was made. Manufacturing experience was based on a listing of manufacturing related jobs or experiences the participant reported having. For those participants with non-zero experience, their descriptions of their experience were reviewed by two MSU Ph.D.

students (other than the primary researcher) and given a ranking from one to five. The rankings assigned by the two reviewing students were then averaged.

4.5.3.4 Lab Experiment Performance Measures

The performance of the participants in the laboratory was gauged using three different metrics.

4.5.3.4.1 Gap

Gap is defined as the ranking given to the correct condition less one. For example, if the correct actual condition was a stationary bottleneck and the participant provided a ranking of "3" for that condition, his/her gap for this question would be 3-1=2. In this instance, the participant's #1 rank was something other than the actual condition, so the choice was incorrect, resulting in a non zero Gap. If, on the other hand, the participant gave the stationary bottleneck a ranking of "1" in this question, he/she would have made the correct choice, judging the actual condition to be the most likely condition (#1 rank). This would result in a Gap of 1-1=0. Thus, a lower gap indicates a more accurate response. By capturing Gap in this manner, not only are "right" and "wrong" answers apparent (Gap = 0, Gap > 0, respectively), but the results are in a variable scale, greatly facilitating statistical analysis.

4.5.3.4.2 Confidence

Confidence was given by the participant in the answer to question 2 on the instrument. This measure ranged from 0 to 100% and was *not* objective, but rather was the participant's own opinion of his/her performance. Since this is also a variable scale, statistical analysis was facilitated.

4.5.3.4.3 Time

Time, or efficiency, was indicated by the time taken for the participant to analyze the information provided and provide answers to questions 1-3. Participants were asked to indicate their beginning and ending time for each condition identification and their total time was determined by subtracting one from the other. Participants were instructed to use one timepiece for this consistently, since it was not as important to note actual clock time as it was to calculate elapsed time. Times were always given by the participants to the nearest minute and thus this measure has some inherent imprecision.

It is recognized that this is a self reported measure, but the alternative was to have the researcher physically receive each participant's completed instrument and note the time himself. It was felt that this would have entailed excessive walking around the lab room and shuffling papers and would be too distractive for the participants in return for little improvement, if any, in accuracy.

4.6 Data Analysis

The data analysis methodologies that address Propositions #1 and #2 are relatively straightforward and do not require any additional discussion beyond that already provided in chapter 3. However, the analysis proposed for Phase 4 (Hypothesis #2) is more in-depth and requires more justification, which is provided in the following sections.

4.6.1 *A Priori* Analysis (Phase 4)

Phase 4 is at the core of this research in that it is evaluating information users' performance in utilizing the two information types to identify shop floor problems and conditions. In evaluating the results of Phase 4's experiment, several different analyses are made. First, the demographics of the two different information type groups and the two different schools from which participants were drawn were compared. This difference in means was evaluated with t tests and/or Analysis of Variance (ANOVA) and was done to determine if there were any differences between the groups that may have contributed to different performance.

Next, performance in the laboratory was evaluated. Since all participants examined five conditions, a repeated measures Analysis of Covariance (ANCOVA) was the first analysis done to evaluate the *a priori* hypothesis ($H_{0\text{-}1}$). Each separate performance measure (Gap, Confidence, Time) was the repeated measure. ANCOVA was chosen over ANOVA since it allows for comparison of mean performance but also allows for the inclusion of covariates (Keppel, 1991).

A significant main effect of Type (between subjects), indicates that the type of information (aggregate vs. disaggregate) had an effect on the identification of the condition, but no one condition was more identifiable than any other, regardless of information type used. If there were only a significant main effect for Gap (within subjects), this would indicate that the condition being evaluated makes a difference in identification, but such difference was not the result of the information type. One or more conditions would be more identifiable than the others, but it would be so regardless of information type used.

A more interesting result is a significant interactive effect between information type and Gap (within subjects). This indicates that some conditions (DR, DD, etc.) may be more identifiable than others, *depending on the information type used.* This result would dictate further *post hoc* analysis, as discussed briefly in the next section.

4.6.2 *Post Hoc* Analysis

A significant Information Type x Gap interaction warrants additional analysis. An ANCOVA for each individual condition (DR, DD, etc.) would be made for the specific performance measure for which significance was discovered. The results found such a significant interaction for Gap and Time only. Further analyses determined for which conditions there exists a significant difference in participants performance.

Although there were three dependent variables (Gap, Confidence and Time), the results for each variable were analyzed separately, rather than combining them into an analysis such as Multivariate Analysis of Covariance (MANCOVA). This was done primarily to keep the analyses congruent with the original research questions. Although data were gathered on three performance measures, only one of them, Gap, which deals with the accuracy of condition identification, is of paramount interest. This goes back to research question #2 which states: "To what extent can a database populated with

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disaggregated data be *more useful* in completely describing shop floor performance and in *identifying* operational problems that may not be detectable with traditional aggregate measurements?" The question deals with issues of usefulness and, particularly, identification. The interaction, if any, between the various dependent variables was not an issue addressed by the research questions, thus the inclusion of a MANCOVA did not seem appropriate.

4.6.2.1 Distributional Analyses

While the ANCOVA for Gap evaluates the differences in mean performance between the information type groups, it does not provide any indication of how many correct (Gap = 0) versus incorrect (Gap > 0) identifications were made by each group. Determining this may be useful in that one group, say the disaggregate, may have a lower overall mean gap ($\mu_D < \mu_A$), while the aggregate group may in fact have more correct answers. To test this, further post hoc analysis was performed, by way of a Chi square analysis, to examine if the distributions of correct and incorrect identifications for each information group were significantly different from each other and from what would be expected randomly.

In addition to the mean and right/wrong performance, the underlying pattern of responses of the two groups was also of interest to determine if any differences in means can be attributed to differences in the actual distributions of data. For this comparison, a Kolgoromov-Smirnov (K-S) test was performed.

4.6.3 Clarity of Training and Information Presentation

The follow up questions asked of the participants (section 4.5.1.5) attempted to address the impact, if any, of the presentation of training and information on performance. Since responses to the questions consist of a scores on a seven point Likert scale of agreement/disagreement, comparison of mean responses is appropriate.

To evaluate the difference in mean responses of the two groups, Analysis of Variance (ANOVA) was used. Further, to determine if there was a significant difference in the underlying pattern or distribution of responses of the two groups, K-S test was performed.

4.6.4 Phase 4 Outcome

Phase 4 deals with the determination of the actual usefulness of the different information types. This usefulness is directly measured by the lab participants' performance in identifying various operational conditions and by the participants' ranking of the various measures used. Thus, this phase of the research acts as a test of the conceptual data model and the operationalized simulation model and database developed in previous phases. After analysis of the lab's results, it was possible to identify for which conditions a particular information type provided an advantage in identification.

4.7 Potential Limitations of the Research Design

While this work does address the research questions and applies the appropriate statistical analysis, there are some inherent limitations to its design. These are discussed further in this section.

4.7.1 Significance Level (α)

Cascio and Zedeck (1983) presented several different options to develop the appropriate power for statistical analysis in research. Two of them, setting one's sample size and evaluating prior probabilities, are not suitable in this research. Sample size was established by the available pool of volunteers for the lab experiment and, by the time statistical analysis began, was finalized. Prior probabilities refer to previous researchers evaluating these same issues in this manner, which has not been done.

When one's sample size is set and is somewhat limited (the case in this research) and if the research is of an exploratory nature, Cascio and Zedeck (1983) suggest increasing the level of probability that will indicate significance. Traditionally, the level of choice in such research becomes 0.10, rather than the traditional 0.05. Since this research is exploring issues not previously studied and is basically of a theory testing nature, a level of 0.10 will be used. This has been shown to be effective in other exploratory research (Magnan, 1994) and acts to identify effects that may be too weak to appear when the threshold is 0.05, thus encouraging additional research along the same lines.

4.7.2 External Validity and the Generalizability of Results

This research is using a laboratory experiment methodology to gain insights into the way information users in actual settings *may* behave and perform. The cavet "may" is stressed because it is not a certainty that all results obtained in the lab can be directly generalized to the real world and, in fact, such generalization may not even be desirable.

This issue of lab-to-field generalizability has been the topic of much discussion in the organizational behavior and industrial organizational psychology literature. Locke (1986) discussed at some length the concept of ecological representativeness, that is, how similar the lab setting is to a real word setting and how important that similarity may be to generalizability. He concluded that achieving complete similarity is impossible and, in fact, unnecessary. What is important, he felt, is that the essential features are similar. These may amount, for example, to merely the lab subjects' willingness to try for a certain goal, as they did in this research. In addition, attempting to make a lab setting identical to a field setting may limit generalizability only to those real world settings that are the same as the carefully contrived lab setting.

Berkowitz and Donnerstein (1982) also maintain that exact ecological representativeness is neither achievable nor desirable, maintaining that the meaning the subjects assign to their situation may be more important to making an experiment's results generalizable than the sample's demographic representativeness or the setting's realism. What is important, they maintain, is to use the lab to establish what *may* happen, as opposed to what *will* happen. Significant results in the lab should be taken as an indication of what can happen in a field setting, not necessarily of what will happen. This point is also stressed by Mook (1983) who maintains that direct generalizability should not always be a goal. The laboratory, he states, should be a tool to help us explore the interactions of various carefully controlled variables to test theory and predictions, not make them.

Despite the deemphasis among researchers of the direct generalizability of lab results to a field setting, there is ample evidence that results of lab and field research are quite similar in several different areas of research. Figure 26 (summarized from Locke, 1986) shows the percentage of the two different types of studies (lab and field) in which significant results were found:

Result	Percentage of Lab Studies Significant	Percentage of Field Studies Signifcant
Expectancy theory predicted job choice	80%	90%
Rater training on accuracy of performance appraisals	74%	80%
Challenging goals lead to higher performance	90%	90%
Relationship between job scope and job satisfaction	100%	96%

Figure 26: Summary of Lab and Field Research Results

It can be seen that not only are significant results found with both methodologies but, more importantly, the percentage of findings across the two methodologies are very similarly high, indicating a great deal of congruence between what is found in the field and the laboratory.

Concerns have also been voiced that using exclusively students in lab research limits generalizability. However, Locke maintains that focusing on the differences between student lab subjects and real world employees ignores many similarities between the two groups, namely that they are both human beings (1986). Moreover, many employees were once students and likewise most students will one day be employees (it is hoped). In the case of this research, at least one-third of the subjects (primarily those from LSSU) were currently employed. And, although the tasks in the lab and real world settings may be different, they have characteristics in common, such as skill requirements, repetitions and consequences (rewards).

Since this research is attempting to address several specific questions and to test the theoretical assertion that disaggregate information provides more useful information than aggregate measures, the proposed lab setting seems appropriate. The primary interest is in what *does* happen in the lab and how that indicates what *may* happen in the real world. Using students to perform carefully defined tasks should, according to previous researchers (Locke, 1986; Mook, 1983; Fromkin and Streufert, 1976), provide a reasonable basis for generalizing to what is achievable with actual employees in a real world setting.

4.8 Summary

The original research problem, that of the inadequacy of current simulation data and information management techniques, is being evaluated in the context of a data model-enhanced simulation model. Such evaluation has included the development of a conceptual data model of a shop floor, which can act as a template for not only an RDB, but also a simulation model. Such model development allowed us to specify and capture the necessary data that can populate an RDB and that can be used to generate performance measures not available from conventional simulation models. The actual usefulness of such measures is being determined by participants who, in a controlled lab setting, have the opportunity to use one of two information types, with their performance compared.

Thus the methodology proposed has a solid basis in conceptual and theoretical concepts from the IS field, and includes some more traditional aspects of the OM field. Although the first three phases of the research do not lend themselves to rigorous testing, the results will be instructive in that they will point to ways in which the data/simulation modeling approach may be improved. The fourth phase's results will be statistically analyzed and will indicate if information type is a significant factor in shop floor performance evaluation. A graphic outline of the four research phases is shown in figure 27.

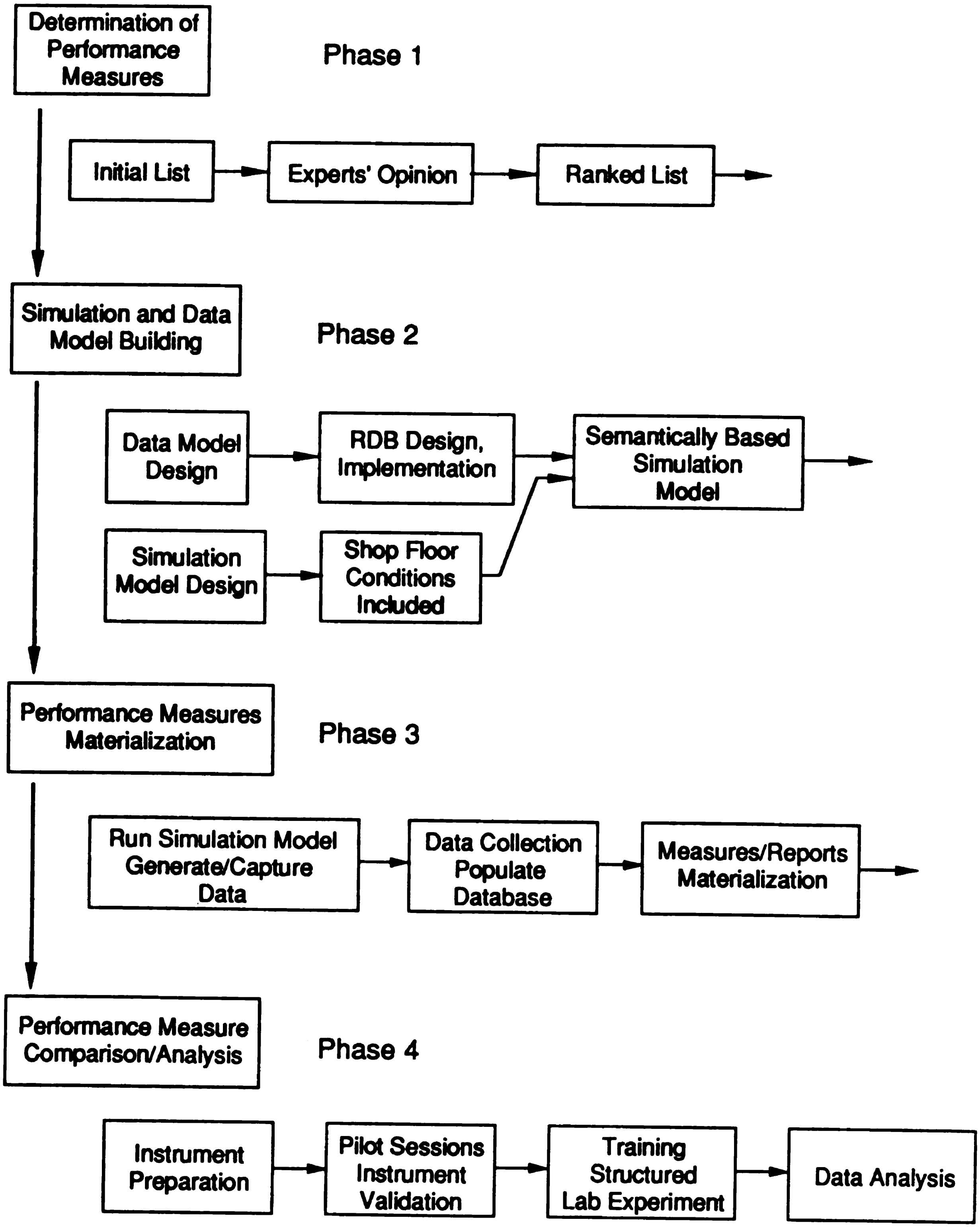

Figure 27: Research Phases Summary

5.0 Experimental Analysis and Results

5.1 Chapter Overview

The preceding chapters introduced the research problem, the setting for the problem, its rationale and justification and the research methodology used. This chapter presents the data, summarizes the analysis, presents the major findings generated by the analysis and discusses the findings.

This chapter is organized into six major sections, including this introductory section. The second section (5.2) validates the use of non-conventional performance measures by briefly summarizing the major observations and results gained from the interview of expert practitioners. This section provides evidence for the differences between the aggregated and disaggregated measures that are subsequently evaluated. The third section (5.3) focuses on feasibility by addressing the question of whether it is possible to generate a set of meaningful disaggregated measures. These measures are critical since they form the main input to the laboratory experiment.

The fourth section (5.4) deals with the issue of effectiveness as measured by the ability of the laboratory participants to identify underlying shop floor conditions given aggregated or disaggregated measures. This section begins by examining the data for two potential sources of confounding, those being due to differences in the participant groups and those due to the distributional form of the laboratory dataset. Differences in performance means are then evaluated using a repeated measures ANCOVA. Also, several nonparametric tests are performed, including a Kolgoromov-Smirnov (K-S) test of the underlying distribution and a Chi square analysis of the difference in the distributions of correct and incorrect identifications.

The final portion of the fourth section deals with the issues of efficiency and user acceptability, as judged by the secondary performance measures of Time and Confidence, respectively. A repeated measures ANCOVA is performed to compare the mean performance of each group as is as a K-S test to examine the distributions of the responses. In addition, the fifth section also contains an analysis and summary of further user acceptability issues, including the participants' ranked usefulness of the measures used and the quality of the data presentation.

The fifth and final section of this chapter discusses the results. The more interesting results are emphasized and are weighed against expectations and evaluated in terms of what they may be revealing about the research questions and hypotheses. Inferences are drawn and explanations offered for the results. Finally, directions for future research are presented.

5.2 Determination of Performance Measures

This section verifies the need or attractiveness of disaggregated measures. Interviews with two shop floor control experts were conducted. A survey instrument (see Appendix B) was then sent to these two experts for assistance in determining the measures and information to be used in the lab experiment. Both experts have more than 30 years experience and are designated as CPIM[1]. The survey consisted of listings of several measure/information types with questions as to their usefulness. The measure types were (1) aggregate- traditional simulation based measures; (2) financial measures; and (3) non-conventional measures- information that could be derived from more detailed, disaggregated datasets.

5.2.1 Expert Selected Measures

The positions of the experts on the relative importance of the measures are summarized in Figure 28. The experts were given a nine by five matrix where the nine rows represented various measures drawn from the literature, and the five columns represented dimensions of usefulness. These dimensions were: (1) Consistency with Corporate Goals; (2) Good Snapshot of Ongoing Operation; (3) Enhances Monitoring; (4)

[1] Certified in Production and Inventory Management by the American Production and Inventory Control Society (APICS), a nationally recognized association of production management professionals.

Problem Identification and (5) Problem Diagnosis. For each cell of the matrix, the experts were asked to assess the usefulness of the measures for that particular dimension on a 1 – 5 scale, with "1" being not useful at all and "5" being very useful. The values were then averaged over the five dimensions to determine the relative ranking for each expert, which was calculated on a 1 – 9 scale, with 1.0 representing the most useful measure. Ties in ranking were broken by averaging. For example, expert A believed that mean queue length and per job measures were of equal importance, so both were assigned an 8.5 value.

	EXPERT	
MEASURE	A	B
AGGREGATE MEASURES		
Mean time in system	6.0	6.0
Mean Lateness	1.0	4.5
Mean tardiness	5.0	4.5
Mean queue length (s)	8.5	2.0
Financial measures *	3.0	7.0
Per job measures	8.5	8.5
DETAILED REPORTS		
Distribution of job activity, process time, IATs	7.0	8.5
Bottleneck identification	2.0	3.0
Distribution of queue lengths	4.0	1.0

Figure 28: Expert Survey Summary

* Financial measures consisted of those identified as important by Goldratt (1990) and period shop net profit and per job cost and revenue.

With the exception of A's top ranking of mean lateness, the experts, for the most part, gave the traditionally top rated simulation measures- mean time in system, mean lateness and mean tardiness (Blackstone *et. al.*, 1982)- only average rankings. These measures were deemed less useful than detailed information on shop floor conditions. Another conventional measure– mean queue lengths– received very mixed marks, with A believing that it was the least important of the measures presented (rank = 8.5), and B that it was almost the most important (rank = 2.0). Consistent with the position taken by Goldratt (1990), both experts ranked per job measures as the least useful. According to these experts, the most important measures captured information not reported in traditional simulation research, such as distribution of queue lengths and bottleneck identification. While these findings are based on a very limited sample, they do provide overall support for the presence and use of non-conventional disaggregated measures and for the position that they meet definite needs experienced in shop floor performance evaluation.

5.3 Development of Semantically Based Simulation and Database Models

This section focuses on the feasibility of the semantic data modeling approach to simulation information management. It includes the development of the models and the materialization of the measures and also explores the issues of the practicality and reasonableness of this approach. Specifically, it addresses the first research question and the first two propositions:

RQ-1. Can an events-based model of a shop floor completely and accurately capture disaggregated shop floor data in a manner that allows for the efficient transfer of that data into an events-based database for information storage and presentation?

PRP-1: The means of conventionally (non-semantically) derived performance measures are comparable to the means of the same measures that have been derived from a semantically based disaggregated dataset.

PRP-2: It is possible to materialize useful measures through the use of a database enhanced simulation model and its resulting disaggregated dataset.

5.3.1 Expected Results

It was expected that the actual value of a performance measure would be independent of the method of derivation, indicating support for PRP-1. It was also expected that a semantic database approach to data management would be able to materialize measures determined to be useful by shop floor experts, indicating support for PRP-2.

5.3.2 Measurement Derivation Results (PRP-1)

Research Question #2 addresses the issue of feasibility, that is, will a database approach to shop floor information management produce useful results? In developing the model and accompanying dataset, it was found to be feasible to the extent that data could be generated and transferred to a relational database. However, PRP-1 provides a more specific evaluation of feasibility by examining whether performance measures created in a conventional manner by a simulation model are similar to those created from a disaggregated dataset.

In comparing results from the two forms of information collection, it is important to note that steady state conditions were not achievable under some shop floor conditions. Given the objectives of this study, achieving steady state was not a prerequisite to data collection, nor was it required for data analysis. However, where possible, efforts were made to eliminate start up conditions and to achieve steady state. For each shop floor condition only one run of the model was made. This was consistent with the purpose of the simulation model, to generate data for laboratory evaluation rather than statistical analysis.

Figure 29 shows the three most commonly used mean aggregate measures (Blackstone *et. al.*, 1982): time in system (TSYS), lateness (LATE) and tardiness (TARDY), under two different scenarios- as derived conventionally from the simulation model (Agg) and as materialized from the disaggregate dataset (Disagg). These results are summarized by condition. The first column of each section of figure 29 indicates the specific condition present (DR, DD, etc.) and the time at which the measures were captured. For all conditions, the final set of observations was taken at approximately 2800 hours. The next set of columns represent each of the three measures taken, TSYS, LATE and TARDY. In the final row of each section, discrepancy indicates the percentage by which the measure as derived from the disaggregate dataset differs from the measure derived conventionally, as of 2800 hours.

Dispatch Rule (DR)

	Disagg	Agg	Disagg	Agg	Disagg	Agg
Time (hrs)	TSYS (hrs)		LATE (hrs)		TARDY (hrs)	
700	156.92	157.61	-590.92	-593.61	23.13	23.27
1400	278.38	278.14	-446.69	-446.95	54.25	54.34
2100	380.32	380.17	-298.91	-300.13	105.73	105.18
2800	517.25	517.27	-220.79	-220.26	174.88	175.17
Discrepancy		0.03%		0.23%		-0.01%

Due Date (DD)

Time (hrs)	TSYS (hrs)		LATE (hrs)		TARDY (hrs)	
700	156.87	156.11	-1114.05	-1108.22	23.75	23.62
1400	276.48	276.07	-1352.24	-1354.64	29.34	29.28
2100	377.44	377.36	-1498.27	-1497.08	49.89	49.82
2800	488.91	491.37	-1339.38	-1335.68	77.38	77.48
Discrepancy		0.09%		-0.15%		-0.09%

Irregular Release (IR)

Time (hrs)	TSYS (hrs)		LATE (hrs)		TARDY (hrs)	
700	195.95	194.78	-922.67	-917.45	35.83	36.04
1400	327.64	327.32	-1319.36	-1317.81	31.12	31.17
2100	413.32	413.44	-1406.47	-1404.01	53.92	54.00
2800	509.48	508.91	-1306.63	-1304.28	78.12	78.11
Discrepancy		-0.13%		-0.22%		0.16%

Stationary Bottlenck (SB)

Time (hrs)	TSYS (hrs)		LATE (hrs)		TARDY (hrs)	
700	161.78	160.93	-490.55	-488.05	35.69	35.53
1400	288.64	288.24	-404.86	-403.96	60.69	60.75
2100	370.36	369.37	-406.13	-406.63	102.53	102.35
2800	541.22	540.21	-229.91	-232.02	174.44	174.08
Discrepancy		-0.21%		-0.06%		-0.18%

Moving Bottleneck (MB)

Time (hrs)	TSYS (hrs)		LATE (hrs)		TARDY (hrs)	
700	157.56	156.89	-593.61	-590.92	23.14	23.24
1400	278.15	278.39	-446.95	-446.69	54.25	54.34
2100	380.24	380.31	-300.13	-298.91	105.73	105.18
2800	517.34	517.17	-220.26	-220.79	175.17	174.89
Discrepancy		-0.03%		-0.23%		-0.18%

Figure 29: Comparison of Conventional (Agg) and Materialized (Disagg) Measures

In all cases, the final discrepancy is very small (< 0.24%). Consequently, it is reasonable to conclude that there is no practical difference between the differently derived measures, thus supporting PRP-1. The results summarized in figure 29 are consistent with what was observed when studying the actual shop on which the simulation model was based. The mean due date allowance for the jobs in the model was 2091 hours (approximately 87 days). Although this is high, it must be noted that 50% of the jobs were Project jobs that had a due date allowance of between 15 and 165 days. In addition, approximately 38% of the jobs were either Walk-in or Crib jobs, which had due date allowances of between 15 and 60 days. Only 12% of the jobs, those designated Quick Response, had relatively short allowances, mostly one day. For all the model's jobs combined, the due date allowances are relatively uniformly distributed across their range (1 to 165 days). Under this job mix assumption, one that had been confirmed by discussions with the shop's management, these allowances were reasonable and consistent with how they were assigned on a day to day basis.

While the actual mean total processing time of the jobs was 312 hours (13 days), more than 50% of the jobs had processing times less than 10 days, while the maximum processing time was approximately 40 days. Thus the substantial negative lateness (i.e., earliness) of the jobs was expected and is reasonable. Discussions with management indicated that, consistent with these results, the shop was able to complete most of its jobs early, with the exception of the quick response jobs, which made up a relatively small proportion of the total. This further supports the model's being a realistic representation of the shop floor being studied. It should also be noted that the multiplier between actual work content (processing time) and due date allowance is approximately 7.0, which is consistent with previous work (Christy and Kanet, 1988; Weeks and Fryer, 1977).

5.3.3 Derivation of Experts' Useful Measures (PRP-2)

Of the experts' two most highly ranked non-conventional measures, bottleneck identification and distribution of queue lengths, only the latter was actually derived. The former, bottleneck identification, is not a measure *per se*, and as such it was left as a task for the laboratory phase of this research. The measures actually derived and used in the laboratory experiment were primarily distributional in nature, and consisted of more than just queue lengths. However, the derivation one of the experts' highly ranked measures as well as other similar measures, offers support to PRP-2.

5.4 Laboratory Evaluation of Performance Measures and Information (Phase 4)

This phase of the research required participants to utilize different information sets to identify the conditions present in a shop floor environment. It dealt with the issues of quality and utility and addressed Research Question #2 and Hypothesis #1:

> RQ-2. To what extent can a database populated with disaggregated data be more useful in completely describing shop floor performance and in identifying operational problems that may not be detectable with traditional aggregate measurements?

> $H_{o\text{-}1}$ Information and measures materialized from a semantically based historical dataset do not result in significantly different performance by users in identifying and describing shop floor operational problems and conditions, as opposed to using traditional aggregate tactical measures.

As shown above, the null hypothesis maintained that there would be no differences between the performance of users of aggregate versus disaggregate information. It was expected that users of the disaggregate information would significantly outperform those using aggregate measures.

5.4.1 Sample Description

The sample of participants consisted of students at Michigan State University (MSU) and Lake Superior State University (LSSU). Figure 30 summarizes the characteristics of the overall sample by treatment group. Although the participants were assigned randomly to the two groups, a t test ($\alpha = 0.10$) indicated a significant difference in age between the two information type groups.

The sample was analyzed to determine if there were any significant differences in the demographics of the participants between the two schools. T-tests were performed and no significant differences in any of the demographics of the two schools' students were found. However, since there still could be differences between the populations at the two universities, School was used as a factor in all analyses.

	Total	Male (n)	Female (n)	Mean Age (year)	Mean GPA	Mean Experience	Mean Year in College
Total Sample	53	31	22	28.1	3.53	0.8	4.7
LSSU	16	8	8	30.5	3.46	0.38	4.7
MSU	37	23	14	26.9	3.57	0.93	4.6
Disaggregate	26	16	10	25.8*	3.42	0.94	4.5
LSSU	5	4	1	38.8	3.75	1.30	5.0
MSU	21	12	9	22.7	3.32	0.85	4.4
Aggregate	27	15	12	30.2*	3.64	0.54	0.48
LSSU	11	4	7	35.7	3.74	0.87	5.0
MSU	16	11	5	27.4	3.66	0.31	4.7

Figure 30: Sample Characteristics

5.4.2 Assumptions of Analysis of Covariance

Analysis of Covariance embodies certain assumptions, among them the presence of normally distributed data and of homogeneity of variance between the sample groups. Of these assumptions, the homogeneity of variance is the more critical (Neter and Wasserman, 1974; Keppel, 1991).

A repeated measures ANCOVA test was done on the original data to see what factors and/or covariates were significant, regardless of adherence to the assumptions, and to generate descriptive statistics and residuals, which were used in a Levene's test (1960) for homogeneity of variance. The ANCOVA showed that Gap interacted significantly with Information Type and Age. Levene's test was then performed on the residuals of the ANCOVA to see if the variances among the testing groups were equal.

The Levene test yielded significant results ($p < 0.002$), indicating that the variances were significantly different between the two information types. Therefore, it became necessary to transform the data to bring the variances into equality.

Several transformations were attempted in accordance with the guidelines recommended by Neter and Wasserman (1974). Since many of the Gap values were zero (accurate identification), a reciprocal or logarithm transformation was infeasible. Ultimately, using the results generated by the Cox-Box Power transformation (performed with SPSS, version 8.0 for Windows), the following transformation was determined to be effective in correcting the problem:

$$Y' = 1/(1+Y)^3$$

This transformation brought the variances into equality ($p < 0.263$; Levene's test), although a K-S test with Lilliefors on the transformed data revealed that the assumption of normalcy was still not met ($p < 0.05$), similar to the original data. However, since the key assumption of homogeneity of variance was satisfied, it was felt that the lesser important non-normalcy was not a serious deficiency. The transformed data were then analyzed using ANCOVA. The term Gap' is used to denote transformed data.

5.4.3 Lab Analysis Results

For all ANCOVAs in this and the following sections, the abbreviations in figure 31 apply.

DR	Dispatch Rule Variation
DD	Due Date Assignment Change
IR	Irregular Job Release
SB	Stationary Bottleneck
MB	Moving Bottleneck
Disagg	Disaggregate Data Measures Group
Agg	Aggregate, Traditional Measures Group
LSSU	Lake Superior State University Students
MSU	Michigan State University Students

Figure 31: Analysis Abbreviations

The means and standard deviations of the original *untransformed* Gap for each of the shop floor conditions are presented in figure 32. These values will be referred to later and are presented to demonstrate the differences in performance between the two groups.

Experimental Condition	GAP	
	Disagg	Agg
DR	1.39 (1.42)	0.35 (0.56)
DD	0.71 (1.43)	0.80 (1.12)
IR	2.58 (1.64)	2.19 (1.36)
SB	0.46 (1.24)	0.44 (1.26)
MB	0.96 (1.54)	2.18 (1.90)

Figure 32: Experimental Results- Mean (Standard Deviation) Values

The repeated measures ANCOVA results for Gap' are presented in table 33. No main effects were found, although Year in School (Yr) was a significant covariate (p <

0.078). However, significant interactions were found for Gap' x Type ($p < 0.011$) and Gap' x Age ($p < 0.035$). Consequently, individual ANCOVAs were performed for each shop floor condition. These are presented in panels A through F in table 34.

Between Subjects

Source	SS	DF	MS	F	P
Type	0.000	1	0.000	0.002	0.964
School	0.062	1	0.062	0.347	0.560
Type x School	0.073	1	0.073	0.406	0.528
Age	0.209	1	0.209	1.161	0.289
GPA	0.036	1	0.036	0.201	0.657
Yr	0.595	1	0.595	3.303	0.078*
Exp	0.001	1	0.001	0.004	0.951
Error	6.129	34	0.180		

Within Subjects

Source	SS	DF	MS	F	P
Gap'	0.451	4	0.113	0.763	0.551
Gap' x Type	2.314	4	0.579	3.914	0.005*
Gap' x School	0.121	4	0.030	0.205	0.935
Gap' x Type x School	0.915	4	0.229	1.547	0.192
Gap' x Age	1.752	4	0.438	2.964	0.035*
Gap' x GPA	0.122	4	0.030	0.206	0.935
Gap' x Yr	0.319	4	0.080	0.540	0.706
Gap' x Exp	0.571	4	0.143	0.966	0.428
Error	20.102	136	0.148		

Figure 33: Repeated Measures Gap' ANCOVA

* Indicates significance at $\alpha = 0.10$

Panel A, Dispatch Rule (DR)

Source	SS	DF	MS	F	P
Type	0.849	1	0.819	4.879	0.034*
School	0.006	1	0.006	0.033	0.856
Type x School	0.356	1	0.356	2.046	0.162
Age	0.274	1	0.274	1.576	0.218
GPA	0.000	1	0.000	0.001	0.978
Yr	0.109	1	0.109	0.624	0.435
Exp	0.014	1	0.014	0.082	0.776
Error	5.915	34	0.174		
R^2	0.338				

Panel B, Due Date (DD)

Source	SS	DF	MS	F	P
Type	0.326	1	0.326	1.468	0.234
School	0.001	1	0.001	0.004	0.949
Type x School	0.429	1	0.429	1.933	0.173
Age	0.026	1	0.026	0.117	0.735
GPA	0.016	1	0.016	0.073	0.789
Yr	0.015	1	0.015	0.067	0.797
Exp	0.000	1	0.000	0.000	0.991
Error	7.555	34	0.222		
R^2	0.074				

Panel C, Irregular Job Release (IR)

Source	SS	DF	MS	F	P
Type	0.105	1	0.105	1.893	0.178
School	0.001	1	0.001	0.010	0.922
Type x School	0.001	1	0.001	0.017	0.898
Age	0.103	1	0.103	1.853	0.182
GPA	0.096	1	0.096	1.719	0.199
Yr	0.152	1	0.152	2.736	0.107
Exp	0.384	1	0.384	6.911	0.013*
Error	1.891	34	0.056		
R^2	0.270				

Panel D, Stationary Bottleneck (SB)

Source	SS	DF	MS	F	P
Type	0.109	1	0.109	1.374	0.249
School	0.053	1	0.053	0.663	0.421
Type x School	0.005	1	0.005	0.067	0.797
Age	1.537	1	1.537	19.369	0.000*
GPA	0.002	1	0.002	0.027	0.871
Yr	0.363	1	0.363	4.578	0.040*
Exp	0.040	1	0.040	0.508	0.481
Error	2.698	34	0.079		
R^2	0.425				

Figure 34: Gap' ANCOVAs for Shop Floor Conditions

* Indicates significant at $\alpha = 0.10$

Panel E, Moving Bottleneck (MB)

Source	SS	DF	MS	F	P
Type	0.925	1	0.925	3.849	0.058*
School	0.124	1	0.124	0.515	0.478
Type X School	0.196	1	0.196	0.816	0.373
Age	0.022	1	0.022	0.090	0.766
GPA	0.044	1	0.044	0.182	0.673
Yr	0.276	1	0.276	1.148	0.292
Exp	0.133	1	0.133	0.552	0.463
Error	8.173	34	0.240		
R^2	0.145				

Figure 34 (continued)

Information type was significant for the dispatch rule ($p < 0.034$) and the moving bottleneck ($p < 0.058$) shop floor conditions. As shown in figure 31, identification was better (Gap = 0.35 versus 1.39, *original data*) for those participants who used the aggregate measures for the DR condition, whereas participants who used disaggregate measures performed better (Gap = 0.96 versus 2.18, *original data*) for the MB condition. Information type was not a significant factor when participants were presented with the shop floor conditions of due date assignment method (DD), irregular job release (IR) and the stationary bottleneck (SB). Manufacturing Experience (Exp, $p < 0.013$) was a significant covariate only for the identification of IR, while Age ($p < 0.000$) and Yr ($p < 0.040$) were significant for SB. Separate ANCOVAs for the original data (not shown here) resulted in the same significant results for the same two conditions.

An examination of the original data showed that disaggregate measures were better (lower Gap) in one identification (MB), and were equal to the aggregate measures in three other conditions. Interestingly, the only condition for which the aggregate measures were significantly better was in the situation for which a manager should have the most knowledge, the dispatch rule (DR) condition.

The R^2 values for the transformed data's ANCOVAs ranged from 0.074 to 0.425. Given the small sample size, this was not unusual. While this research controlled for all of the traditional variables used in behavioral research, other factors were likely present.

However, the values obtained are consistent with the results of previous lab experiments (c.f. DeVader, Bateson and Lord, 1986; Podsakoff and Williams, 1986; Stone, 1986).

5.4.4 Differences in Distributions

In addition to the means comparisons of the ANCOVA, the distribution of the lab responses was analyzed through the use of the K-S test. This supplements the ANCOVA in that it tests the assumption of equivalently distributed datasets between the two information types.

Figure 35 summarizes the K-S analysis of the transformed dataset's two distributions' fit with respect to each other. The distribution of responses between the two groups were significantly different only for DR.

Condition	GAP'
DR	0.429+ (0.035)*
DD	0.095 (1.000)
IR	0.238 (0.546)
SB	0.095 (1.000)
MB	0.238+ (0.546)

* Indicates significance (KS) at $\alpha = 0.10$
\+ Indicates significant difference in Repeated Measures ANCOVA

Figure 35: Kolmogorov-Smirnov Test Results for Condition Identification. Maximum difference (significance level)

In addition to the K-S test, a Chi-square test was performed to examine the distribution of those answers considered "correct" and "incorrect." Since Gap varies from zero to six with only one technically "correct" answer (Gap = 0), the definition of "correct" was expanded to include those responses where the correct condition was given as the first *or* second choice. The distribution of correct ($0 \leq \text{Gap} \leq 1$) and incorrect ($\text{Gap} \geq 2$)

answers for each condition was then tested against what would be expected due to randomness. Figure 36 summarizes the coefficient values calculated.

	DR	DD	IR	SB	MB
Pearson's	9.339*	0.020	0.170	0.267	5.200*
Likelihood	10.539*	0.020	0.171	0.269	5.313*
Yates	7.359*	0.045	0.012	0.002	3.981*

* Indicates significance at $\alpha = 0.10$

Figure 36: Chi Square Test Coefficients for Correct/Incorrect Distributions

Consistent with the ANCOVA results, the two conditions for which there were significantly different performance means of Gap (DR and MB) also showed significantly different distributions of correct and incorrect answers. Thus, the differences in means were more likely due to actual correct and incorrect answers by the two groups and not to one group being mildly wrong (eg. $2 \leq \text{Gap} \leq 4$) and the other group being very wrong (eg. $5 \leq \text{Gap} \leq 6$).

5.4.5 *Post Hoc* Analysis

The participants were also asked to record their starting and ending times (to the nearest minute) for the identification task as well as their confidence in their first choice. Time was the difference of the self-reported start and stop times, and confidence, also self-reported, was on a scale of 0 to 100, with 0 being completely unconfident and 100 being completely confident in their choice. The means and standard deviations of time and confidence are reported in figure 37.

Experimental Condition	CONFIDENCE		TIME (minutes)	
	Disagg	Agg	Disagg	Agg
DR	72.65 (16.62)	78.23 (16.98)	6.92 (2.91)	4.35 (1.67)
DD	82.58 (14.93)	70.96 (23.65)	3.75 (1.51)	4.28 (1.74)
IR	74.87 (24.79)	68.27 (17.20)	2.96 (1.37)	3.69 (2.13)
SB	82.77 (13.59)	79.80 (15.03)	3.85 (2.95)	3.12 (1.50)
MB	77.46 (13.98)	72.67 (18.74)	8.65 (11.62)	5.29 (2.71)

Figure 37: Confidence and Time Results- Mean (Standard Deviation) Values

A Levene test for homogeneity of variance was performed for both Confidence and Time, with results indicating that the variances among the groups were not significantly different ($p < 0.748$ and $p < 0.122$, respectively). As a result, ANCOVAs were performed on the original untransformed data.

5.4.5.1 Time

A repeated measures ANCOVA was performed for Time with the results presented in figure 38. Significant interactions were found for Time x Type ($p < .002$) and Time x School ($p < .002$), and a main effect for the covariate GPA ($p < .014$). The participants with the higher GPA actually performed the task more slowly. The main effect for School ($p < .016$) must be interpreted in light of the interaction with Time. Consequently, a series of ANCOVAs on each shop floor condition were performed and the results are presented in panels A through E of table 39.

Between Subjects

Source	SS	DF	MS	F	P
Type	15.649	1	15.649	2.045	0.162
School	49.383	1	49.683	6.453	0.016
Type x School	19.845	1	19.845	2.593	0.117
Age	3.172	1	3.172	0.414	0.524
GPA	51.681	1	51.681	6.756	0.014*
Yr	15.905	1	15.905	2.078	0.159
Exp	14.810	1	14.810	1.935	0.173
Error	260.20	34	7.653		

Within Subjects

Source	SS	DF	MS	F	P
Time	11.653	4	2.913	0.988	0.410
Time x Type	51.254	4	12.814	4.345	0.002*
Time x School	52.131	4	13.033	4.419	0.002*
Time x Type x School	14.508	4	3.627	1.230	0.301
Time x Age	12.815	4	3.204	1.086	0.366
Time x GPA	7.476	4	1.869	0.634	0.639
Time x Yr	3.838	4	0.960	0.325	0.861
Time x Exp	20.934	4	5.233	1.775	0.138
Error	401.09	136	2.949		

Figure 38: Repeated Measures ANCOVA for Time

* Indicates significance at $\alpha = 0.10$

Panel A, Time ANCOVA Results for Dispatch Rule (DR)

Source	SS	DF	MS	F	P
Type	76.988	1	76.988	12.570	0.001*
School	7.273	1	7.273	1.187	0.282
Type x School	8.986	1	8.986	1.467	0.232
Age	4.011	1	4.011	0.655	0.423
GPA	8.551	1	8.551	1.396	0.244
Yr	2.467	1	2.467	0.403	0.529
Exp	0.406	1	0.406	0.066	0.798
Error	263.37	43	6.125		
R^2	0.288				

Panel B, Time ANCOVA Results for Due Date (DD)

Source	SS	DF	MS	F	P
Type	2.025	1	2.025	0.866	0.357
School	0.452	1	0.452	0.193	0.662
Type x School	0.014	1	0.014	0.006	0.938
Age	6.717	1	6.717	2.873	0.098*
GPA	9.636	1	9.636	4.121	0.049*
Yr	0.257	1	0.257	0.110	0.742
Exp	0.412	1	0.412	0.176	0.677
Error	95.86	41	2.338		
R^2	0.257				

Panèl C, Time ANCOVA Results for Irregular Job Release (IR)

Source	SS	DF	MS	F	P
Type	4.834	1	4.834	1.805	0.186
School	0.926	1	0.926	0.346	0.560
Type x School	2.980	1	2.980	1.113	0.298
Age	2.196	1	2.196	0.820	0.370
GPA	3.587	1	3.587	1.339	0.254
Yr	3.375	1	3.375	1.260	0.268
Exp	16.485	1	16.485	6.154	0.370
Error	112.51	42	2.679		
R^2	0.311				

Panel D, Time ANCOVA Results for Stationary Bottleneck

Source	SS	DF	MS	F	P
Type	8.762	1	8.762	1.732	0.195
School	20.322	1	20.322	4.018	0.051*
Type x School	14.584	1	14.851	2.884	0.097*
Age	6.414	1	6.414	1.268	0.266
GPA	25.883	1	25.883	5.118	0.029*
Yr	6.452	1	6.452	1.276	0.265
Exp	2.128	1	2.128	0.421	0.520
Error	217.47	43	5.058		
R^2	0.220				

Figure 39: Time ANCOVAs for Shop Floor Conditions

* Indicates significant at $\alpha = 0.10$

Panel E, Time ANCOVA Results for Moving Bottleneck

Source	SS	DF	MS	F	P
Type	50.077	1	50.077	0.798	0.377
School	21.463	1	21.463	0.342	0.562
Type x School	26.455	1	26.455	0.421	0.520
Age	0.029	1	0.029	0.000	0.983
GPA	87.893	1	87.893	1.400	0.243
Yr	34.018	1	34.018	0.542	0.466
Exp	274.15	1	274.15	4.366	0.042*
Error	2762.86	44	62.792		
R^2	0.253				

Figure 39 (continued)

For the dispatch rule condition (DR), Information Type was significant ($p < .001$), with the participants who used the aggregate measures performing the identification faster, on average, than the participants with the disaggregate measures (4.35 versus 6.92 minutes). Information Type and School were not significant for the identification of the due date assignment method (DD), irregular job release (IR), and moving bottleneck (MB). Age and GPA ($p < 0.098$, 0.049, respectively) were significant for DD, while School ($p < .051$) and Information Type x School ($p < .097$) were both significant for SB. The other significant results obtained in the individual ANCOVAs are not discussed since there is no overall significance obtained in the repeated measures ANCOVA. A larger sample size may result in more significant factors.

It appears that the significant Time effect was driven solely by the performance on DR. There were no other significant time performance differences between groups. This result provides support for the use of disaggregate measures. The participants had significantly more information in the disaggregate condition, yet only in one instance did they take significantly more time (and for that condition that they should have the most prior knowledge, dispatch rule, if this was an actual shop floor). Only for SB was school significant ($p < 0.097$).

5.4.5.2 Confidence

The participants' subjective confidence was also analyzed through a repeated measures ANCOVA (figure 40). A significant main effect was found ($p < 0.099$), as were several significant interactions- School ($p < .094$), GPA ($p < .071$), and Manufacturing Experience ($p < .002$). The individual conditions' ANCOVAs are shown in Panels A through E of figure 41.

Between Subjects

Source	SS	DF	MS	F	P
Type	445.375	1	445.375	0.602	0.443
School	12.297	1	12.297	0.017	0.898
Type x School	6.654	1	6.654	0.009	0.925
Age	1215.52	1	1215.52	1.644	0.208
GPA	1.418	1	1.418	0.002	0.965
Yr	466.61	1	466.61	0.631	0.432
Exp	117.06	1	117.06	0.158	0.693
Error	25138.1	34	739.36		

Within Subjects

Source	SS	DF	MS	F	P
Conf	1913.48	4	478.37	1.991	0.099*
Conf x Type	1034.37	4	258.59	1.077	0.371
Conf x School	1948.44	4	487.11	2.028	0.094*
Conf x Type x School	674.85	4	168.71	0.702	0.592
Conf x Age	1408.63	4	352.16	1.466	0.216
Conf x GPA	2128.07	4	532.02	2.215	0.071*
Conf x Yr	358.46	4	89.62	0.373	0.828
Conf x Exp	4316.31	4	1079.08	4.492	0.002*
Error	32668.13	136	240.21		

Figure 40: Repeated Measures ANCOVA Results for Confidence

Panel A, Confidence ANCOVA Results for Dispatch Rule (DR)

Source	SS	DF	MS	F	P
Type	885.32	1	885.32	3.053	0.088*
School	1.78	1	1.78	0.006	0.938
Type X School	157.36	1	157.36	0.543	0.465
Age	556.02	1	556.02	1.917	0.173
GPA	7.34	1	7.34	0.025	0.874
Yr	281.41	1	281.41	0.870	0.330
Exp	282.20	1	282.20	0.973	0.329
Error	12470.58	43	290.01		
R^2	0.139				

Panel B, Confidence ANCOVA Results for Due Date (DD)

Source	SS	DF	MS	F	P
Type	867.01	1	867.01	1.988	0.166
School	14.62	1	14.62	0.034	0.856
Type X School	38.28	1	38.28	0.088	0.768
Age	205.31	1	205.31	0.471	0.496
GPA	136.88	1	136.88	0.314	0.578
Yr	46.61	1	46.61	0.107	0.745
Exp	67.22	1	67.22	0.154	0.697
Error	18312.92	42	436.02		
R^2	0.120				

Panel C, Confidence ANCOVA Results for Irregular Job Release (IR)

Source	SS	DF	MS	F	P
Type	13.65	1	13.65	0.030	0.863
School	323.89	1	323.89	0.712	0.404
Type X School	167.48	1	167.78	0.368	0.547
Age	0.42	1	0.42	0.001	0.976
GPA	852.01	1	852.01	1.872	0.179
Yr	282.00	1	282.00	0.619	0.436
Exp	990.33	1	990.33	2.175	0.148
Error	19119.37	42	455.22		
R^2	0.134				

Panel D, Confidence ANCOVA Results for Stationary Bottleneck

Source	SS	DF	MS	F	P
Type	0.673	1	0.673	0.004	0.951
School	44.64	1	44.64	0.249	0.620
Type X School	600.88	1	600.88	3.354	0.074*
Age	831.93	1	831.93	4.643	0.037*
GPA	398.20	1	398.20	2.222	0.143
Yr	21.31	1	21.31	0.119	0.732
Exp	35.85	1	35.85	0.200	0.657
Error	7704.48	43	179.17		
R^2	0.241				

Figure 41: Confidence ANCOVAs for Shop Floor Conditions

* Indicates significance at $\alpha = 0.10$

Panel E, Confidence ANCOVA Results for Moving Bottleneck

Source	SS	DF	MS	F	P
Type	502.07	1	502.07	2.165	0.148
School	569.84	1	569.84	2.457	0.124
Type x School	682.40	1	682.40	2.942	0.093*
Age	2512.35	1	2512.35	10.832	0.002*
GPA	27.04	1	27.04	0.117	0.734
Yr	78.17	1	78.17	0.337	0.565
Exp	3.46	1	3.46	0.015	0.903
Error	10205.06	44	231.93		
R^2	0.267				

Figure 41 (continued)

Confidence had a significant main effect in the identification of the DR condition, with those using the aggregate measures being more confident. Information Type and School interacted significantly for both bottleneck conditions, SB and MB. In addition, Age was a significant covariate for the two bottleneck conditions as well.

5.4.6 Specific Measures' Usefulness per Condition

During the laboratory sessions, the participants were asked to rank the usefulness of the various information sets (i.e., measures) that were actually used to identify the shop floor condition. These responses consisted of rankings on a scale of one and up, depending on the number of measures used. As a result, there may be only one or two measures indicated (with rankings one and/or two) or there may be as many as seven or eight measures indicated, each with a ranking. In all cases, a "1" ranking indicated the most useful measure as judged by the respondents.

For the analysis of the responses the following question was asked: *For a given information type and condition (e.g., aggregate and DD), how would you rank the various measures as to their usefulness in identifying the condition?* It was not possible to compare the reported usefulness of measures between the aggregate and disaggregate treatment groups since the measures differed across the two groups. Each group received different types of information, hence, the provided rankings corresponded to entirely different information. So, comparisons of perceived usefulness were made *across* the conditions *within* each information type group.

It was not possible to analyze this information statistically due to the widely varying and sometimes limited sample sizes. For a given condition, some participants did not even use a particular measure and, therefore, gave it no ranking at all, while other participants did. To assess the responses, the following information was evaluated: (1) the mean and standard deviation of each measure's ranking for each condition; and (2) the number of participants that actually ranked the measure for that condition. The latter value was important to provide some perspective on the perceived usefulness of each measure. For example, a measure may have been ranked very highly, but only by the three or four participants who used it. All other participants (as many as 20) may not have used it at all. In addition, the usefulness rankings were separated into groups- those who answered correctly ($0 \leq \text{Gap} \leq 1$, consistent with the Chi square test criteria) and those who answered incorrectly ($\text{Gap} \geq 2$).

Although no specific hypotheses were developed for the analysis of this section, there were several expectations. Since the DR condition consisted of introducing the SPT dispatch rule versus the FCFS base case, the expectation was that those who correctly identified the condition would rely on the time in system measure, since the most common manifestation of using SPT is a reduction in throughput time (Blackstone *et. al.*, 1982). On the other hand, for those who incorrectly identified DR, the expectation was a higher usage and ranking of measures other than time in system. Correct identification of the DD condition should be accompanied by a relatively high ranking of the due date allowance measures, while correct identification of the bottleneck conditions, SB and MB, should show a reliance on the queue length measures, either means or time series. As with DR, incorrect identification of DD and the bottlenecks should be accompanied by a relatively high ranking of measures other than due date allowance and queue lengths, respectively. There was no *a priori* expectation as to the most useful measure in identifying IR.

Because of their length and complexity, tables with the means and standard deviations of the participants' usefulness rankings are reserved for Appendix A. Figure 42, however, summarizes the analysis and indicates the number of respondents who chose certain measures as *the* most useful in identifying the shop floor condition. Note that data for both information types is included, as is that from respondents who answered both correctly and incorrectly. Also indicated in bold type is the measure that is consistent with expectations.

	DISAGGREGATE				AGGREGATE			
Cond	Correct		Incorrect		Correct		Incorrect	
DR	**Tsys***	**8**	Tsys	2	**Tsys***	**8**	Tsys*	2
	Job Late	1	Job Late	0	Job Late	7	Job Late	0
	Proj Job Late	2	Proj Job Late	0	Proj Job Late	1	Proj Job Late	0
	Job Tardy	0	Job Tardy	0	Job Tardy	0	Job Tardy	0
	DD Allowance	0	DD Allowance	1	DD Allowance	1	DD Allowance	0
	Queue Length	4	Queue Length*	7	Queue Length	7	Queue Length	0
	Job Activity	1	Job Activity	0				
DD	Tsys	0	Tsys*	1	Tsys	1	Tsys	0
	Job Late	0	Job Late	1	Job Late	1	Job Late	2
	Proj Job Late	0	Proj Job Late	1	Proj Job Late	0	Proj Job Late	0
	Job Tardy	0	Job Tardy	0	Job Tardy	1	Job Tardy	0
	DD Allow*	**19**	DD Allowance	1	**DD Allow***	**17**	DD Allowance*	3
	Queue Length	0	Queue Length	0	Queue Length	0	Queue Length	0
	Job Activity	0	Job Activity	0				
IR	Tsys*	1	Tsys	7	Tsys	2	Tsys	5
	Job Late	2	Job Late*	3	Job Late	1	Job Late	0
	Proj Job Late	2	Proj Job Late	3	Proj Job Late	2	Proj Job Late	1
	Job Tardy	0	Job Tardy	1	Job Tardy	0	Job Tardy	0
	DD Allowance	0	DD Allowance	1	DD Allowance	1	DD Allowance	0
	Queue Length	1	Queue Length	1	Queue Length*	3	Queue Length*	11
	Job Activity	0	Job Activity	2				
SB	Tsys	3	Tsys*	1	Tsys	0	Tsys	0
	Job Late	1	Job Late	0	Job Late	0	Job Late	0
	Proj Job Late	1	Proj Job Late	1	Proj Job Late	0	Proj Job Late	0
	Job Tardy	0	Job Tardy	0	Job Tardy	2	Job Tardy	0
	DD Allowance	0	DD Allowance	0	DD Allowance	1	DD Allowance	0
	Que. Length*	**19**	Queue Length	0	**Que. Length***	**18**	Queue Length*	4
	Job Activity	0	Job Activity	0				
MB	Tsys	0	Tsys	1	Tsys	3	Tsys*	3
	Job Late	1	Job Late*	1	Job Late	1	Job Late	1
	Proj Job Late	1	Proj Job Late	0	Proj Job Late	1	Proj Job Late	5
	Job Tardy	0	Job Tardy	0	Job Tardy	0	Job Tardy	0
	DD Allowance	1	DD Allowance	0	DD Allowance	1	DD Allowance	0
	Que. Length*	**16**	Queue Length	3	**Que. Length***	**5**	Queue Length	6
	Job Activity	1	Job Activity*	1				
Total Participants			n=26				n=27	

* Most highly ranked measure for usefulness (lowest mean measure among all used). Two asterisks indicate a tie in the mean ranking.

The totals of correct and incorrect responses for each condition may not be equal due to some participants not performing some conditions' identification and/or some not providing a ranking of the most useful measure.

Bold indicates conformance with expectations

Figure 42: Summary of Most Highly Ranked Measure for Nature of Responses

Participants in both information type groups who *correctly* identified the conditions consistently ranked as highest the measure they were expected to chose. Those who answered incorrectly and who used disaggregate information, however, ranked as highest those measures not normally associated with correct answers. Thus, those who answered incorrectly seemed to rely on the wrong measures, possibly leading to their incorrect results, which is consistent with expectations.

Those respondents who answered incorrectly and used aggregate information ranked as most useful the measures normally associated with correct answers- those that were expected to be associated with *correct* answers. Thus, those using aggregate measures and answering both *correctly* and *incorrectly* all ranked as most useful the same measures, with the exception of the MB condition.

5.4.7 Clarity of Information Presentation

The participants were also asked to respond to eight follow-up questions at the end of the experimental sessions. These questions attempted to assess how well the information was presented and how well it described the shop floor environment and conditions. The respondents were asked to indicate their level of agreement with the following questions:

1. As a result of the training session, I knew how to use the information presented.
2. I could have made sense of the information presented without the training session.
3. The information presented with the cases was insufficient for me to answer the questions.
4. The information presented with the cases was excessive and was difficult to sift through.
5. The information presented with the cases was concise in nature and adequate to allow me to answer the questions.
6. The information presented with the cases clearly and completely described the overall structure of the shop, its flows and layout.

7. The information presented with the cases allowed me to clearly understand and identify the changes in conditions affecting the shop.

8. The presentation of data in graphical/tabular (*disaggregate group/aggregate group*) format made it difficult to use.

Question 8 was modified according to the treatment group to which it was addressed. The *disaggregate information group* was presented with graphical information and was asked their opinion of how difficult it was to use. Similar for the *aggregate group* regarding their tabular data.

Each question was to be answered with a value from one to seven, ranging from strongly agree (1) to strongly disagree (7). An Analysis of Variance (ANOVA) was performed to determine if the two groups answered the questions in a significantly different manner

Although no hypotheses were put forth for this portion of the research, there were some expectations in terms of the results, as summarized in figure 43. The ">" refers to the relative mean sizes with a "larger" result indicating a higher expected level of disagreement. For example, for question #3, dealing with the sufficiency of the information presented, it was expected that the mean for the disaggregate group (D) would be significantly greater than that for the aggregate group (A). The aggregate group was expected to agree more strongly that the information was insufficient, as it consisted of only point means and standard deviations. For question #4, a higher level of agreement from the disaggregate group that the information was excessive was expected, since that information consisted of multiple pages of graphs. Similarly, question #5 asked about the conciseness of the information, which was expected to be more acknowledged by the aggregate group. Finally, although question #8 was asked slightly differently to each group, it was expected that the aggregate group would rate their tabular information as more difficult to use (more strongly agree) than the disaggregate group. Figure 43 shows the expected direction of the relative value of the means.

QUESTION	Expected Result
(1) Training resulted in knowing how to use information	None
(2) Information would have been understandable without training	None
(3) Information was insufficient to answer the questions	D > A
(4) Information was excessive and difficult to sift through.	D < A
(5) Information was concise and adequate to answer questions	D > A
(6) Information clearly described the shop structure, layout and flows	None
(7) Information made the changes in conditions understandable	None
(8) Information presentation (graphical or tabular) made it difficult to use	D > A

D = disaggregate group
A = aggregate group

Figure 43: Expected Results- Clarity of Information Presented

The results of the ANOVA are summarized in figure 44.

QUESTION	Disagg mean	Agg mean	F-Value (p)
(1) Training resulted in knowing how to use information	2.92	3.15	0.559 (0.458)
(2) Information would have been understandable without training	5.04	5.44	0.886 (0.351)
(3) Information was insufficient to answer the questions	5.11	4.19	6.042 (0.017)*
(4) Information was excessive and difficult to sift through.	5.19	4.78	1.339 (0.253)
(5) Information was concise and adequate to answer questions	2.69	3.52	4.997 (0.030)*
(6) Information clearly described the shop structure, layout and flows	3.73	3.59	0.095 (0.759)
(7) Information made the changes in conditions understandable	3.12	4.00	7.275 (0.009)*
(8) Information presentation (graphical or tabular) made it difficult to use	5.50	5.59	0.045 (0.833)

Figure 44: ANOVA Results for Follow Up Questions. Means, F value and (significance level, * indicates $p < 0.10$)

A lower mean value shown corresponds to a higher level of agreement with the statement.

The ANOVA results revealed that three questions (3, 5 and 7) had significantly different responses between the two information groups. Question 3's results show that the disaggregate group had a significantly higher level of disagreement with the question, indicating that they agreed more strongly that the information was sufficient to make the identification, consistent with expectations. Question 5's results show that the disaggregate group agreed more strongly that the information presented was concise and adequate to answer the questions, which was contrary to expectations. The results for question 7 show that the disaggregate group agreed more strongly that the information presented allowed them to understand the changes in conditions on the shop floor, which was key to making the identifications. The results for questions #3 and #5 were consistent with expectations.

5.4.8 Summary of Results

While several different results were reported in the preceding sections, the more important ones are listed below. These findings either directly address the research questions or provide a means of addressing them, as indicated in the italicized discussion.

- The experts surveyed expressed an interest in non-traditional disaggregate measures while not embracing traditional aggregate measures as identified in the literature.

  This allowed the research to proceed to the development of the laboratory instrument.

- The development of a semantically based shop floor simulation model was found to be quite feasible.

  This provided the basis for the development of the simulation model and the relational database.

- The values of conventionally derived measures and those from a disaggregate dataset were very comparable.

  This provided a "proof" of concept in that the non-conventionally derived values were essentially equal to those derived in the conventional manner.

- Both aggregate and disaggregate measures provided an advantage in shop floor condition identification, depending on the condition. In some instances, neither provided an advantage.

  This finding directly addressed Hypothesis #1 in that it allowed comparison of the utility of the two types of measures.

- For participants using disaggregate information, the measures judged most useful differed greatly between those who made correct and incorrect identifications; for users of aggregate measures, there was no such difference.

This finding pointed out an interesting result in terms of how the two information type groups interpreted the measures.

- In general, users of disaggregate information judged the information more sufficient and adequate to make the identifications.

  This goes to the heart of Hypothesis #1, in that it provides justification for the theoretical position that disaggregate information and measures are superior.

5.5 Discussion of Results

The results of the limited experts' survey of performance measures' utility were already adequately discussed in section 5.2, along with the presentation of the results. For this reason, the following sections will begin discussing the remaining key findings, as listed above.

5.5.1 Development of a Semantically Based Simulation Model

The development of the semantic data model of the shop floor was relatively straightforward. Resources, Events and Agents on the affected portion of the shop floor were identified, however, they were not modeled as an REA model, *per se* (McCarthy, 1982). Since the ultimate goal of this exercise was to provide a template for the generation of shop floor data, only those entities that were relevant to this were included. Thus, although most events in the model have an accompanying agent and resource, there is not a clearly defined "inside" and "outside" agent nor is there a strictly defined incremented and decremented resource for each event, as McCarthy (1982) specified. However, the model developed does capture the entities and relationships important to day to day shop operation and did provide an excellent basis for developing the relational database.

Within the data model, several generalization hierarchies (Smith and Smith, 1977) were established, which helped to further define the model. This turned out to be very important since there were several entities with multiple types that, without any generalization, could not be adequately modeled. These entities were JOBS, MULTI-JOB ORDERS and EMPLOYEES.

The development of the data model readily allowed the design of the relational database. The various types of the generalizations constituted separate tables, as customary. Concatenated keys were required for some entities, such as OPERATION and JOB-WC (Job#-WC#). In order to allow repeat visits to each work center, these entit es required a triple concatenated key within the data model, adding Sequence# (Seq#). However, once the data were transferred to the database and the actual compilation and querying of data began, it was discovered that one more key was required-- that of the simulation model run number. Since the database stored data from all separate runs of the model (i.e., the different conditions inserted to the model), a distinction had to be made for the different datasets. For this reason, an additional entity, RUN, was established in the database and its primary key, Run#, became part of the key of the three main entities of the model-- JOB, OPERATION and JOB-WC. An additional entity (DAYS) and relationship (DAYS-WC) were also required to allow for the daily aggregating of certain shop floor data. While DAYS-WC could have been considered part of the conceptual model, doing so would imply some prespecification (i.e., daily) of what measures and information were desired. However, since the data were not actually preaggregated in the database, but only "flagged" with certain attributes, specifically Day#, the events-based model (McCarthy, 1979) was not actually violated. Moreover, if an overriding managerial concern is with daily summaries and reports, as may well be, then including DAYS and DAYS-WC may be appropriate. RUN, on the other hand, is strictly an artifact of the experimental design and does not belong in the data model. Thus this research showed some very interesting implementation issues when such a data model and database were actually used to store and present historical operational information. Such additions were not required in the conceptual model and did not become necessary until actual implementation, of which this research is one of the first in this field.

5.5.2 Derivation of Measurements and Information

Proposition #1 looked at comparing the difference in the measures that were derived conventionally, that is with the simulation software's built in functions, and those that were materialized from the disaggregated dataset. To do this, the two different values of Time in System (TSYS), Mean Lateness (LATE) and Mean Tardiness (TARDY) were compared. Since only one model run for each condition was made, it was not possible to statistically test the differences. However, this one run also dictated that the measures would be derived from the same dataset, thus it was expected that the results would match very closely.

The disaggregated measures were derived from the entire dataset as generated by the relational database. To obtain mean TSYS at time = 1400 hours, for example, the records between 700 hours and 1400 hours were averaged to determine the mean time an exiting job had been in the system. The aggregate measures, on the other hand, consisted of a rolling average of jobs exiting between 700 and 1400 hours. This value was calculated by the simulation software and posted at 1400 hours. Thus, the two values should have matched very closely since they were calculated from the same jobs. In fact, the discrepancy between the two methods is very small, less than 0.4% in most instances. Thus, even without formal statistical testing, it is very reasonable to conclude that deriving traditional shop floor measures in an unconventional manner (from disaggregate data) yields nearly identical results to more conventional derivation.

5.5.3 Participants' Identification of Shop Floor Conditions ($H_{0\text{-}1}$)

Information Type interacted significantly with two performance measures, Gap and Time, indicating that the type of information did have a significant effect on the participants' accuracy and efficiency of condition identification. Subsequent analysis for each separate condition revealed that for the dispatch rule (DR), the participants who had the traditional aggregate measures performed more accurately and more quickly than did those with the disaggregate measures, that is, their mean Gap and Time values were lower.

However, in identifying the moving bottleneck (MB), those with the disaggregate measures performed significantly more accurately (lower Gap).

These results provide partial support for Hypothesis #1 in that access to the disaggregate measures improved the identification of shop floor problems and conditions. In the case of a moving bottleneck the disaggregate-based measures provided an advantage in identification. It should be noted that this is the one condition that is not static, or set, at the beginning of the model's run. With a moving bottleneck, the available capacity is varied from work center to work center throughout the run of the model. Thus, the queue lengths vary considerably over time. The other conditions– dispatch rule choice (DR), irregular order release (IR), due date assignment method (DD) and stationary bottleneck (SB)– consist of implementing a governing condition at the outset of the simulation run and not varying it. Thus, aggregate measures may be sufficient to identify relatively static conditions, or at least, disaggregate measures do not provide an advantage. However, when the shop floor is experiencing a condition such as the moving bottleneck, in which conditions are quite dynamic and changing with some frequency over time, disaggregate measures could provide an edge in problem identification.

The one exception is the identification of the dispatch rule (DR). In this experiment, the participants were asked to identify when the dispatch rule changed from First Come First Served (FCFS), which was the base case, to Shortest Process Time (SPT), which was introduced into the model. The identification of SPT with the aggregate measures raises some interesting issues. SPT is typically known to both decrease the mean and increase the variance of time in system (TSYS) (Blackstone *et. al.*, 1982). Given this fact, it may be more identifiable than other conditions since users may tend to focus in on the mean and standard deviation of TSYS, both of which were presented to the aggregate information group with relatively unambiguous point measures. This was substantiated by the fact that the correct identifies overwhelmingly used and ranked TSYS as the most useful measure. On the other hand, the disaggregate group was presented with, among others, a graph of the Distribution of Time in System. Comparing two distributional graphs to ascertain the differences in their means and standard deviations may be somewhat more cumbersome than simply comparing point values. Thus it is possible that the disaggregate group was not as well equipped to deal with a condition such as the dispatch rule changing to SPT.

The results of DR's and MB's Gap measures, as discussed above, are consistent with the results of a Chi square analysis done of the distribution of correct and incorrect answers. The Chi square test indicated that the two groups, for these two conditions, had significantly differently distributed right and wrong answers. Thus the significantly different means are likely due simply to more correct answers in one group versus the other. This provides further substantiation that using the aggregate measures for DR and the disaggregate measures for MB led participants to more often correctly identify the underlying condition.

In addition to allowing more accurate identification of DR, participants using the aggregate measures identified the condition significantly more quickly than those using the disaggregate measures. Perhaps, as discussed previously, it is due to the substantially lower volume and simpler nature of the information presented.

This finding lends additional weight to the uniqueness of the SPT dispatch rule as a shop floor condition. Not only is it one of only two conditions for which the type of information makes a significant difference in identification (and the only "static" one), but it is also the only condition for which the type of information makes a significant difference in the *time* to identify. SPT, therefore, appears to have some unique properties that make it worthy of further research.

5.5.3.1 Covariates

In addition to the differences discussed above, there were several cases in which one or more of the covariates were significant ($\alpha = 0.10$). Figure 45 summarizes those covariates that had a significant effect.

Repeated Measures		
Measure	Between Subjects	Within Subjects
Gap		Gap x Age
Time	School GPA	Time x School
Confidence		Conf x School Conf x GPA Conf x MfrExp

Separate ANCOVAs		
Condition	Performance Measure	Significant Covariate
DR		
DD	Time	GPA
	Time	Age
IR	Gap	School
	Gap	Age
	Gap	MfrExp
SB	Time	GPA
	Time	School
	Time	Type x School
	Conf	Type x School
	Conf	Age
MB	Gap*	GPA
	Time	MfrExp
	Conf	Type x School
	Conf	Age

Figure 45: Significant ($\alpha = 0.10$) Covariates

Under the repeated measures analysis for Gap, a significant interaction between Gap and Age is noteworthy. Recall that Gap x Type was significant, leading to further analysis to determine which condition led to such difference. Referring to the analysis of the demographics in figure 30, one can see that the ages of the two information type groups were significantly different. This raises an additional issue, specifically the effect of a person's age on his or her performance. Exploration of this idea is reserved for future research.

Similarly, the significant interaction between Time and School indicates that the school the participants attended (MSU versus LSSU) may have influenced the speed at which they completed the assigned tasks.

In the separate ANCOVAs, note that for MB, GPA is a significant covariate for Gap. Apparently, this is the only condition for which a significant covariate may have affected the performance measures sufficiently to cause a significant difference. In all other cases, significant covariates were apparently insufficient to cause differences in performance. Given the nature of the ANCOVA, it is not possible to observe if the covariates had a positive or negative effect on the performance measure. Such topics are outside the scope of the original research questions and thus are left to future research.

5.5.4 Participants' Judgement of Measures' Usefulness

As indicated in the presentation section and Appendix A, there is a great deal of data associated with this portion of the research. The purpose of including these questions in the instrument was to record the users' judgement as to which measures were more useful in identifying the shop floor conditions. Of interest was if the users' feelings matched the *a priori* expectations in terms of the most commonly used measures for those who correctly *and* incorrectly identified the conditions.

A number of consistencies with expectations were discovered. All correct respondents in the disaggregate and the aggregate group chose measures consistent with expectations in four out of five conditions, the exception always being IR, for which there were no expectations.

There was another very interesting finding as shown in figure 42, namely that in the aggregate group, in four out of five conditions, those respondents who answered correctly and those who answered incorrectly ranked the same measures as most useful. However, in the disaggregate group, those respondents who answered correctly ranked as the most useful very different measures than did the respondents who answered incorrectly. Thus, regardless of the correctness or accuracy of identification (Gap score), all users of aggregate information tended to rely on the same measures. This was not the case, however, with the disaggregate information group where the measures judged most useful were different, depending on the accuracy of identification.

What this analysis has revealed is that the process of interpreting the performance measures may differ for the two different information types. As shown in figure 46, the experimental design attempted to control for various inputs to the participant's interpretation process, however it did not explicitly monitor or control the process itself.

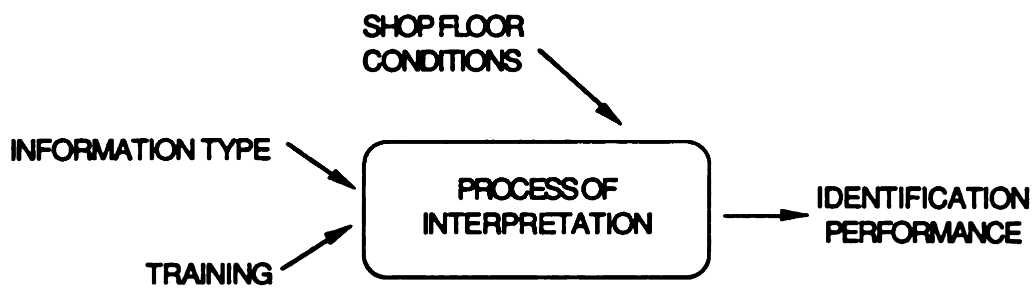

Figure 46: Mapping of Experimental Design

With disaggregate measures, it appears that the users can more correctly identify the best measures or information to use. With the aggregate measures, it may not be as easy to do so, perhaps due to its high degree of compression and aggregation. Aggregate measures do not appear to speak as clearly to information users as do disaggregate measures. This result indicates a potential systemic problem when using aggregate measures for shop floor performance evaluation and is a rich area for future research, as will be discussed in chapter 6.

5.5.5 Clarity of Information Presented

There were three questions in this portion of the research that had significantly different mean responses between the two information type groups. What is important about this finding is that all three questions dealt with the usefulness of the information presented. Question #3 ("Information was insufficient to answer the questions") addressed the sufficiency of the information presented. It was found that the disaggregate group felt more strongly that the information was sufficient, which can be considered as a key element of usefulness.

The analysis for question #5 ("Information was concise and adequate to answer the questions") revealed that the disaggregate group agreed more strongly that the information was concise and adequate to answer the questions. This was contrary to expectations in that it was anticipated that the aggregate group would rate their information as more concise since it consisted of merely point estimates, such as means and standard deviations. However, this result may point to a potential problem with question #5, rather than simply an interesting finding. Including both "concise" and "adequate" in the question may have led to confusion as these two words may be construed as being mutually exclusive. "Adequate" normally is thought of as "enough" whereas "concise" normally refers to "brevity." It is possible that participants were focusing more on the word "adequate" rather than "concise." Such an interpretation would be consistent with the expectation that disaggregated information is more adequate or more capable of allowing correct identification. Had the question included only the word "concise," users of aggregate measures may have agreed significantly more strongly with it.

The analysis for question #7 ("Information made the changes in conditions understandable") revealed perhaps the most encouraging result of all, that the disaggregate group agreed more strongly that their information allowed them to understand the changes made in the shop floor environment. Thus, on the dimension that perhaps most directly affected the ability of the participants to identify the shop floor conditions– their understanding of them– the disaggregate information was seen as significantly superior. This result was expected and supports the underlying theoretical assertion of this research.

Lastly, the results for question #8 (Presentation of data in graphical/tabular [*disaggregate group/aggregate group*] format made it difficult to use) bear further examination and discussion. The means for the two groups are not signficantly different and, by inspection, are both approximately equal to 5.5. Since 4 is the midpoint of the scale, this indicates a similar level of slight disagreement that the presentation of data made it difficult to use. The disaggregate information group had exclusively graphical data, while the aggregate information group had exclusively tabular data. Despite the substantial differences in style, both groups had roughly the same feelings for the way in which the data were presented. Strong advocates of either style would not find much solace in these results. It appears that users of information make do with what they are given and do not complain very much.

5.6 Possible Confounding Factors

Although an attempt was made to eliminate or control for posssible confounding factors in this research, some were inevitably present that warrant some attention and discussion.

5.6.1 Sample Size

There were only 53 participants in the lab experiment portion of this research. This was due to the time constraints of the research and to the limited pool of qualified volunteers. While the repeated measures ANCOVA lent more power to this sample size (approximately 120 records for each analysis), the overall sample size is still somewhat limited, particularly for the individual conditions' ANCOVAs. While in this case, it was not feasible to increase the sample size, future research in this field should strive to do so, to more definitively establish whether certain effects are significant, as argued in Cascio and Zedeck (1983).

5.6.2 Learning Effect

All participants were exposed to the same training scenario prior to undertaking the identification tasks, although the scenarios were different for each information type group, to account for the differences in the data presented.

To equalize the learning effect among the participants, all were given ample opportunity to study example tasks and to work on one as a group and then individually, with input from the researcher. Thus all participants had the same preparation prior to the identification task although, granted, some participants were more capable and/or more experienced than others. However, every attempt was made to bring all participants to the same level of understanding prior to the task.

An alternate approach, and one that might be considered by future researchers, would be to incorporate this exercise into a regular OM class during which the participants would be trained in the shop floor environment and problems. Thus their learning would take place more slowly and consistently over a longer period of time. More discussion would be allowed and participants would have the opportunity to receive more feedback on similar tasks prior to the actual experiment. Such an experimental design may well reduce the effects of unequal learning and produce participants who are more equally and adequately trained for the task.

5.6.3 Use of Student Participants

The participants in this research were all students, predominantly in graduate business programs, whose experience in manufacturing varied. It has been argued by Locke (1986) that such subjects are appropriate for this type of research and that the results can be generalized to the workplace, provided the task being performed is similar to what might be done in a real world setting. What is important to note is that laboratory experiments such as this are to test theory and to establish not necessarily what *will* happen outside of the lab, but rather what *may* happen (Berkowitz and Donnerstein, 1982; Mook, 1983).

Although the laboratory setting in the research was somewhat artificial, namely, it may not have resembled actual working conditions, it has been argued that such artificiality may not be a serious flaw of laboratory experimentation (Fromkin and Streufert, 1976). Most differences between the laboratory and the real world, including the predominant use of student subjects, have not been found to be a serious indictment of lab work (Locke, 1986).

However, even though the literature generally supports the use of laboratory research as a proxy for actual business settings and maintains its generalizability, the use of relatively inexperienced students (with an average manufacturing experience of 0.80 years) is still a possible confounding factor in this research and one that bears further examination in the future. Given the nature of laboratory experimental design, this potential problem may never be completely resolved.

5.6.4 Fatigue Effects

One concern in a laboratory setting is that the sessions may become too long and arduous, with the result being that participants' performance suffers. While this factor was not measured or controlled for in this research, it was felt that the nature and length of the sessions precluded this being a major factor. All sessions were limited to approximately 2.5 hours and participants were given the opportunity to take breaks during the training and task sessions. Food and refreshments were also provided in an attempt to make the sessions more comfortable. Moreover, the completely voluntary nature of the experiment allowed participants to essentially come and go as they pleased, should the session become uncomfortable.

Admittedly, this was not a factor that was actively monitored during the experiment. However, given the overall length of the sessions and the apparent willingness of the participants to complete each task, fatigue effects did not appear to be a major factor.

5.6.5 Motivation

Since this research was voluntary, some consideration was given to motivation so that all participants would try their best at the tasks. As outlined in chapter 4, several things were done to help assure a motivated group of participants. For recruits from one class, the professor offered to give some additional class participation points for those volunteering for the experiment. In addition, all recruits were told of four prizes that could be won by participating (a new bicycle and cash prizes). Although all participants had a chance to win the prizes, they were informed that those who performed better had a higher probability of winning.

So while the participants were not as motivated as they might have been in an actual work setting, whenever possible they were provided with incentives to participate and to perform to the best of their ability.

5.7 Results Discussion Summary

The results of the work blending a semantic data model with a discrete events simulation model were encouraging. It was found that by first developing a complete data model, it was possible to identify clearly which entities and relationships were important to data collection and their corresponding critical attributes. With this done, it was much easier to design the simulation model so that the proper data could be captured. This sequential approach is recommended for any future work in this area. Incorporating a data model and its corresponding data tables into a simulation model did require that more memory be allocated within the PC during the model runs, but such allocation requirements are well within the capability of PCs on the market today.

Once the data and simulation models were built and run and data were generated, materializing the required information and measures was done readily. While materializing the measures for use, it was found that several additional entities and relationships were needed that were not in the original data model. While not needed from a conceptual standpoint, they were necessary to allow the proper organization of data in the implemented database. Thus despite attempts to prespecify the conceptual data model as much as possible, there were some refinements in the actual implementation stage.

In terms of the key research question- does the type of information presented make a difference in identifying shop floor conditions?- the answer was found to be "sometimes." For one condition, the dispatch rule, aggregate measures actually improved the accuracy of identification, while for another condition, the moving bottleneck, the disaggregate measures were more useful. With this result, it was concluded that perhaps disaggregate data is more helpful for those conditions that are more dynamic and less stable. For those conditions that employ a more static operational rule, with the exception of the dispatch rule in this case (SPT), information type does not appear to make a difference in identification.

The results dealing with the users' perceptions of the measures' usefulness conformed to *a priori* expectations quite consistently, for the most part. That is, the participants' feelings as to which measures were most useful for which conditions were close to what was anticipated. This is heartening in that it implies that information users, some of whom were quite inexperienced, gravitated towards the same measures for the identification of conditions as did more experienced users. In addition to these findings, it was found that users of aggregate information tended to use the same measures, regardless of whether they correctly or incorrectly identified the conditions.

Finally, in evaluating what participants thought of the actual information presented (i.e., the measures), there were some significant differences between the two groups, all of which pointed towards the disaggregate measures being more useful in identification. On dimensions such as sufficiency, adequacy and aiding in understanding shop floor conditions, participants ranked the disaggregate-based measures more highly. Despite this, however, there was no difference between the two groups in their opinion as to the ease of use of the information. Both groups agreed, although slightly, that the information was relatively easy to use.

Figure 47 summarizes the overall results according to research question and hypothesis/proposition and shows expected and actual results.

Research Question Hypothesis/Proposition	Expected Results	Actual Results
RQ#1 Viability of events based model within simulation environment?		
PRP-1 Means of aggregate and disaggregate measures equal.	Support for null.	Essentially equal (error < 1%) for all conditions.
PRP-2 Experts' measures can be derived from events based model.	Support for proposition.	Measures similar to experts' preferences were derivable from database.
RQ#2 Can a database of disaggregate data generate measures that are more useful in identifying operational conditions on shop floor?		
H_{0-1} Use of different types of measures results in different performance.	Rejection of null; Disaggregate data to yield improved performance.	Superior performance for disaggregate measures with most dynamic condition (MB): reject null. Aggregate measures superior for DR (SPT): reject null. Other conditions no difference.

Figure 47: Expected and Actual Results Summary

6.0 Conclusions and Future Directions

6.1 Chapter Overview

This chapter summarizes the findings of this research and suggests some areas for future research. First, the research problem is restated as is the general research methodology. Major findings are then listed and discussed. Next, new research questions are presented to address the unresolved paradoxes identified in this h mo. The chapter closes with a summary of the findings of this research.

As first presented in Chapter 1, this research addressed the problem of the inadequacy of conventional mean and aggregate reporting measures in fully describing shop floor performance. The level of detail required to properly document and assess shop floor operations is too substantial to be adequately described by such measures. This research proposed a method by which more detailed and disaggregated data on shop floor operations could be utilized in performance evaluation. A combination of shop floor simulation and database modeling was used to generate various performance measures that were then evaluated by users in a controlled laboratory setting. The success of the users in describing the shop floor's operation was evaluated based on the type of measures they used.

The following list summarizes the more important overall areas and findings of this research.

- The use of semantic data modeling in conjunction with simulation modeling was found to be useful.
- The type of information presented to users (aggregate versus disaggregate) proved to be a significant factor in identifying shop floor problems in some instances.
- Disaggregate data was found to be more understandable and more useful than aggregate measures on several dimensions.

- The process by which users interpreted the performance measures appeared to be influenced by the type of measures used.

6.2 Semantic Data Modeling with Simulation Models

The portion of this research dealing with the development and use of a semantic data model in conjunction with a simulation model yielded results that conformed to expectations. The research demonstrated that such a data modeling approach could be used prior to developing a simulation model and that such an approach may be of use even with a traditional simulation model. The exercise of identifying all relevant entities (Resources, Events, Agents- McCarthy, 1982) helped to better define the final simulation model. One issue fairly specific to data modeling, generalizations of entity types (Smith and Smith, 1977), was handled quite readily in the model once separate and generalized entities were established. This was a further indication of the two approaches' ability to coexist.

The simulation model in this research was patterned after a support tool room for a major automobile manufacturer. As a result, it not only consisted of various work centers and different types of jobs and operational rules, but it also generated a great deal of disaggregated operational data. As different conditions were introduced into the model, different datasets were generated. The use of a relational database as a repository for all this historical operational data was effective as a means of allowing the materialization of different performance measures for managerial review. This substantiates the theoretical work of Roberts (1991), who suggested that the relational database could be used for this purpose.

While it was possible to materialize most measures completely within the database, it was found that it was sometimes much easier with a spreadsheet, due to its unique data manipulation abilities. This was particularly the case when the measures to be created relied on information from only one entity or relation within the database. However, when the measures required data from more than one entity, it was necessary to perform the materialization within the database. Thus the usefulness and necessity of the database as a vehicle for materializing information seems to increase with more complex inter-entity queries. As management's need for information becomes more demanding, thest dynamic database may well evolve into the primary source of information and reports.

6.3 Condition Identification

When considering the relative usefulness of aggregate and disaggregate information, it was found that in four out of five cases, disaggregate information was either as effective or more effective in identifying shop floor problems. In only one case did aggregate measures provide an advantage in identification. And, despite the greater amount of data, disaggregate information, in four out of five cases, did not cause the participants to take significantly more time for problem identification. Additionally, participants who received the disaggregate data believed that they had sufficient information to make the identification, while the participants with the aggregate data generally wanted more information.

The only case in which the aggregate group performed better (both more accurately and more quickly) was in identifying a change from the FCFS dispatch rule in the base case to SPT. SPT has already been identified as unique among the dispatch rules in that it normally results in the lowest mean but highest variance of throughput time. It is a strong performer on other measures as well (Blackstone, *et. al.*, 1982). As a result, SPT may be more identifiable with only mean and aggregate measures, particularly time in system. For this reason, one should be leery of dismissing disaggregate information's usefulness for all dispatch rule identification and reserve judgement for future research.

The disaggregate information was most helpful in the identification of the moving bottleneck (MB) which was also the most dynamic and least stationary of all the conditions. The moving bottleneck is indicative of continuously changing resource constraints that resulted in continuously changing queue lengths. Thus it may be that disaggregate information has its greatest use when shop floor resources are in flux and when the rules of operation are changing during the course of operation- a very likely scenario in the real world.

6.4 Usefulness and Clarity of Measures

Expectations regarding the usefulness and clarity of the various measures were borne out with some consistency. For every condition and for both information types, participants judged as most useful the expected measure at least 75% of the time. Participants who used aggregate information perceived the same measures as the most useful regardless of whether or not they correctly identified the conditions. This was not the case, however, with the disaggregate group. Participants who incorrectly identified the conditions preferred different (incorrect) measures whereas participants who correctly identified the condition preferred the correct measures. Participants in both groups who correctly identified the conditions ranked the expected measures as most useful.

There appears to be a difference in the way the participants of the two different groups interpreted the measures. Aggregate measures appeared to confuse the users so that they tended to use the same measures, whether or not they answered correctly. While it was expected that those using aggregate measures who answered incorrectly would do so because they used the wrong measures, it was found that they used the same measures as did those who answered correctly, and those were the measures that were expected to lead to the correct identification. This apparent misinterpretation leads to some interesting future research directions, as discussed in the following sections.

It was also discovered that the participants judged the disaggregate information as superior on three dimensions- sufficiency, adequacy and understandability. The most important of these three dimensions, in light of the research questions, is that of understandability; that is, the participants believed that the disaggregate information was significantly more effective in making the shop floor conditions more understandable. This is an extremely important result of this research in that it addresses the key issue of *condition identification through understanding*. One goal in presenting the two different types of information was to test which type was seen as more useful for identifying conditions and problems. Thus, while the actual results of the identification exercise were mixed, there was no such ambiguity on the part of the participants in labeling the most useful information.

6.5 Future Research

While this research addressed many issues and resulted in some interesting findings, it also raised some compelling questions that could not be addressed by the existing research design. Therefore, several extensions to this research, as discussed below, are being proposed that will address these new issues and questions.

6.5.1 Managers' Perception of Measures' Usefulness

The first phase of this research consisted of interviewing and surveying two shop floor experts to receive their feedback on the relative usefulness of various performance measures. Although there were no specific research questions or hypotheses for this phase, in keeping with the basic theoretical assertion of this research (section 3.2.2), it was expected that disaggregate information would be preferred by the experts. The results of the survey, however, were very mixed, with the experts divided on the usefulness of a number of measures, both aggregate and disaggregate. There are several possible explanations for this, among them being that it was due to the limited sample size, that it was a function of the orientation or background of the experts themselves or was a function of the nature of the organizations in which they work. The precise factors responsible for the discrepancy in the responses were not identified in this research. To better address these uncertainties, in addition to incorporating a larger sample size, the following research questions are proposed for future work.

- Is the preference for disaggregate or aggregate measures a function of the users' managerial level or their functional area within the enterprise?
- Is the preference for disaggregate or aggregate measures a function of the type of company in which they are used, or the stage of development of the company?
- Is the preference for disaggregate or aggregate measures a function of the uses to which the information is put- descriptive, explanatory or predictive?

These questions can help further define users' preferences for certain measure types. The first question addresses specific work-related characteristics of users and whether they influence their preference for disaggregate or aggregate measures. With the exception of years of manufacturing related experience, these were not evaluated in this research. The second question explores whether the differences are due to characteristics of the company at which the information is being used. This could include the type manufacturing company (job shop, repetitive assembly, continuous flow) or if it is a service company. It could also address the effect of the company's development or maturity on the managers' information preferences. The third question explores the issue of depth. How much is being asked of the information? Managers who require only relatively simple descriptive statistics regarding their shop floor operations may have different preferences or alternate information sources than those who rely on performance measures to explain unusual behavior or to provide a model for predicting when such behavior is likely to recur.

To adequately address the proposed questions and to provide sufficient statistical power to any future analysis, it is recommended that the survey be distributed to a much wider sample. Expanding the survey would likely involve reducing the complexity of the instrument to avoid the necessity for interviewing. This approach may lead to the loss of some insights that were obtained with a smaller group of respondents, but could allow the researcher to more definitively conclude which measures are deemed more useful, by whom and for what reason.

A previous survey/interview conducted by McKinnon and Bruns (1992) involved contacting numerous manufacturing managers to determine what information was deemed useful. The insights generated by this research were considerable in that it was one of the first instances in which a large sample of manufacturing executives were interviewed regarding the usefulness of specific information. A similar effort is proposed here, but one that would focus on the relative usefulness of two very distinct types of information, aggregate and disaggregate measures. Thus it would expand upon McKinnon and Bruns' work on information's usefulness, but would deal with the very specific information types discussed in this research and provide additional support (or lack of support) for the use of aggregate or disaggregate measures.

6.5.2 Non Stationary Conditions

The condition that was identified more readily with disaggregate information, the moving bottleneck (MB), has already been characterized as being the most dynamic or non stationary of all the conditions introduced to the shop floor. Conditions other than the MB were more stationary and were linked to specific planning procedures (dispatch rule, due date assignment rule) where rules and resources were fixed at the outset of operations and not allowed to vary. The MB, on the other hand, as a non stationary condition, represents a problem for which the symptom is changing over time. Thus, while the simulation model in this research created an artificial MB by sequentially varying machine resources, the result was a set of disaggregate measures similar to those that might be observed when other non stationary conditions are present. The question that is raised by this finding is whether disaggregate measures consistently provide an advantage in identifying other non stationary conditions.

Problems that lead to non stationary behavior might include those that do not deal with specific resource or planning rules, such as varying product mix on the shop floor, changing scheduling or dispatching rules, certain order release rules or varying personnel and equipment resources. The potential presence of these non stationary conditions leads to the following questions:

- What other shop floor conditions may contribute to or create non stationary behavior on the shop floor?
- To what extent are non stationary conditions more readily identified with disaggregate measures?

The first question addresses the issue of what leads to non stationary behavior on the shop floor. Addressing this question can provide researchers with a framework for identifying those conditions for which disaggregate measures may provide an advantage in identification. The second question addresses the issue directly raised- do disaggregate measures provide an advantage in identifying other non stationary conditions? Exploring this issue may reveal if the results of this research are generalizable to other conditions.

In addition to MB, other non stationary conditions may include dynamic order release rules that use shop floor congestion and loading information in their release mechanism. Release rules similar to this have been explored in the past (Ragatz and Mabert, 1988; Melnyk and Ragatz, 1989). Another complex environment may involve the dynamic use of different dispatch rules, depending on the conditions on the shop floor. For example, the shop may start up using FCFS, but change to SPT or EDD as conditions change. These situations clearly represent environments in which the operational rules are changing during the course of operation.

The dynamic environment tested in this research, the moving bottleneck, involved constraining just the machine resource of the floor. However, employees may similarly be the constraint that leads to a moving bottleneck. Another possibility is the dynamic use of the tooling resource on the shop floor, extending the work of Melnyk, Ghosh and Ragatz (1989). Or, dynamic and complex employee transfer rules, simpler versions of which were evaluated by Trelevan (1987), could be implemented.

6.5.3 Dispatch Rules

Identifying the dispatch rule SPT was done more accurately and more quickly with aggregate information, contrary to expectations. However, the question remains, is this result unique to SPT, or would the same result hold true with other dispatch rules? SPT is one of the most local of all dispatch rules and uses only one dimension of job information- the imminent process time. Other dispatch rules use different dimensions of job information, such as due date (Earliest Due Date- EDD) or due date and process time (Minimum Slack- MinSlk). At this point it is not clear if other dispatch rules are equally more identifiable with aggregate measures or if such identification is a function of the type of dispatch rule chosen. To address these issues, the following future research questions are proposed:

- Does one type of measure (aggregate or disaggregate) provide a significant advantage in identifying dispatch rules from shop floor performance information?
- Do aggregate measures consistently result in superior SPT identification in all shop floor environments?

Repeating this research with different dispatch rules as conditions to be identified would help to determine if information type's effect on identification accuracy is dependent on the individual dispatch rule or, perhaps, on the type of information used by the dispatch rule. Specifically, the identification of dispatch rules using one dimension of job information (process time) could be compared with that of rules using a different dimension (due date). More complex rules, such as MinSlk, that use two dimensions of job information could also be evaluated. There is some support in this research for the conclusion that more complex and dynamic conditions are more readily identified with disaggregated based measures. Extending the research in this manner to evaluate more complex dispatch rules could further substantiate this conclusion.

Actual shop floor operations are likely to be quite complex. In fact, practitioners have commented in the past that OM research does not fully reflect the complexity of real world shops (Melnyk, Vickery & Carter, 1986; Schafer, 1997). Thus, as simulated shop floors increase in complexity, they may begin to better approximate their counterparts in the manufacturing world. As a result, the role of disaggregate information in simulation based research may well increase.

6.5.4 Users' Process of Interpreting Information

In the *post hoc* analysis it was found, somewhat unexpectedly, that the users of aggregate information tended to use the same measures, regardless of whether or not they correctly identified the appropriate condition, whereas those using disaggregate information used different measures depending on the correctness of their identification. Thus, it appears that the cognitive processes employed by the users to interpret the measures and information are different depending on the type of information presented. This is shown graphically in figure 48.

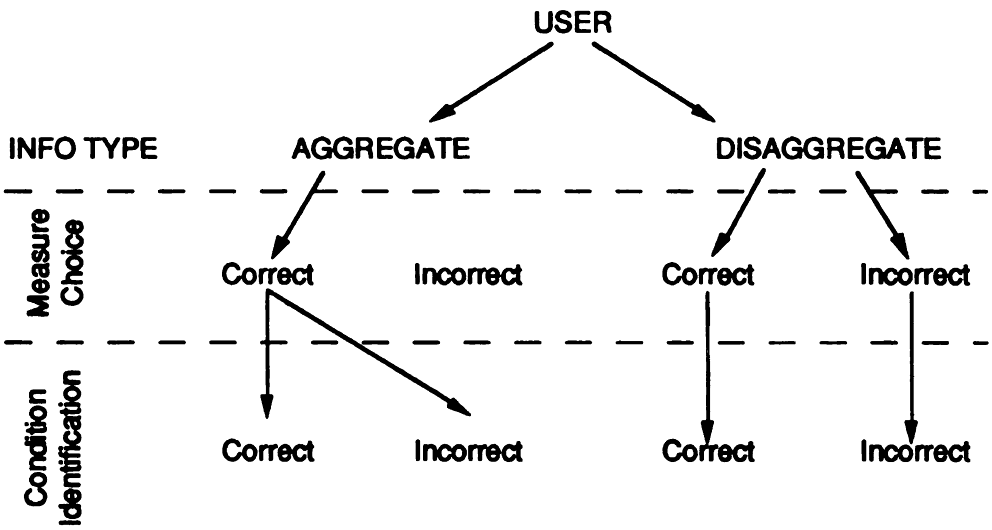

Figure 48: Interpretation Process Steps

As shown above, participants using aggregate measures tended to make only one choice for measures, which was the one that was expected of them for making the correct identification. However, once that choice was made, these participants made both correct and incorrect identifications. Users of disaggregate information, on the other hand, tended to make distinct choices as to which measures they would use, and from then went on to make the expected identification. Thus, the choice of measures was critical to their success in identifying the correct condition. These results indicate that the decision making process, both in choosing measures and in then identifying the condition, is different for the two groups. Since the laboratory experimental design only measured the actual outcomes (measures chosen and conditions identified), there is no indication of the actual decision making process. Thus, it is proposed that this issue be explored further to gain a better understanding of the process. To do this, the following research questions are proposed.

- How does the type of measures (disaggregate versus aggregate) influence the users' process of choosing and interpreting the measures to identify shop floor conditions?
- How does the type of condition introduced to the shop floor influence the users' process of choosing and interpreting measures to identify the condition?

These two questions begin to address the issue of the information users' processes of interpreting the measures while they attempt to identify the conditions. The first question examines the effect, if any, that the information type has on this process. It asks if the nature of the measures influences the way users think about them and use them. The second question is similar, but explores the influence the type of condition has on process. This question asks if the condition type (DR, DD, MB, etc.) influences the way users formulate their responses. Since this research utilized only a limited number of conditions, it is not known whether the apparent interpretation discrepancy is due to information type or condition type.

Both questions can be evaluated in a similar setting to that utilized in this research. It is suggested that similar lab experiments be conducted in the future, but with the following additions and refinements:

- Have the participants provide concurrent verbal protocols so that the underlying reasoning processes could be determined. The focus could be on how and why the choices were made and what the participants found useful and why.
- Include more process related questions into the questionnaire for all participants.

Summarizing the previous sections is figure 49, showing a listing of the possible future research topics related to this work.

Managers' perception of measures' usefulness
    Expand initial survey to include widespread audience
    Focus on differences among respondents and their companies

Identification of other dynamic conditions
    Complex order review and release rules
    Dynamically changing dispatch rules
    Employee or tool resource constraints
    Employee transfer rules

Identification of other dispatch rules
    Other single dimension rules (EDD)
    Multiple dimension rules (MinSlk)

Analysis Users' Interpretation Process
    Expand lab experiment format to include subsequent interviews
    Include use of Verbal Protocol Analysis in methodology
    Incorporate more process related questions into questionnaire

Figure 49: Summary of Possible Future Research Topics

6.6 Summary

This research makes a significant contribution to the understanding of the uses of aggregate and disaggregate information within a manufacturing environment. The combination of several different methodologies- survey, interviews, semantic data modeling, simulation modeling and laboratory experimentation- provides a unique approach to the study of the adequacy of information for managerial decision making. Through this work the relative benefits and shortcomings of traditional aggregate measures as well as those derived from a more disaggregate dataset were explored. The results of the research, while supporting the claims of usefulness of different information types, begin to answer some of the research questions. In addition, some very compelling future research issues were also identified: further examination of the design and use of relational databases for managing manufacturing performance information; the exploration of additional shop floor conditions as to their specific behavior; and an examination of the actual interpretation process information users go through when identifying shop floor conditions. The results obtained in this research are seen as a very encouraging beginning and it is hoped that they will aid shop floor managers and encourage others to further develop this line of research.

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APPENDIX A

Simulation Model Description

Shop Floor Conditions Description

Disaggregate Measures Materialization

Perceived Measure Usefulness Presentation/Discussion

SIMULATION MODEL DESCRIPTION (section 4.3.2.1)

A.1 Job Types

There are four primary types of jobs in the shop, each of which has its own characteristics in terms of size, interarrival times, routing and due date assignment. The job types are Projects, Walk-ins, Quick Response and Cribs.

Project Jobs: These jobs are part of large multi-job orders (10-180 jobs), which are introduced to the shop in relatively large batches of 10-60 jobs at a time. All jobs within a project are typically assigned one aggregate due date. While the shop historically has handled a relatively low proportion of project jobs in its total work load, this has been changing in recent years with the proportion of project jobs increasing. This proportion is a factor in this research, as will be discussed later.

Walk-in Jobs: These jobs enter the shop more continuously than projects, with their interarrival times varying by the day of the week and the particular shift. They consist of smaller work, usually only one job. The customer service clerk makes a determination upon each job's entry as to its status as a regular walk in or a quick response, which is discussed in the next paragraph. The jobs designated simply "walk in" are routed and scheduled normally.

Quick Response Jobs: Quick response jobs are walk in jobs that have been designated by the customer service clerk as emergency. They are expedited through the shop and have an overriding priority in a work center's queue.

Crib Jobs: These jobs are inventory replenishment items for other divisions of the company. They also enter the shop fairly continuously but only during day shift on weekdays and represent a relatively steady load on the shop. They are of a recurring nature and thus are familiar to the operators and schedulers and do not represent near the scheduling challenge as do the other types.

A.2 Job Routing

The routing for each job will vary by its job type and is determined by empirically derived tables. Approximately 500 historical job records were examined to determine the routing patterns of the various job types. It was found that the work center to which a job was likely to proceed was a function of its present work center. Thus, the shop experienced sequence dependent routing. This is captured within the model with probability look up tables. Figure 50 is a portion of such a routing table.

Work Center	1	2	3	4
3	0.000	0.000	0.312	0.408
4	0.250	0.250	0.318	0.318
5	0.000	0.450	0.517	0.623

Figure 50: Work Center Routing Look up Table

Routing of jobs in the model is accomplished in the following manner: The model generates a random number on the interval (0, 1), which is used to determine to which work center the job will be sent. For example, if the job is at work center #5 and the random number generated is 0.457, the next stop for the job will be at work center #3, since 0.517 is the first value in row 5 greater than or equal to 0.457, and is in column 3, as shown by the shaded cells in figure 56. Note that if a job is in work center #4, it has no probability at all of being routed to work center #2, since there is no difference in the cumulative values in columns 1 and 2 in row 4.

A.3 Process Times

The same 500 historical jobs that were reviewed to determine job routing were also analyzed to determine jobs' process times at the various work centers. It was found that process times were independent of job type, but were dependent on the work center. For example, all job types have the same distribution of process times at, say, the lathe. However, the distribution of process times at the boring mill will be different than at the lathe. This is captured within the model with an additional probability look up table. An example of such a table is shown in figure 51.

Work Center / Process Time (hours)	0.50	1.00	1.50	2.00
3	0.000	0.125	0.350	0.423
4	0.132	0.251	0.251	0.338
5	0.000	0.625	0.687	0.701

Figure 51: Process Time Look up Table

As with the routing table, the model generates a random value on (0, 1) and looks up a process time, depending on the work center. For example, if a job is scheduled to go to work center #4, and the generated random value is 0.321, the process time chosen will be 2.00 hours, since 0.338 is the first value in row 4 that is greater than or equal to 0.321, and is in the column labeled "2.00," as shown in the shaded cells in figure 51. Note that a job in work center #4 will never have a process time of 1.50 hours, since the value in that cell (0.251) is unchanged from that in the cell to its immediate left.

SHOP FLOOR CONDITIONS DESCRIPTION (section 4.3.2.3)

A.4 Bottleneck Resource

Both a stationary and moving bottleneck were conditions inserted into the model. In both cases, the actual constraint was simulated by a very limited number of machines in a particular work center. To establish a moving bottleneck, machine availability was deliberately scheduled such that various work centers had very limited capacity (1-2 machines versus 4-6) at varying sequential times. This caused the bottleneck to move throughput the shop.

A.5 Irregular order or job releases

During a previous empirical study of the subject shop (Marsh and Melnyk, 1994; 1995), it was determined that Project Jobs had order release rules that could be altered. These release mechanisms ranged from continuous individual releases to very disjointed and large batch (60+ jobs) releases. Therefore, in this research, the effect of such varying project job releases was studied. The actual practice of releasing large batches of jobs was modeled, as was a more continuous job release.

A.6 Due Date Assignment

The shop being modeled experienced a similar problem as has been reported in the literature (section 2.6.3)– that of one common due date versus individual due dates for jobs within one order. Project Jobs had traditionally been given one common due date, despite the fact that the actual dates the various jobs are needed can be quite different. In some cases, a project may have an overall due date six months in the future, but certain components are needed within a few weeks. Similarly, some components are not required for several months. However with a common due date method, all components are assigned the same due date– six months out. For this reason, and in conjunction with previous reported research (Cheng, 1988; 1989), it was determined that evaluating the differences in performance attributed to common versus individual job due date assignment was appropriate.

A.7 Different Job Types

Another experimental condition introduced into the model is the mix of job types, that is, how many of each job type there will be. It was found that for the actual shop studied, the percentage of job mix can be a crucial strategic, as well as operational factor. For example, taking on more large project work in lieu of emergency work shifts the shop away from being a service and cost center towards being its own profit center. But, due to the jobs' different nature, moving to such a job mix has operational ramifications for management as well. The strategic perspective of varying job mix is described in more detail in Marsh and Melnyk (1995). In this research, the mix is varied by adjusting the interarrival times for project and emergency (quick response) jobs.

A.8 Dispatch Rules

The final inserted condition is the choice of dispatch rule. Several different rules were used, each one constituting a different model run and resulting measurement or data set. The dispatch rules studied are First Come First Served (FCFS), Shortest Process Time (SPT) and Earliest Due Date (EDD). For this research, only FCFS and SPT were given to the laboratory participants.

DERIVATION/MATERIALIZATION OF DISAGGREGATE MEASURES (section 4.4.3)

A.9 Derivation of Time_out

Helix Express® is what is known as a non-SQL relational database, meaning it does not use the standard Structured Query Language (SQL) queries common among relational databases (Date, 1981). The queries used to derive Time_out and other values are not familiar SQL commands but rather are created with objects within the Helix database. Previous research has shown this to be effective in deriving other operational data from a disaggregate dataset (Marsh, 1996). Figure 52 shows the query used to derive Time_out within the JOBS relation. Note that it is obtaining its information from the OPERATIONS relation.

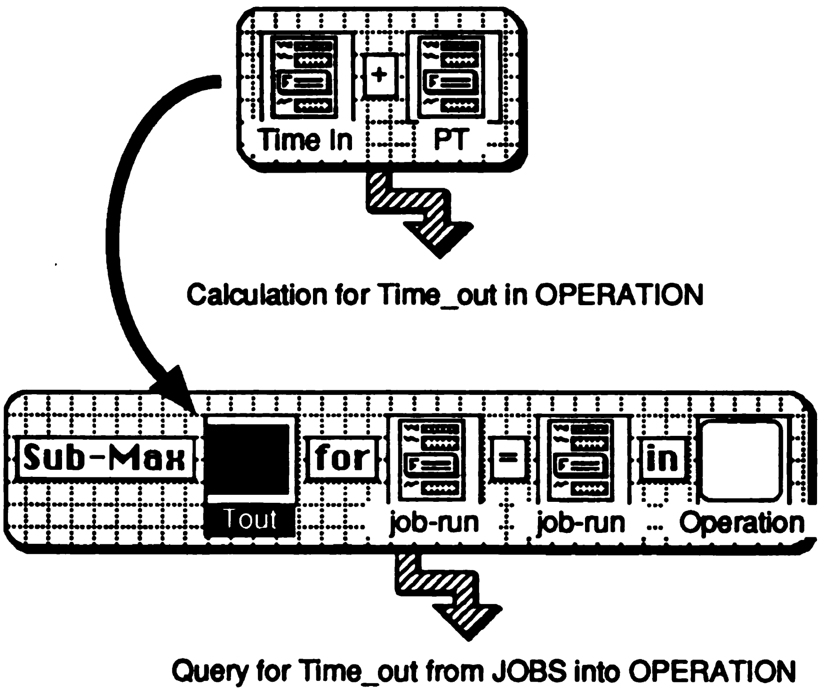


Figure 52: Job Completion Time (Time_out) Query/Calculation in Database

Time_out is being calculated in the OPERATION relation as shown, and is being queried by and extracted to the JOBS relation by the "Sub Max" procedure. This procedure searches the OPERATION relation for the maximum Time_out of each Job and returns it. Note that this procedure queries by Job-Run. This is because the actual database contains information from all seven runs of the model and the runs must be distinguished from each other in order to retrieve the correct value for the appropriate condition. A double, concatenated key is used for this since Job# by itself is no longer unique in the OPERATION table.

A.10 Derivation of Operational Measures

Within the Excel spreadsheet, the following measurement information was derived: Time in System (TSYS), Lateness- all jobs and project jobs (LATE), Tardiness (TARDY) and Due Date Allowance (DD Allow). To accomplish this and to present the data graphically, additional refinements were necessary. For instance, TSYS is the difference between a Job's entry and completion times. However, for those Jobs which were not yet completed as of the end of the simulation model's run, there would be no completion time (Time_out is a null value) and TSYS will be undefined. The same concept applies to LATE and TARDY– a completion time is needed to calculate each. To accomplish this, some relatively simple formulas were used within Excel, the flowchart logic of which are shown in figures 53 and 54.

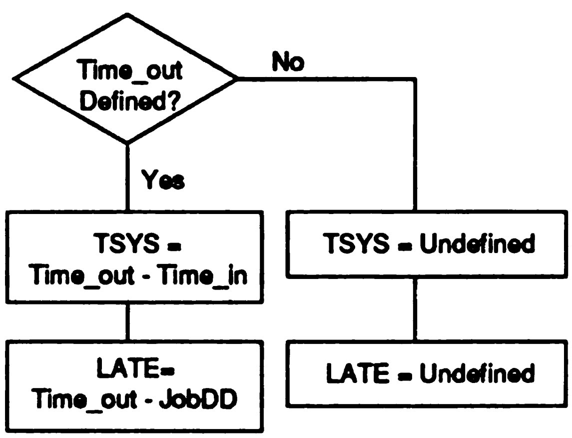


Figure 53: TSYS and LATE Calculations within Spreadsheet

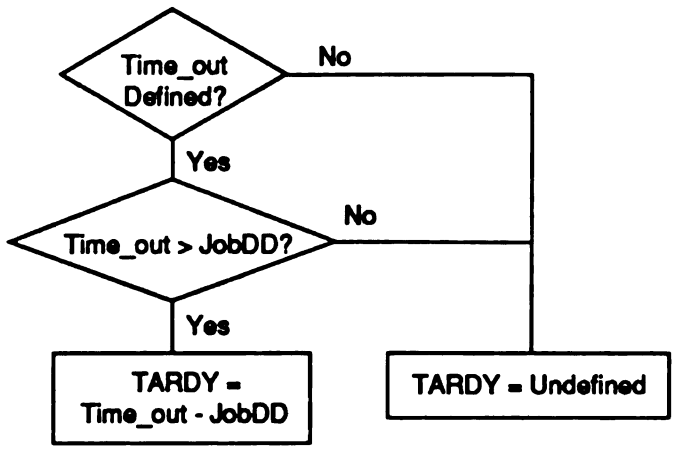


Figure 54: TARDY Calculation within Spreadsheet

The calculations shown in figures 53 and 54 are done quite simply within Excel. Note that TARDY has an additional conditional step, to determine if the the Job was indeed tardy, or behind schedule. If not, TARDY is undefined.

DD Allow is calculated with a simple non-conditional calculation as follows:

$$DD\ Allow = JobDD - Time\_in$$

While the simulation model does calculate a due date allowance when setting each Job's due date, only the date itself is captured and transferred to the database. Thus, the allowance has to be recalculated based on the entry time and the assigned due date.

In the spreadsheet, then, the following values make up the JOB worksheet:

Job#	Job Type	Job DD	Total PT	Time in	Time out	TSYS	LATE	TARDY	DD Allow

Excel's Histogram tool was then used to create the required distributional graphs. TSYS was calculated for all jobs as was LATE, TARDY and DD Allow. LATE was further compiled just for the Project jobs by sorting the worksheet based on Job Type (project job type = 1) and creating a histogram just for that type.

It is important to note that the calcuations for TSYS, LATE, TARDY and DD Allow could have readily been done within the relational database, with the completed values transferred to the spreadsheet. The decision was made to use Excel to derive the values simply for computational convenience. Since all the data needed for these values was completely within the JOBS relation and no "look ups" to other relations were necessary, they could be derived outside of the database. For demonstration purposes, however, figure 55 shows the calculation for TARDY as it would have been done within Helix.

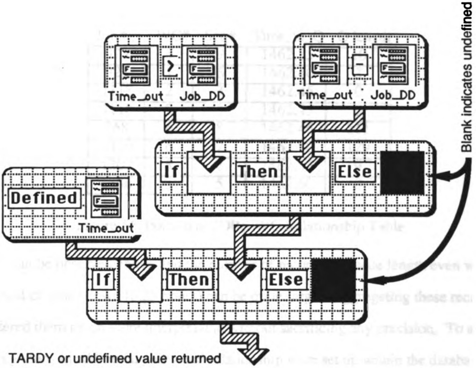


Figure 55: TARDY Calculation in Database

There were seven runs made of the model resulting in seven different worksheets in Excel for which the above calculations and graphs were made.

A.11 JOB-WC Relation Measures Materialization

Two additional measures/information sets were derived for presentation to the lab participants: Time Series of Queue Lengths and Jobs Processed per day. The data for these were taken from the JOB-WC relationship and the OPERATION entity, respectively.

Time Series of Queue Lengths presents the queue length data in average number of Jobs in the queue per day. That is, it plots daily average queue lengths versus the days of the model's run. Since the database is quite disaggregated and records queue lengths for each job, many of which may enter the queue (JOB-WC relation) in a given day, some initial aggregation was needed to derive daily average queue lengths. For example, figure 56 shows a portion of the data file from the JOB-WC relation, including queue length.

Job#	WC#	Seq#	Time_in_Q	Q length
973	5	9	1462.35	10
928	1	6	1462.40	3
1118	2	3	1462.45	0
1118	2	3	1462.45	0
768	6	8	1462.46	111
1410	6	2	1462.50	129
1202	5	2	1462.55	9
1336	3	5	1462.60	0

Figure 56: Portion of JOBS-WC Relationship Table

It can be observed above that the number of records of queue length even within the short period of time shown (0.25 hours) can be quite large. Aggregating these records per day rendered them much more interpretable without sacrificing any precision. To achieve this aggregation, an additional entity and relationship were set up within the database: DAYS and DAYS-WC. Each day within DAYS was the aggregation of 24 hours of run time. DAYS-WC is a relationship necessary to track the daily queue lengths *per work center* (WC). Figure 57 shows the query used to calculate average daily queue length per work center.

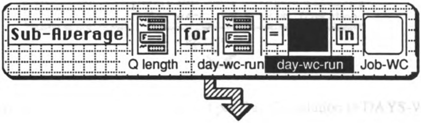


Figure 57: Daily Average Queue Length Calculation in DAYS-WC

Helix has a built in Average procedure that allows us to easily obtain the value required. Note that the query is by Day and WC into JOB-WC. Each record in JOB-WC is within a given day, thus this search criteria. And, as before, the records are further queried by the Run#, which indicates the storage of multiple runs within the database. The above procedure returns the daily average queue length by work center to DAYS-WC from where the records are transferred to the spreadsheet.

The other measure derived from the JOB-WC and OPERATION tables, Jobs Processed per day, is a distributional look at work center activity. It is a histogram of the number of jobs processed each day by the entire shop (all work centers). It tracks individual operations completed per day, but not necessarily completed jobs. That is, many jobs will have operations completed in a given day, but far fewer jobs will actually be completed in their entirety. For this measure, of interest is the number of operations completed daily. To determine this, DAYS and DAYS-WC can be used in the database. Figure 58 shows the calculation for this value.

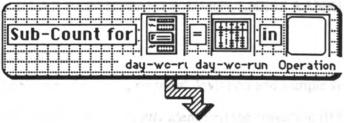


Figure 58: Number of Jobs Processed per Day Calculation in DAYS-WC

For this calculation, another of Helix's built in procedures was used: the Counting function. This procedure merely counts the number of records per day per work center in OPERATION.

The result of the above queries and calculations is the following text file in the JOB-WC relationship:

Day#	WC#	# of jobs	Q Length

Once this file is in Excel, the number of jobs per day is summed across all work centers. These values are then used to create a histogram of the distribution of work center activity. The queue lengths are put into a single time series graph showing the time varying lengths of all four work centers' queues.

EVALUATION OF LAB PARTICIPANTS' USEFULNESS RANKINGS (section 5.4.6)

A.12 Disaggregate Group

Figure 59 indicates the mean, standard deviation and sample size for each condition and measure for participants who *correctly* identified the condition (0 ≤ Gap ≤ 1) while using the disaggregate based measures. Shown in the final row is the total number of respondents who correctly identified each condition.

Measure / Condition	DR	DD	IR	SB	MB
Distribution of Time in System	2.19 (1.47) *16*	4.71 (1.18) *7*	2.33 (0.94) *3*	3.05 (1.74) *22*	3.11 (1.10) *18*
Distribution of Job Lateness	3.00 (1.25) *9*	2.40 (0.49) *15*	2.40 (1.36) *5*	3.18 (1.10) *17*	3.15 (1.17) *13*
Distribution of Project Job Lateness	2.67 (1.70) *9*	2.76 (0.73) *17*	2.50 (1.35) *6*	3.76 (1.11) *17*	3.43 (1.24) *14*
Distribution of Job Tardiness	3.63 (1.49) *8*	5.00 (1.49) *9*	3.75 (1.48) *4*	4.44 (1.06) *16*	4.50 (0.91) *14*
Distribution of Due Date Allowance	5.25 (2.17) *4*	1.00 (0.00) *19*	4.00 (1.22) *4*	5.30 (2.10) *10*	4.60 (2.15) *10*
Time Series of Queue Length	2.64 (1.44) *14*	5.67 (1.70) *6*	4.00 (2.00) *5*	1.38 (0.81) *24*	1.30 (0.71) *20*
Distribution of Job Process Activity	3.22 (1.31) *9*	6.00 (1.00) *6*	6.67 (0.47) *3*	3.75 (1.79) *16*	3.70 (2.19) *10*
TOTAL RESPONDENTS	**16**	**19**	**7**	**24**	**20**

Figure 59: Usefulness Rankings for Correct Identification Using Disaggregate Data-Mean, (Standard Deviation) and *Number Responding*

Figure 60 represents similar information as shown in figure 59 above, but summarizes the usefulness rankings by those participants using disaggregate data and who *incorrectly* identified the condition (wrong answers- Gap ≥ 2).

Measure / Condition	DR	DD	IR	SB	MB
Distribution of Time in System	2.44 (1.26) *9*	1.00 (0.00) *1*	3.09 (2.23) *11*	2.00 (1.00) *2*	3.50 (1.50) *4*
Distribution of Job Lateness	4.57 (1.05) *7*	2.00 (0.82) *3*	2.64 (1.72) *11*	2.50 (0.50) *2*	2.75 (1.48) *4*
Distribution of Project Job Lateness	4.50 (1.38) *6*	2.67 (1.25) *3*	3.09 (1.83) *11*	3.50 (2.50) *2*	3.00 (1.00) *4*
Distribution of Job Tardiness	3.88 (1.43) *8*	3.67 (1.25) *3*	3.56 (2.06) *9*	3.00 (1.00) *2*	4.00 (1.26) *5*
Distribution of Due Date Allowance	4.40 (2.42) *5*	1.80 (0.75) *5*	3.73 (1.66) *11*	5.00 (0.00) *2*	5.50 (1.50) *4*
Time Series of Queue Length	1.50 (0.81) *10*	7.00 (0.00) *1*	3.64 (1.82) *11*	5.50 (1.50) *2*	2.83 (2.34) *6*
Distribution of Job Process Activity	4.43 (2.50) *7*	5.50 (0.50) *2*	4.20 (2.44) *10*	6.00 (0.00) *1*	2.75 (1.92) *4*
TOTAL RESPONDENTS	**10**	**5**	**15**	**2**	**6**

Figure 60: Usefulness Rankings for **Incorrect** Identification Using Disaggregate Data-Mean (Standard Deviation) and *Number Responding*

To clarify the above tables, consider some comparisons. For instance, for those who correctly identified the DR condition (figure 59), the most useful measure (highest ranked) was Distribution of Time in System, which was also the most widely used (16 out of 16 respondents). On the other hand, figure 60 shows that of those who incorrectly identified the DR condition, the most highly ranked measure was Time Series of Queue Length, which was used by all respondents. This indicates that the perceived most useful measure for the same condition varies depending on how successful the participants were in identifying the condition, as expected. Similarly, those who correctly identifed DD ranked Distribution of Due Date Allowance as the most useful, while those who made an incorrect identification felt that Distribution of Time in System was the most useful.

However, with only one incorrect respondent ranking distribution of time in system, few conclusions can be drawn. For those who correctly identified the two bottleneck conditions, SB and MB, there was a strong reliance on the queue length measure, with it being the most highly ranked for correctly identifying both conditions. Those respondents who incorrectly identified the bottleneck conditions used the queue measures, but did not rank them as the most useful. This was particularly the case for SB, where Time Series of Queue Length was ranked as the second to the least useful. The measures ranked as the most useful by those respondents for SB and MB, Time in System and Job Lateness/Job Process Activity, respectively, are not those that would be expected to be useful in this identification. Note that those measures ranked most highly for the DR, DD, SB and MB conditions also had either the lowest or next to the lowest standard deviation of responses, indicating relative uniformity of feeling of usefulness, and at or near unanimous usage.

A.13 Aggregate Group

The following tables summarize the usefulness rankings of the participants using the aggregate based measures. The first table below (figure 61) is for those correctly identifying the condition ($0 \leq \text{Gap} \leq 1$)

Measure Condition	DR	DD	IR	SB	MB
Time in System	1.91 (0.79) *23*	3.13 (1.15) *15*	2.25 (0.97) *8*	2.90 (0.77) *20*	2.23 (1.03) *12*
Job Lateness	2.30 (1.20) *23*	2.29 (0.70) *21*	3.12 (1.45) *8*	3.73 (0.85) *15*	3.17 (0.99) *12*
Job Tardiness	3.67 (1.00) *18*	3.38 (1.11) *16*	3.44 (1.83) *9*	2.63 (1.09) *19*	3.67 (1.18) *12*
Due Date Allowance	4.29 (1.22) *14*	1.38 (0.95) *21*	4.25 (1.39) *8*	5.10 (1.58) *10*	3.91 (1.68) *11*
Queue Lengths	2.30 (1.12) *23*	4.00 (1.00) *12*	2.00 (1.00) *8*	1.14 (0.34) *21*	2.17 (1.46) *12*
Machine Utilization	5.38 (1.11) *24*	5.67 (0.47) *6*	5.25 (1.30) *4*	6.33 (0.47) *6*	6.14 (0.64) *7*
TOTAL RESPONDENTS	**24**	**21**	**9**	**21**	**12**

Figure 61: Usefulness Rankings for **Correct** Identification Using Aggregate Data- Mean (Standard Deviation) and *Number Responding*

Figure 62 summarizes the results from the group using aggregate data but incorrectly identifying the condition (Gap ≥ 2).

Measure Condition	DR	DD	IR	SB	MB
Time in System	1.00 (0.00) *1*	3.40 (0.80) *5*	2.10 (1.37) *10*	2.33 (0.47) *3*	2.14 (0.74) *14*
Job Lateness	3.00 (0.00) *1*	2.00 (1.10) *5*	2.58 (0.86) *12*	4.50 (0.50) *2*	6.08 (10.5) *12*
Job Tardiness	4.00 (0.00) *1*	3.00 (1.00) *2*	2.88 (1.11) *16*	4.33 (1.70) *3*	2.40 (1.36) *15*
Due Date Allowance	6.00 (0.00) *1*	1.60 (0.80) *5*	4.38 (1.11) *8*	3.50 (0.50) *2*	4.33 (1.37) *6*
Queue Lengths	2.00 (0.00) *1*	3.50 (0.87) *2*	2.07 (1.65) *15*	1.0 (0.00) *3*	2.18 (1.27) *11*
Machine Utilization	5.00 (0.00) *1*	5.50 (0.50) *2*	5.17 (1.21) *6*	4.00 (2.00) *2*	4.71 (1.67) *7*
TOTAL RESPONDENTS	1	5	16	3	15

Figure 62: Usefulness Rankings for **Incorrect** Identification Using Aggregate Data- Mean (Standard Deviation) and *Number Responding*

In evaluating figures 61 and 62, similar results can be observed as those presented previously for the disaggregate information group. For those who correctly identified DR, the most useful measure, as expected, was Time in System and the measure was used by almost all respondents. Moreover, Time in System had the lowest standard deviation, indicating broad agreement on the measure. However, for those who incorrectly identified DR, Time in System was also ranked as the most useful, somewhat contrary to expectations. All of those who both correctly *and* incorrectly identified DD ranked due date allowance as the most useful, which was contrary both to expectations and to what was found in the disaggregate group. As expected, all of those who correctly identified the bottleneck conditions, SB and MB, ranked the queue lengths as most useful measure. Among those who incorrectly identified the bottleneck conditions, time series of queue length was deemed as most useful for SB while time in system was ranked highest for MB.

The expected most useful moving bottleneck identifier, queue lengths, was ranked as next most useful, but was not as widely used.

APPENDIX B

Survey Form to Shop Floor Experts

Summary of Experts' Responses

PERFORMANCE MEASUREMENT EVALUATION

The following pages are possible performance measures that can be obtained from a simulated job shop. The intent of this exercise is to gauge your assessment of the measures' usefulness from a shop floor management standpoint and on several dimensions. To that end, five tentative dimensions (A-E) of evaluation are indicated in the columns. Please rank each measure from 1 to 5, with 1 being very useful and 5 being not useful at all, *on each dimension.* The dimensions are provided below:

A. Consistency with Corporate Goals- How well can this measure help shop management align their goals with those of the overall corporation? Granted, this will depend somewhat on the varying goals of different companies, so please answer this question in terms of your own experience.

B. Good Snapshot of Ongoing Operation- How well does this measure provide a good instantaneous snapshot of what is happening on the shop floor? Can it be used by management to gauge what is happening dynamically from "snapshot to snapshot."

C. Enhances Monitoring- Does this measure enhance the day-to-day or week-to-week monitoring as you deem necessary for shop floor management?

D. Problem Identification- Does this measure help to identify problems on the shop floor? Can it enable management to see things that may not be possible with other measures? Please use a broad definition of "problem" and provide some explanation of the specific problems you envision.

E. Problem Diagnosis- Does this measure help to identify the direct or indirect *cause* of problems? This is distinct from (D) above in that it goes beyond merely identification and goes to the heart of the problem. Why does the problem exist? Again, please use a broad definition of "problem" and if possible provide some explanation of the specific problems you envision.

Usefulness Scale: 1=very useful; 5=not useful at all

Aggregate Operational	A	B	C	D	E
Mean time in system					
Mean/maximum lateness					
Mean/maximum tardiness					
Mean/maximum queue length					

Additional comments:

Usefulness Scale: 1=very useful; 5=not useful at all

Financial					
Throughput*					
Inventory*					
Operational expense*					
Shop net profit (loss) monthly or for period					
Mean cost per job					
Mean revenue per job					

* As defined by Goldratt (*The Haystack Syndrome*, 1990)

Throughput: The rate at which the system (shop) generates money through sales.

Inventory: All the money that the system has invested in purchasing things which it intends to sell.

Operational Expenses:
All the money the system spends in order to turn inventory into throughput.

Additional comments:

Usefulness Scale: 1=very useful; 5=not useful at all

Detailed Operational	A	B	C	D	E
Per Job Report including:					
Job Type					
Sequence of routing					
Employees involved					
Raw Material Cost					
Sales Price versus labor and/or material cost					
Work Center Reports:					
Distribution of activity by shift, job type					
Distribution of process times, IATs					
Single bottleneck identification					
Double or sequential bottleneck identification					
Distribution of queue lengths, by job type, shift					
Vendor delivery performance					
Scrap/rework reports					
WIP Inventory reports					

Include additional measures you feel would be useful

Usefulness Scale: 1=very useful; 5=not useful at all

Additional Measures	A	B	C	D	E

Please indicate reasoning (why) for any added above:

RESPONSE SUMMARY

Usefulness Scale: 1=very useful; 5=not useful at all

Aggregate Operational		A	B	C	D	E
Mean time in system	Respondent A	1	2	2	4	4
	Respondent B	5	3	5	2	5
Mean/max lateness	Respondent A	1	1	1	1	1
	Respondent B	2	3	2	4	5
Mean/max tardiness	Respondent A	3	2	3	2	2
	Respondent B	2	3	2	4	5
Mean/max queue length	Respondent A	2	3	3	3	3
	Respondent B	2	2	2	2	5

Usefulness Scale: 1=very useful; 5=not useful at all

Financial		A	B	C	D	E
Throughput*	Respondent A	1	1	2	1	3
	Respondent B	5	3	5	5	3
Inventory*	Respondent A	1	1	2	2	4
	Respondent B	3	4	5	5	3
Operational expense*	Respondent A	1	1	3	3	3
	Respondent B	5	3	5	5	3
Shop net profit (loss)	Respondent A	1	1	3	1	1
monthly or for period	Respondent B	1	3	5	5	3
Mean cost per job	Respondent A	1	2	3	4	4
	Respondent B	5	3	5	5	3
Mean revenue per job	Respondent A	1	1	1	1	1
	Respondent B	5	3	5	5	3

* As defined by Goldratt (*The Haystack Syndrome*, 1990)

Throughput: The rate at which the system (shop) generates money through sales.

Inventory: All the money that the system has invested in purchasing things which it intends to sell.

Operational Expenses:

All the money the system spends in order to turn inventory into throughput.

Usefulness Scale: 1=very useful; 5=not useful at all

Detailed Operational		A	B	C	D	E
Per Job Report including:						
Job Type	Respondent A	3	4	4	2	2
	Respondent B	5	5	5	5	5
Sequence of routing	Respondent A	5	4	5	4	3
	Respondent B	5	5	5	5	5
Employees involved	Respondent A	4	4	3	2	2
	Respondent B	5	5	5	5	5
Raw Material Cost	Respondent A	2	2	3	2	2
	Respondent B	5	5	5	5	5
Sales Price versus labor and/or material cost	Respondent A	1	2	2	2	1
	Respondent B	5	5	5	5	5
Work Center Reports:						
Distribution of activity by shift, job type	Respondent A	4	2	3	2	3
	Respondent B	5	5	5	5	5
Distribution of process times, IATs	Respondent A	4	2	3	2	3
	Respondent B	5	5	5	5	5
Single bottleneck identification	Respondent A	3	1	2	1	1
	Respondent B	5	1	1	1	4
Double or sequential bottleneck identification	Respondent A	3	1	2	1	1
	Respondent B	5	1	1	1	4
Distribution of queue lengths by job type/shift	Respondent A	2	2	2	2	2
	Respondent B	4	1	1	1	4
Vendor delivery performance	Respondent A	1	2	2	1	2
	Respondent B	5	2	2	2	4
Scrap/rework reports	Respondent A	1	2	2	1	2
	Respondent B	4	3	3	3	4
WIP Inventory reports	Respondent A	1	1	2	1	1
	Respondent B	4	3	3	3	4

Include additional measures you feel would be useful

Usefulness Scale: 1=very useful; 5=not useful at all

Additional Measures	A	B	C	D	E
Respondent A					
ABC Costing	1	1	2	1	1
Time to Market	1	3	2	1	1
Benchmarking	2	1	2	1	1

Respondent B					
Time in queue vs. standard planned queue	1	1	1	1	4
Standard hours past due in queue by workcenter	1	1	1	1	4
Actual set up time vs. standard	2	2	1	1	4
Actual maintenance hrs by workcenter vs. planned	2	2	2	2	4

APPENDIX C

Recruiting Message

Informed Consent Form

SUBJECT RECRUITMENT PROCEDURE AND SCRIPT

Volunteers were recruited from various undergraduate and graduate classes in MSU's Eli Broad College of Business. Preference was given to junior, senior or graduate MLM majors or those with relevant experience, although other subjects were considered.

The script read to the prospective subjects is (approximately) as follows:

"I am looking for volunteer participants in a research project involving the management and evaluation of shop floor and manufacturing information. In this research, you will be asked to review various information outputs as generated by a computer simulation model of an operating shop floor and to answer several questions.

"The exercise will consist of a single session, divided up into two main parts. The first section is a 45-60 minute introductory and training session in which I will familiarize you with the manufacturing environment being studied, describe the model being used and the different types of information you may be asked to evaluate. The second session will last between one and one and a half hours and will consist of you being presented with various scenarios of data and information and being asked to evaluate certain questions and conditions. Depending on the time of day of the session, appropriate refreshments will be provided.

"The level of difficulty of the task will vary depending on the individual and on what particular information sets you are provided. Ultimately, the tasks are designed to be relatively self explanatory and should not cause any undue burden. The tasks being performed relate directly to manufacturing information management and may provide a good opportunity to evaluate data and to investigate shop floor problems, much as you may be asked to do in your future careers. Thus, it has the potential of contributing to your manufacturing and general business knowledge base.

"All participants will be eligible to win one of four prizes- a new mountain/all terrain bike, \$200, \$100 or \$50- those being first, second, third and fourth prizes of a drawing. The chances to win in the drawing increase with your performance in the exercise.

"Of course, this is a completely voluntary project. Your participation may be terminated by you at any time. Those of you who are interested are free to sign up on the sheet I will leave with your instructor and I will contact you with further details. I expect to schedule experimental sessions within the next couple of weeks. If you have a preference as to a time of day, please indicate so on the form. If there is a day of week preference, indicate that as well. I'll do my best to accommodate you."

SHOP FLOOR INFORMATION MANAGEMENT AND EVALUATION EXPERIMENT

INFORMED CONSENT FORM

1. This research is exploring the usefulness of various types of information and performance measures for the shop floor. Subjects involved in this research will be asked to review different information sets and then to attempt to identify, from a provided list, certain conditions that may be present on the shop floor and that are leading to the observed performance.

   All information and measures are generated from a computer simulation model of a relatively standard shop floor. Subjects will be reviewing the information only, not the model, although the design of the model will be explained prior to the experiment.

2. It is estimated that the following time will be required for the experiment:

Training/information session	45-50 minutes
Experimental, evaluation session	1.5-2 hours

3. In signing this form, you are freely consenting to participate in this experiment. However, participation is and will continue to be completely voluntary. You may choose not to participate in certain parts of the experiment and may terminate your participation at any time.

4. All results will be treated with the strictest confidence and all the subjects will remain anonymous in any report of research findings. You may request and receive information on your participation in the experiment, subject to the aforementioned confidentiality and anonymity restrictions.

5. Compensation for this experiment will be as follows:
   Points will be awarded according to performance on the task, with each participant able to earn between 5 and 11 points. Approximately 60 subjects are expected to participate. Each point will count as one ticket for three drawings. Prizes will be a follows:

1st prize-	New Trek Mountain Bike
2nd prize-	$200
3rd prize-	$100
4th prize-	$50

   The drawing will be done after all sessions are complete. Subjects need not be present to win a prize, but are entitled to be. Please advise the researcher as to how you can be notified as to the drawing's time and location.

6. The researchers involved in this project are:

Robert J. Marsh
Principal Researcher
Department of Marketing and Supply Chain Management
N451 BCC
353-6381
marshro1@pilot.msu.edu

Professor Steven A. Melnyk
Research Committee Chair
Department of Marketing and Supply Chain Management
N327 BCC
353-6381
16513sam@msu.edu

If there are any questions or concerns regarding this experiment they should be directed to the principal researcher. If you wish, you may contact the research committee chair, as shown above.

SUBJECT TO THE CONDITIONS DESCRIBED ABOVE, I HEREBY CONSENT TO PARTICIPATE IN THIS EXPERIMENT. I AM AT LEAST 18 YEARS TO AGE.

______________________________ Date: ____________

____
(please print name)

APPENDIX D

Sample Laboratory Experiment Instruments

- Disaggregate Measures (D-36) Instrument (with follow up questionnaire)
- Aggregate Measures (A-36) Instrument (with follow up questionnaire)

Debriefing Letter

SHOP FLOOR INFORMATION EVALUATION EXERCISE
CASE 36

This package contains information regarding a simulated shop floor and is an exercise designed to assess your ability to identify certain operational conditions based on the shop floor information presented. In reviewing this information, you may refer to the notes provided in the training session. This package consists of two major parts:

I. Performance measurement information

This section consists of nine information sets, each presenting operational performance of the shop floor. Various measures and/or graphics may be presented.

II. Assessment Questions

These questions allow you to assess the usefulness of the information presented in I. when used to evaluate shop floor performance.

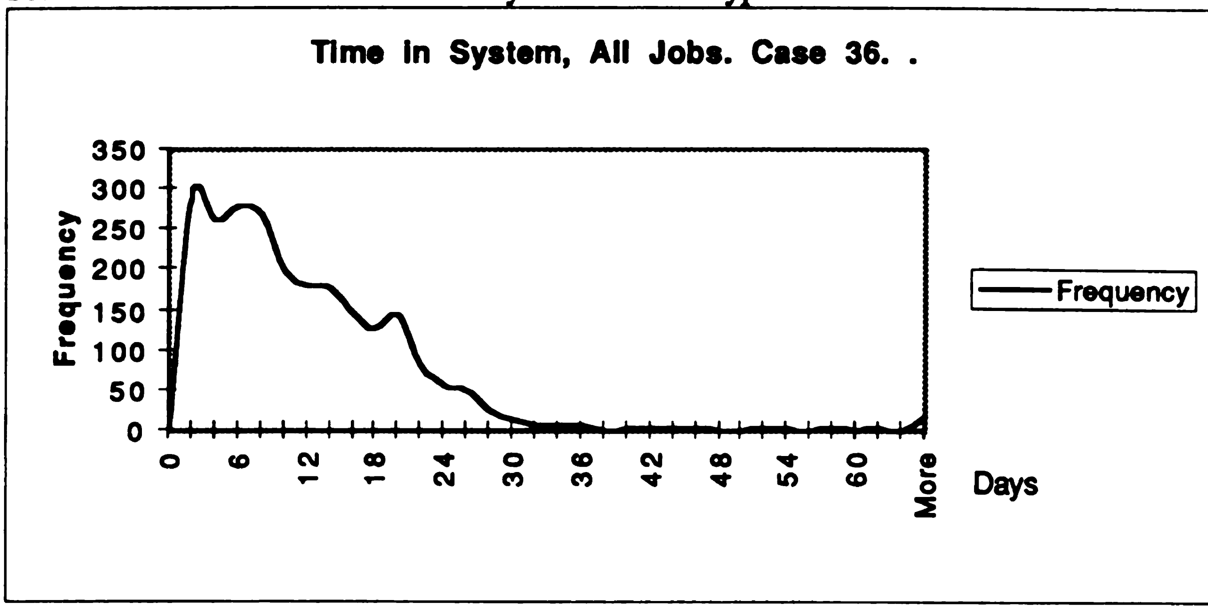
PLEASE ENTER YOUR STARTING TIME HERE: ________

I. PERFORMANCE INFORMATION

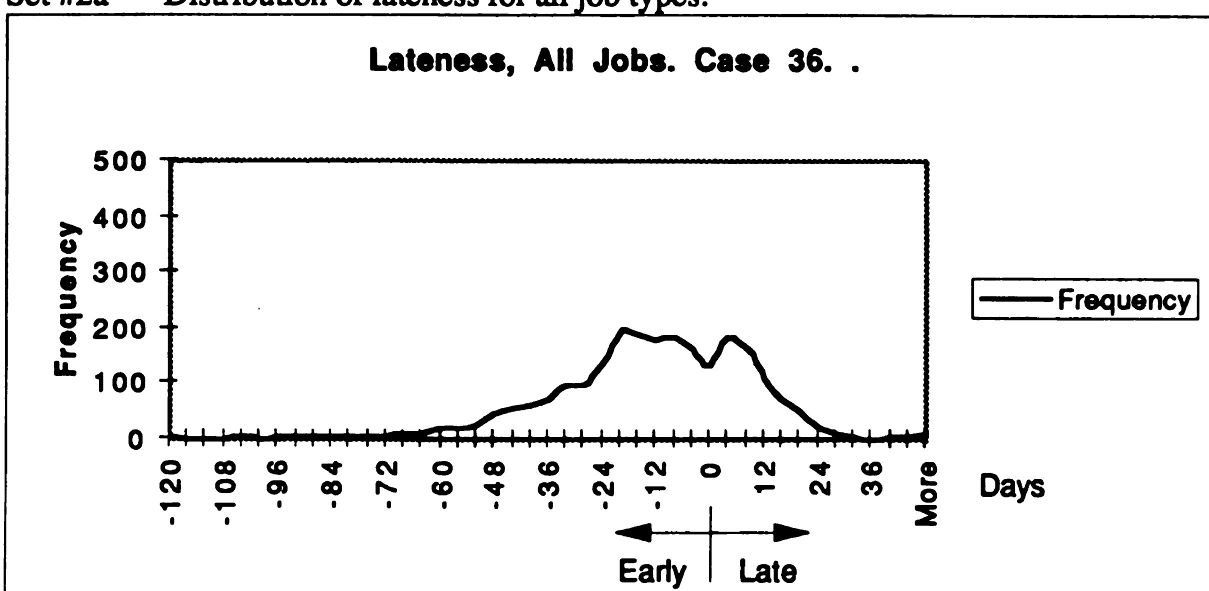
INFORMATION SETS

The information provided in this section consists of nine separate graphs or tables, as presented below. Each set is numbered and described.

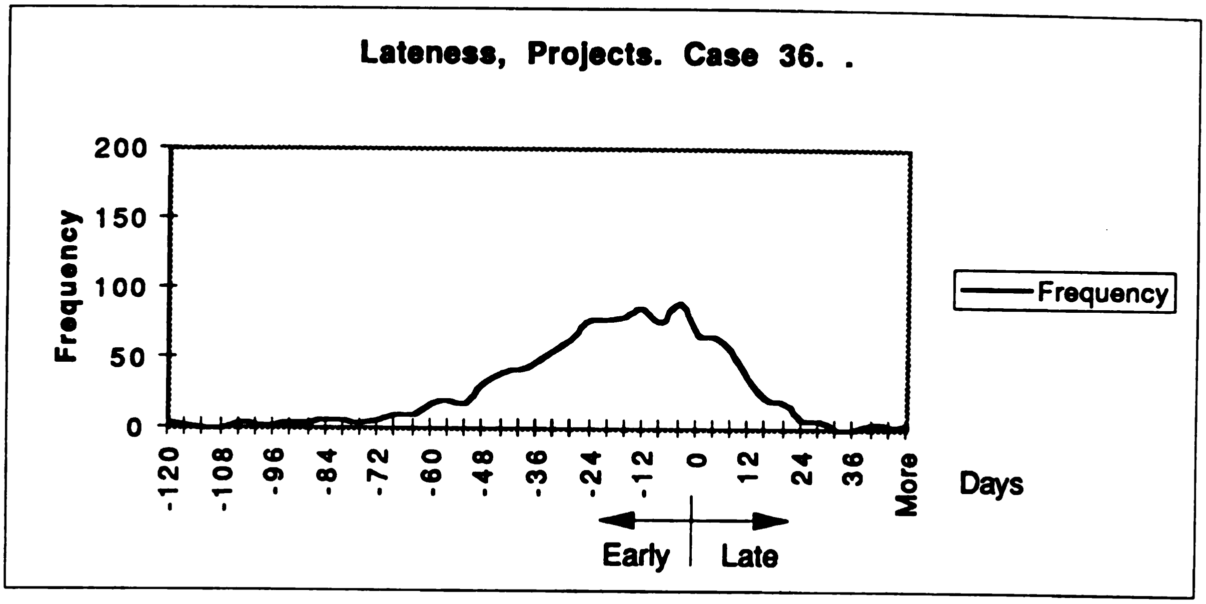
Set#1 Distribution of Time in System- all Job Types



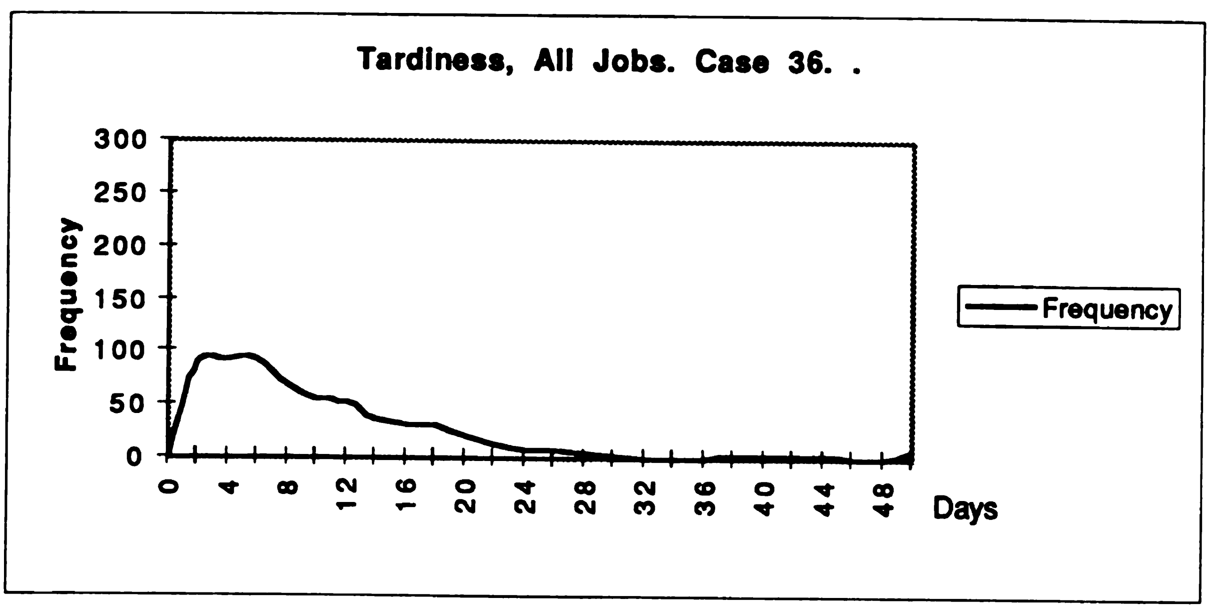
Set #2a Distribution of lateness for all job types:



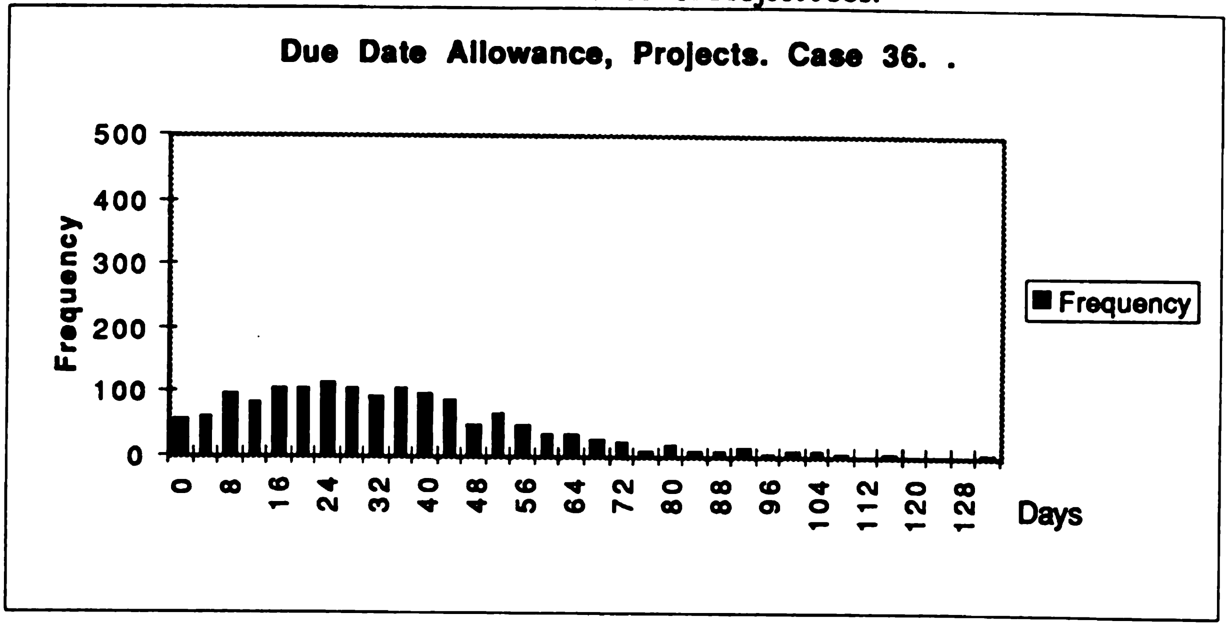
Set #2b Distribution of Lateness for Project Jobs only:



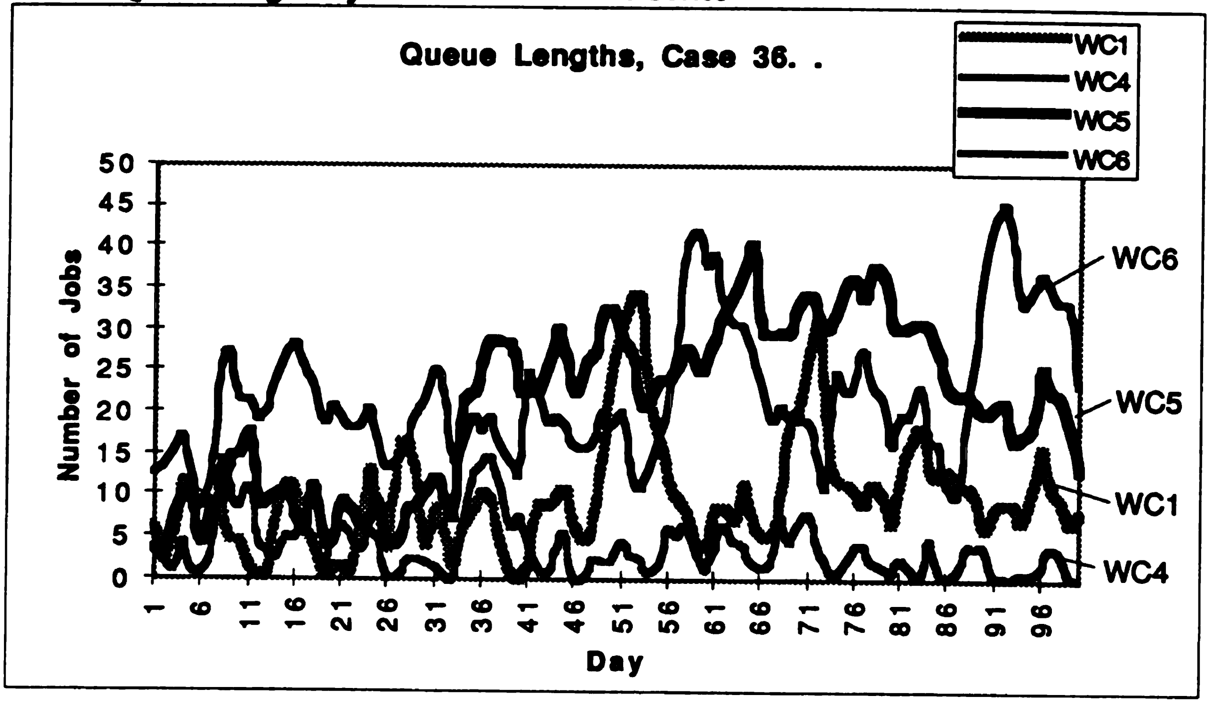
Set#3 Distribution of Tardiness, all Job Types:



Set #4 Distribution of Due Date Allowance for Project Jobs:



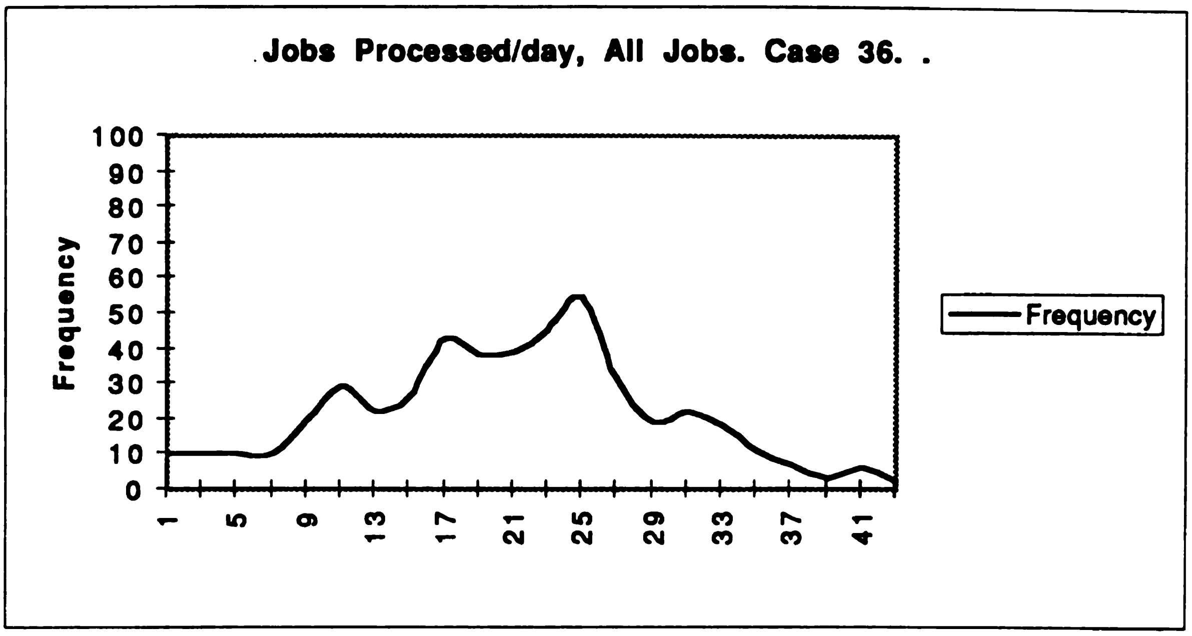
Set#5 Queue Lengths by Work Center- Time Series



Set#6&7 Machine and Labor Utilization

Work Center	Machine Utilization	Labor Utilization
1	97%	90%
4	77%	74%
5	80%	86%
6	96%	96%

Set#8 Distribution of Job Processing Activity



II. ASSESSMENT QUESTIONS

Given the information in I. above, please answer the following questions to the best of your ability:

1) What conditions could be present on the shop floor to cause these results (the information sets in I.)? From the following list, rank order your seven choices from 1 to 7, with 1 being the *most likely* condition, 7 being *least likely*.

___ Stationary bottleneck
___ Moving bottleneck
___ Irregular job release
___ Varying job type mix
___ Dispatch rule variation
___ Aggregate due date assignment
___ No differences in conditions from the base case could be observed

2) How confident are you that your choice for the **most likely** existing condition (ranked 1 above) is actually present on the shop floor? Indicate your degree of confidence on a scale of 0 - 100% below, with 0% being not confident at all and 100% being extremely confident:

_______%

3) Which information sets did you use in coming to your determination in questions 1 and 2 above? Rank order the information sets based on their importance to your decision making, with 1 indicating the most important. ***Please rank only that information actually used.*** The information set numbers correspond to those on the previous page.

___	Set# 1	Distribution of Time in System
___	Set# 2a	Distribution of Job Lateness
___	Set #2b	Distribution of Project Job Lateness
___	Set# 3	Distribution of Tardiness
___	Set# 4	Distribution of Due Date Allowance
___	Set# 5	Queue Lengths
___	Set# 6&7	Machine and Labor Utilization
___	Set# 8	Job Process Activity
___	Set# 9	Summary Statistics by Job Type

PLEASE ENTER YOUR ENDING TIME HERE: ___________

II. ASSESSMENT QUESTIONS (continued)

How did you arrive at the answers on the previous page? *These answers will not affect the number of tickets earned by your performance.* If you need more space, please continue on the back of this page.

A. Of the following information sets, **which** were most useful to you in identifying the most likely shop floor condition and your confidence in your decision? **Why?**

Time in system	Due Date Allowance	Job Process Activity
Job Lateness	Queue Lengths	Job TypeSummary Statistics
Job Tardiness	Machine, Labor Utilization	

B. **How** did you determine your answer to question #1 on page 4 when identifying the shop floor condition that you believe to exist? *If you guessed, please indicate so.*

C. What other information would have made your identification of the shop floor condition easier? Please indicate what you feel the usefulness of such information would have been.

	Somewhat Useful				Very Useful
________________________________	1	2	3	4	5
________________________________	1	2	3	4	5
________________________________	1	2	3	4	5

I. PARTICIPANT INFORMATION

(You must provide Name and Phone# and/or Email to be eligible for prizes)

1. Name: ______________________________ Phone ______________

3. Age: ______ Sex: _____ Email: ______________

   Year in school Fr ___ So ___ Jr ___ Sr ___ Grad ___

4. MLM Course Grades Received (where applicable):

MGT 303 ____ MGT 304 ____ MGT 401 ____ ML 446 ____

MGT 402 ____ ML 345 ____ ML 442 ____ ML 470 ____

Other ______________________________

5. Overall GPA: _____

6. SAT Scores- Overall: ____ Verbal: ____ Math: ____

   ACT Scores- Composite: ____

   (English ____ Math ____ Reading ____ Science ____)

   [*Please provide test scores to the best of your recollection*]

7. Manufacturing or Job Shop Related Work Experience (please briefly describe and indicate number of years at each position- use back of sheet if necessary):

   Position Description Years

____ ________

____

____ ________

____

____ ________

____

Please use back to describe additional experience, if necessary.

FOLLOW UP QUESTIONS

1. As a result of the training session, I knew how to use the information presented.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

2. I could have made sense of the information presented without the training session.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

3. The information presented with the cases was insufficient for me to answer the questions.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

4. The information presented with the cases was excessive and was difficult to sift through.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

5. The information presented with the cases was concise in nature and adequate to allow me to answer the questions.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

PLEASE CONTINUE ON FOLLOWING PAGE

6. The information presentedwith the cases clearly and completely described the overall structure of the shop, its flows and layout.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

7. The information presented with the cases allowed me to clearly understand and identify the changes in conditions affecting the shop.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

8. The presentation of data in graphical format made it difficult to use.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

<u>THANK YOU VERY MUCH FOR YOUR PARTICIPATION</u>!!

SHOP FLOOR INFORMATION EVALUATION EXERCISE
CASE 36

This package contains information regarding a simulated shop floor and is an exercise designed to assess your ability to identify certain operational conditions based on the shop floor information presented. In reviewing this information, you may refer to the notes provided in the training session. This package consists of two major parts:

I. Performance measurement information

This section consists of 6 information sets, each presenting operational performance of the shop floor. Various measures and/or graphics may be presented.

II. Assessment Questions

These questions allow you to assess the usefulness of the information presented in I. when used to evaluate shop floor performance.

PLEASE ENTER YOUR STARTING TIME HERE: __________

I. PERFORMANCE INFORMATION

INFORMATION SETS

Case 36

Set#	Measure	Mean	Std Dev
1	Time in System	11.0 days	10.0
2	Job Lateness	-15.4 days	22.8
3	Job Tardiness	9.7 days	9.7
4	Due Date Allowance	26.7 days	21.2
5	Queue Lengths		
	WC#1	11.5 jobs	5.3
	WC#4	1.7 jobs	1.7
	WC#5	17.0 jobs	7.8
	WC#6	25.4 jobs	10.9
6	Machine Utilization	88%	

II. ASSESSMENT QUESTIONS

Given the information in I. above, please answer the following questions to the best of your ability:

1) What conditions could be present on the shop floor to cause these results (the information sets in I.)? From the following list, rank order your seven choices from 1 to 7, with 1 being the *most likely* condition, 7 being *least likely*.

___ Stationary bottleneck
___ Moving bottleneck
___ Irregular job release
___ Varying job type mix
___ Dispatch rule variation
___ Aggregate due date assignment
___ No differences in conditions from the base case could be observed

2) How confident are you that your choice for the **most likely** existing condition (ranked 1 above) is actually present on the shop floor? Indicate your degree of confidence on a scale of 0 - 100% below, with 0% being not confident at all and 100% being extremely confident:

_______%

3) Which information sets did you use in coming to your determination in questions 1 and 2 above? Rank order the information sets based on their importance to your decision making, with 1 indicating the most important. ***Please rank only that information actually used.*** The information set numbers correspond to those on the previous page.

___ Set# 1	Time in system
___ Set# 2	Job Lateness
___ Set# 3	Job Tardiness
___ Set# 4	Due Date Allowance
___ Set# 5	Queue Lengths
___ Set# 6	Machine Utilization
___ Set# 7	Labor Utilization

PLEASE ENTER YOUR ENDING TIME HERE: ____________

II. ASSESSMENT QUESTIONS (continued)

How did you arrive at the answers on the previous page? *These answers will not affect the number of tickets earned by your performance.* If you need more space, please continue on the back of this page.

A. Of the following information sets, **which** were most useful to you in identifying the most likely shop floor condition and your confidence in your decision? **Why?**

Time in system	Due Date Allowance	Machine Utilization
Job Lateness	Queue Lengths	Labor Utilization
Job Tardiness		

B. How did you determine your answer to question #1 on page 3 when identifying the shop floor condition that you believe to exist? *If you guessed, please indicate so.*

C. What other information would have made your identification of the shop floor condition easier? Please indicate what you feel the usefulness of such information would have been.

	Somewhat Useful				Very Useful
______________________________	1	2	3	4	5
______________________________	1	2	3	4	5
______________________________	1	2	3	4	5

I. PARTICIPANT INFORMATION

(You must provide Name and Phone# and/or Email to be eligible for prizes)

1. Name: ______________________________ Phone ______________

3. Age: ______ Sex: ____ Email: ______________

Year in school Fr ___ So ___ Jr ___ Sr ___ Grad ___

4. MLM Course Grades Received (where applicable):

MGT 303 ____ MGT 304 ____ MGT 401 ____ ML 446 ____

MGT 402 ____ ML 345 ____ ML 442 ____ ML 470 ____

Other ______________________________

5. Overall GPA: _____

6. SAT Scores- Overall: ____ Verbal: ____ Math: ____

ACT Scores- Composite: ____

(English ____ Math ____ Reading ____ Science ____)

[*Please provide test scores to the best of your recollection*]

7. Manufacturing or Job Shop Related Work Experience (please briefly describe and indicate number of years at each position- use back of sheet if necessary):

Position Description Years

____ ________

____

____ ________

____

____ ________

____

Please use back to describe additional experience, if necessary.

FOLLOW UP QUESTIONS

1. As a result of the training session, I knew how to use the information presented.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

2. I could have made sense of the information presented without the training session.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

3. The information presented with the cases was insufficient for me to answer the questions.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

4. The information presented with the cases was excessive and was difficult to sift through.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

5. The information presented with the cases was concise in nature and adequate to allow me to answer the questions.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

PLEASE CONTINUE ON FOLLOWING PAGE

6. The information presented with the cases clearly and completely captured described the overall structure of the shop, its flows and layout.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

7. The information presented with the cases allowed me to clearly understand and identify the changes in conditions affecting the shop.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

8. The presentation of data in tabular format made it difficult to use.

1	2	3	4	5	6	7
Strongly Agree						Strongly Disagree

<u>THANK YOU VERY MUCH FOR YOUR PARTICIPATION</u>!!