MODELING FLUID MILK WASTE USING DISCRETE EVENT SIMULATION AND THE ROLE OF PACKAGING WITHIN THE HOME

By

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ABSTRACT

MODELING FLUID MILK WASTE USING DISCRETE EVENT SIMULATION AND THE ROLE OF PACKAGING WITHIN THE HOME

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U.S. consumers are the largest contributors to food waste generation (FWG), and few models have been created on how households waste food. This study examines how discrete-event simulation (DES) can identify areas for reducing FWG through packaging and consumer behavioral changes. Household model parameters included: amount and type of consumption, type and number of containers bought, buying behavior, and shelf life of milk. Simulations comparing the purchase of quart, half gallon, and gallon milk containers were run for 10,000 days to identify which package type reduced waste for 50 one, two and four-person households. Based on consumption averages from the U.S. National Dairy Council, results from the DES model suggest that if 1 and 4-person households change their purchasing behavior from 1 half-gallon to 1 quart and 2 gallons to 3 half-gallons, then they can reduce their greenhouse gas (GHG) emissions from milk consumption by 33 and 12%, respectively, without reducing their total milk consumption. In simulated scenarios, purchasing more smaller containers equivalent to a larger size, decreased spoilage, but not enough to reduce a consumer's total milk consumption GHG emissions. Our model results also imply that packaging plays a miniscule role, 5% of the total milk consumption GHG impact; most of a consumer's impact comes from milk spoilage and consumption. Additional field-testing is necessary to validate the model.

To my parents Marlena and Frank,
brother and sister, Julia and Filip

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INTRODUCTION

Food waste has become an increasing concern due to the growing population, increasing food requirements, limited arable land, and rapidly filling landfills. Industrialized food nations have been examined for wasting food more than non-industrialized nations, specifically at the consumer level (1). Food waste (FW), which is the amount of food wasted at the consumer and retail level and does not include production and processing losses (2), accounts for 31% of the U.S. food supply (3). Wasted food in the U.S. amounts to 60 billion kilograms, accounting for $162 billion U.S. dollars lost each year (4). Similarly, food production accounts for 80%, or 68 trillion liters, of all freshwater use in the U.S., which means 17% of that fresh water, or 11.6 trillion liters, are lost each year (5, 6). Feed crops compromised the largest portion of total fresh water use, 64% of the total, amounting to 44 trillion gallons used in the U.S. each year (6).

From an environmental standpoint, not all food is created equal. Fresh fruits and vegetables account for the lowest impact while products from ruminants have the highest environmental impact (7, 8). Hence, reducing food waste for higher environmental impact food products, such as meat and dairy, could provide the largest opportunity for environmental footprint reductions in the food supply chain. Previous research has identified that specific food products should be targeted for food waste reductions (9, 10). Thus, cow's milk was chosen as the primary target in this study. Although milk is less impactful than meat, it is consumed in large quantities and accounts for 13% - 7.7 billion kg - of total U.S. food waste – 60 billion kg (4). Consumers account for the largest portion of fluid milk waste generation, 20%, compared to retailers, which account for 12% (3) (see Figure 1). For every kg of fluid milk consumed, approximately 2.05 kg of CO_2e are emitted including end of life scenarios of the package (11). Consumption of milk accounts for 50 billion kg of CO_2e each year. When wasted by the consumer, total waste emissions amount to 10 billion kg of CO_2e released annually.

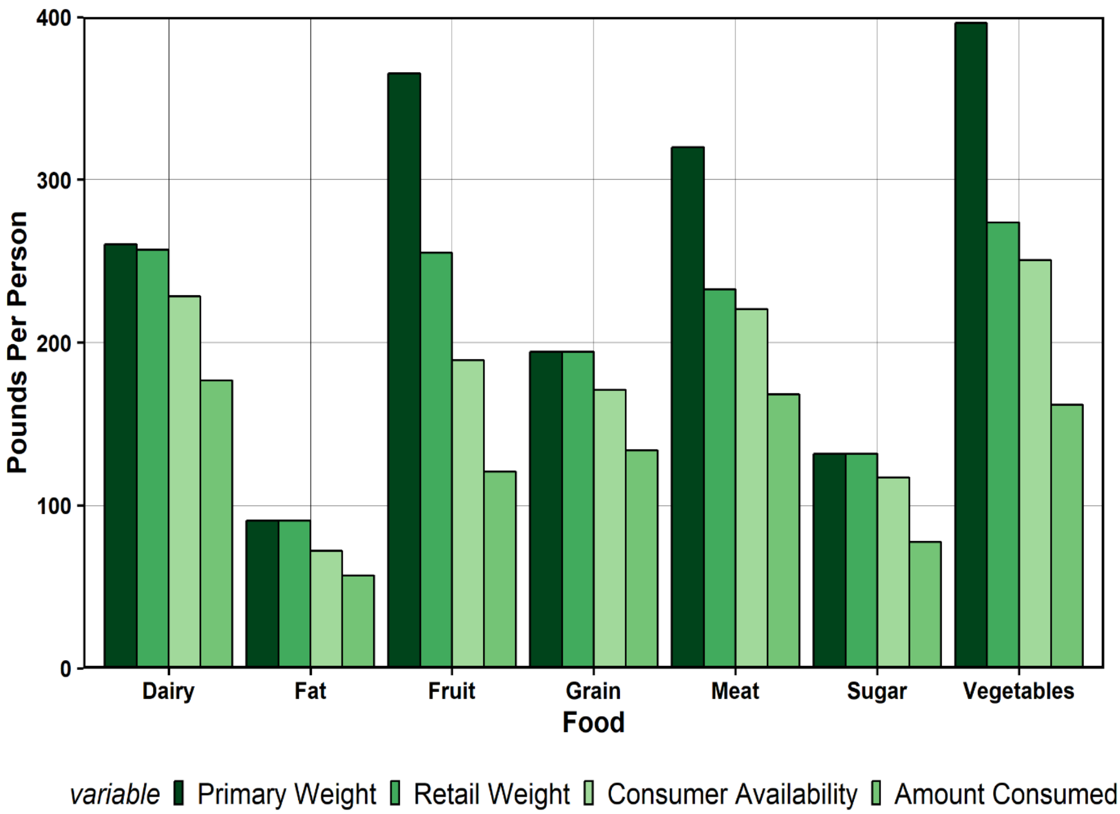


Figure 1: USDA data from 2015 showing the breakdown of food availability. Primary weight indicates the amount of food harvested at the farm. The retail weight is the weight purchased by retailers (i.e. grocery stores, wholesale stores, and supercenters). Consumer availability is the amount available to the consumer and the amount consumed is the amount of food the consumer ate.

There are a variety of reasons as to why consumers waste milk including: hurdles of everyday life, convenience, lifestyle choices, planning, expiration risk, storage, and packaging (12–17). However, it is not known which of these attributes contributes to the largest portion of waste, but there are areas where packaging intervention could reduce waste. According to Hebrok and Boks, the three dominating solutions for reducing consumer food waste are: 1) technology that helps people plan, share, and keep an overview of stock, 2) packaging and storing solutions that extend shelf life, and 3) information and awareness campaigns (12). Licciardello found that the relative environmental impact of milk packaging is small, 8% on average, compared to the impact of milk (18). A review of food LCAs has identified that greater attention must be paid to packaging's impact on the life cycle of a food product (19). In addition, user behavior must be considered when determining the environmental impacts of a food packaging system (20). Therefore, is crucial to consider the package's relative impact compared to the food product when determining how to reduce the total environmental impact of a food-packaging system (18, 21).

Data on current food waste generation is based on total food supply estimates from the USDA Economic Research Service (ERS); they do not estimate waste within individual households (4). Research conducted to understand U.K. consumers used discrete event simulation (DES) to generate data on consumer milk wastage, shopping behavior, package size, consumption, and shelf life to determine which of these factors effect fluid milk waste generation (22). Research in the U.K. did not account for different market shopping probabilities. Other limitations of this research included the inability to model different household types, meaning that all individuals within a house were defined with the same consumption habits. In addition, packaging data from the simulations was not considered when analyzing the GHG emissions of increased packaging use for decreasing milk spoilage. This paper conducts similar DES modeling for the U.S. considering differences in container sizes, living arrangements, and shopping behavior to identify parameters that will decrease waste generation and GHG emissions for U.S. consumers.

CHAPTER 1

1.1 Goal and Objectives

The goal of this project was to model consumers within the home to understand how people waste fluid milk within their homes in relation to packaging and consumer behavior.

The objectives of this project were as follows:

1. Construct a model for U.S. consumers on how fluid milk is consumed. Previously such models have only been created for consumers in the U.K., where behavior and package sizes are substantially different.
2. Develop a computer application that automatically simulates a household for a given period utilizing discrete event simulation.
3. Determine which package size and purchasing behavior decrease household fluid milk waste without compromising current milk consumption.

1.2 Thesis Outline

1.2.1 Determine how people consume food within their homes

It was fist determined how food progresses through a household. Current literature was analyzed to understand how people purchase, store, and consume food. A simple model was created to understand where waste is generated, i.e. from consumption or storage (see figure Figure 9). A computer application was then developed to simulate how much waste is being generated due to shelf-life, purchasing, and storage of milk.

1.2.2 Computer application development

Implementation of a theoretical model to computer software was done utilizing Simevents® from Mathworks® (23). The model was then verified against National Health and Nutrition Examination Survey (NHAHES) data to represent milk consumption habits of specific household types.

1.2.3 Running Simulations at the High-Performance Computing Center

To run simulations for all parameters of interest, large amounts of memory were required, as well as high computing power. A separate piece of software was required to perform an iteration of each parameter combination. Additional scripts were developed in order to effectively run simulations on the High Performance Computing Center (HPCC).

1.2.4 Performance of simulations and data analysis

All data analysis was done using R (24). Large datasets were transferred from the HPCC to a local desktop. Simulations for each household type were then analyzed to determine which package size and shelf-life provided the optimal amount of milk to a household, while minimizing waste. Consumption, spoilage, and the amount of milk unavailable to the consumer were plotted to understand which combination of parameters were ideal for each household type.

1.2.5 Determining the greenhouse gas emissions of household consumption

Once simulations were run, the environmental impact of consumption, spoilage, and packaging were determined. This helped to identify which packaging and behaviors could lower the total greenhouse gas (GHG) emissions of a household. Recommendations can then be made as to how a household can change its purchasing in order to lower its emissions.

CHAPTER 2

LITERATURE REVIEW

2.1 Food Waste

Currently, a third of all food is wasted worldwide. The FAO estimates that the environmental footprint of food produced but not eaten is 3.3 Gtonnes of CO_2 equivalent each year. This puts food wastage as the third largest contributor to global greenhouse gas (GHG) emissions worldwide, behind China and the U.S (25). Water usage from wasted food amounts to 250 km^3, which is approximately 3 times the size of Crater Lake in Oregon. From an economic standpoint, the world wastes 750 billion USD each year, which is equivalent to the GDP of Switzerland (25). Food waste is both a social and economic problem that needs to be addressed. Increasing food production is not only the answer to feeding the world, we already produce enough food to feed the whole world today. If the world were to halve the amount of food waste it produces, there would be enough food to feed the 800 million people that go hungry on a daily basis (6). When comparing regions across the world (see Figure 2) Europe and North America waste the most food per capita. North America and Europe waste 280-300 kg/year per person, while South/Southeast Asia only waste between 120-170 kg/year per person (see Figure 2).

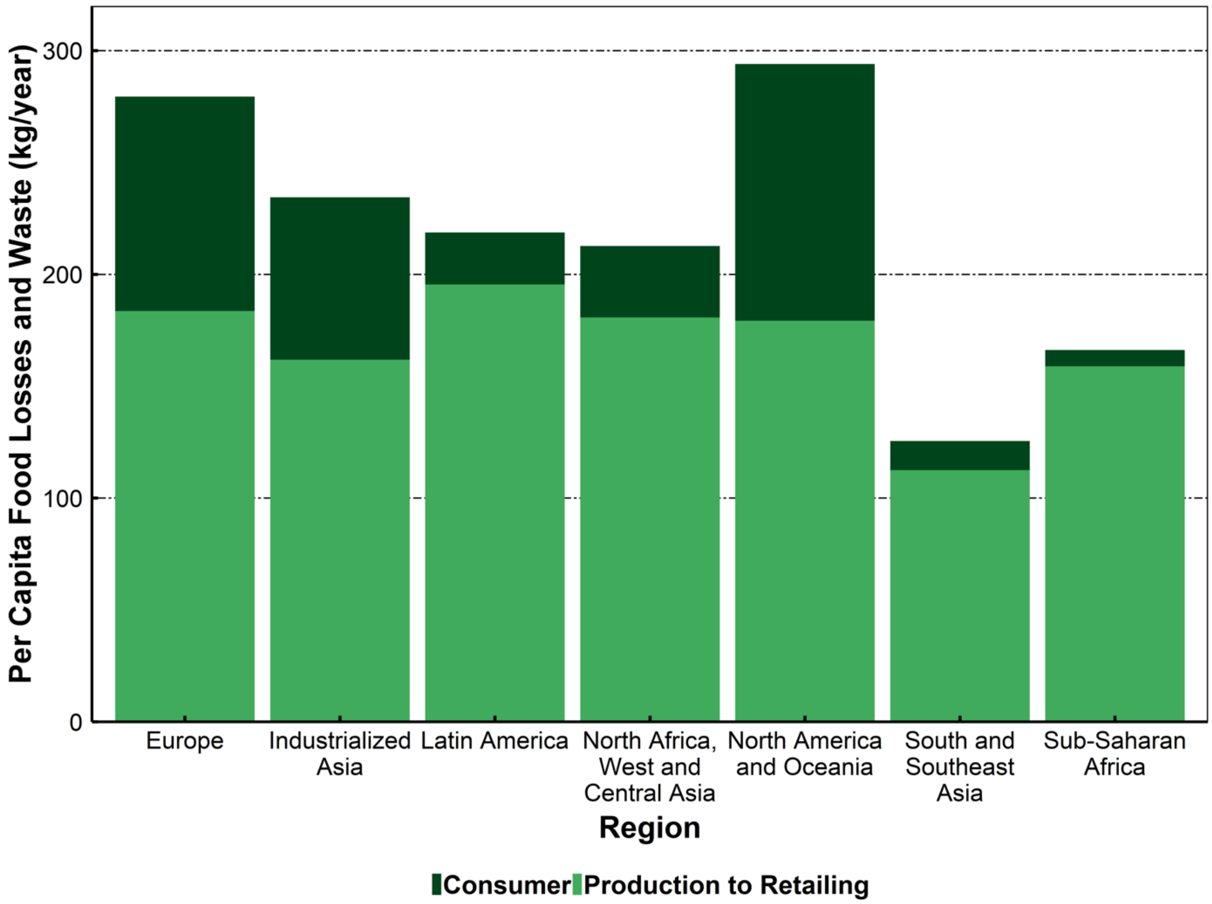


Figure 2: Per capita food loss in Europe, Industrialized Asia, Latin America, North/West Africa and Central Asia, North America and Oceania, South/Southeast Asia, and Sub-Saharan Africa. Data was adapted from the Global Food Loss and Waste report from the FAO (20).

Not only do Europe and North America waste the most food per capita, a large majority of this waste happens at the consumer level (26). Per capita food waste in Europe and North America is 95-115 kg/year, while in sub-Saharan Africa and South/Southeast Asia people waste 6-11 kg/year (26). This means that consumer's in industrialized nations waste approximately the same amount of food that is produced in sub-Saharan Africa. The U.S. has the largest food availability per capita in the world, nearly 430 billion pounds, while it wastes 31 percent, 133 billion pounds at the retail and consumer level (4). Consumers are largely to blame compared to retailers, as they are responsible for 21% and 10%, respectively (4). This presents a large economic and social opportunity for change. Therefore, it is important to understand how and why consumer's waste food in the U.S., and around the world.

According to Mandyck and Schultz, food loss is any food lost during agricultural production and postharvest handling and storage, while food waste is any food discarded by retailers and consumers downstream in the food supply chain (4). Food waste occurs within the home; thus, it is not fully understood as to what the reasons for waste generation are. An National Resource Defense Council issue paper suggested that reasons like: "lack of awareness and undervaluing of foods, confusion over label dates, spoilage, impulse and bulk purchases, poor planning, and over-preparation" cause food wastage within the home (5). Others have paid special attention to packaging as a major contributor of waste. Williams et al. and others have identified that packaging plays a miniscule role in the total environmental impact of a food product, depending on the product (6–8). Table 1 details the discussion of the factors causing household food waste, which are further described in the following section.

Table 1: Breakdown of household causes of food waste and the reasons for waste generation.

Household Food Waste Causes	Reasons for Waste Generation
Values around food	Low evaluation of food leads to waste
Planning	Poor planning methods, and unplanned/impulse buying behavior.
Shopping	Frequency of shopping trips, household income.
Storing	Inadequate knowledge of proper storage conditions
Cooking	Underdeveloped cooking skills.
Eating arrangements	Eating habits, frequency of eating out
Managing leftovers	Improper management of leftovers, leftovers are not saved
Food Risk	Throw away food due to fear of becoming ill
Packaging	Packaging is too large, package is hard to empty

2.1.1 Values around food

Low food prices around the world have been theorized to have caused the large increase in food waste in industrialized nations; scarcity and rising food prices would inevitably reduce food waste in households (10). Some research has shown that higher income households waste more compared to low income households, but others have found that there is no clear correlation between the two (12). When it comes to food waste, consumer's are more motivated by saving money than protecting the environment (12). In addition, it has been found that guilt associated with throwing away food is a dominant driver in household food waste reduction (27). Foods with higher value, novelty, sentimental value have been found to be wasted less (12). Food waste generation is not a mindless task that "bad" intentioned people conduct, rather it is a complex process that involves social interaction, routines, food management, and skills (12). Furthermore, households often think they are wasting less than others, which suggests that few people feel that they are deviating from social norms (27, 28).

2.1.2 Planning

Effective planning has been identified as a way to reduce food waste within the home (29). It has been suggested that people should create shopping lists before going shopping to avoid over-purchasing and impulse buys. Some studies have found that meal planning results in less food waste, while other have not found a clear correlation between the two (30). People often purchase ingredients for a particular recipe and throw out the unused food because they habitually do so, or are not familiar with how to use the ingredient in a different way (31).

2.1.3 Shopping

Overprovisioning has shown to be one of the largest contributors to food waste generation. Households tend to overprovision due to wanting to be a good provider for one's family, differences in taste, desire to eat healthy foods, and time constraints (30). The type of place that people shop at also plays a role in waste generation. When households shop at large supermarkets, they waste more food, compared to when they shop at smaller shops and farmer's markets (30). Shopping frequency has also shown to effect food wastage, households who shop more frequently have been found to have lower waste generation (30).

2.1.4 Storing

Households have been found to store food improperly as well as set their refrigerator temperatures too high (30). Other strategies, such as freezing food, has shown to decrease food-waste through shelf-life extension (30). Even if households take these actions, there is not a direct relation between knowledge about storage and the amount of food wasted (32).

2.1.5 Cooking

Food is often overprepared in households due to fear of not having enough (14). Often, lack of cooking skills leads to larger waste generation because cooks do not use ingredients that are already available within their households (14). Lastly, households that tend to rely on convenience purchase ready-made meals and restaurant take-out, producing larger amounts of waste (14).

2.1.6 Eating arrangements

Households with children have been found to waste more food than living arrangements that only contain adults (30). People who tend to eat out often have been shown to waste more food with lower levels of guilt (29). Spontaneity incurred from eating out with friends or unexpected invitations often throw schedules off kilter, leading to increased waste (30).

2.1.7 Managing leftovers

People who tend to utilize their leftovers have been found to waste less food, as expected (30). Many households have trouble using leftovers due to food safety issues, feelings of sacrifice and thrift, laziness, feeling of disgust, boredom, and guilt (12, 30). In addition, portioning has proven to be difficult for households, as it is hard to predict how much people will eat, and people want to make sure that there is more than enough food for everyone, leading to more waste (12, 31). The refrigerator acts as a medium between dinners and the trash, people will often save leftovers without the intention of ever eating them (12).

2.1.8 Food risk

Research by Neff et al. suggests that people use a mix of judgements to determine whether food is still good or not; two of the most practiced are looking at date labels and the use of smell/sight (33). Unsurprisingly, it has been found that avoiding risk and ensuring food safety have greater priority over avoiding food waste (12). It is often difficult for households to find the balance between having healthy fresh food available, and reducing the amount of wasted food (12), which is likely why fruits and vegetables are wasted the most by weight (4).

2.1.9 Packaging

The role of food packaging is to protect, preserve and inform. Williams et al. found that 25% of food waste can be attributed to packaging, citing that the three main drivers are: 'too big of packages', 'packages are difficult to empty', and 'confusion over date labeling' (16).

Usually packaging only accounts for 5% of global warming impacts, and in some cases as low as 1% (34). Other studies have found that date labels impact behavior and the value of the food that they intend to waste, therefore there should be consistency within the language among manufacturers (15, 31). Consumers anticipated wasting food of a higher value when presented with a “Use By” date compared to “Fresh By” and “Best By”, therefore this could be a source of reduction (15, 35). People often buy larger package sizes due to the quantity discount, but these savings are lost when food goes to waste (15). It was found that people view packaging as something bad, rather than something that preserves the food product. Many businesses have made packaging the focus of their environmental reduction efforts, but there are not as many directives toward reducing food waste (16). When looking at the whole food supply chain, packaging that provides better protection during distribution and a longer shelf life have been identified as ways to reduce food waste. In addition, the adoption of new packaging materials and technologies that extend shelf life implementing intelligent packaging that increases data sharing and reduces excess inventory are necessary for waste reductions (14).

Studies have suggested that food waste must be included when doing life cycle assessment studies comparing food and packaging (34, 35). If the food quantity in a package is greater than the turnover rate in a certain household type, then consumers will likely waste the food due to the product being out-of-date. It is suggested that packaging needs to communicate things like portion sizing, to better inform consumers on what food product they should buy (35). Presenting consumers with multiple packaging options for one food product could reduce food waste generation because the product “contains the desired quantity”. Food products with high waste levels and environmental impact are the best candidates for packaging measures that will reduce food waste (35). Previous work on rice and yoghurt has shown that if packaging can reduce food waste by 8%, then the total environmental impact of a food product can be reduced by approximately 1kg of CO_2e, despite an increase in packaging. Therefore, the most important environmental issue for packaging development is to reduce food waste, from field to fork (35).

2.2 Modeling techniques for food waste

2.2.1 Fuzzy modeling

A fuzzy cognitive map is a cognitive map that maps the relationships between elements (e.g. concepts, events, resources) in order to compute the "strength of impact" of each element (36). Fuzzy cognitive mapping (FCM) can be used to map the relationships among different variables and identify which element has the greatest effect on a specific problem. FCM has been used to understand how policy changes effect food security in developing countries, healthy diet assessment and bio-food production (37). The first step in performing this type of modeling is to identify, which variables have the greatest effect on FWG. Once all the variables have been identified, they are assigned with a positive or negative value to denote a positive or negative causal relation (37). Once all the variables have been mapped in a square weighted matrix, simulations can be run to identify the interactivity between variables. Fuzzy inference uses a specific algorithm to calculate the system variable iteratively, which allows researchers to verify whether the system will converge to a steady state under different conditions (37). Researchers can simulate different policy conditions by changing values of the policy variables to identify whether certain variables, such as specific policy changes, will influence the food waste system (37). Although this method is useful for understanding large scale effects, it does not provide valuable information for how consumers can change their purchasing/consumption behavior on a household level. Each household is composed of people of variable ages and socioeconomic classes, which are important factors to consider when modeling consumer behavior. Results from fuzzy inference simulation concluded that “Public food waste rules”, “Investments and infrastructure”, and “Small-scale farming” are particularly effective policy elements in developing a more sustainable consumption model.

2.2.2 Machine learning algorithms and linear modelling

Machine learning algorithms, such as the Random Forest classification algorithm, have been used to assess which variables effect household FWG the most (38). In this study, researchers used the R (24) Boruta package in order to utilize the Random Forest classification algorithm on their dataset. The dataset on UK consumers was used by the Boruta package to determine which variables had the highest Z-score. Variables with a low Z-score were deemed unimportant and were removed from the dataset. This algorithm ran until all variables were confirmed/rejected or until the maximum number of trees was used, 500 (38). Of the 50 variables used in the original model, only six were chosen in the final model. Variables included in the most parsimonious model were presence of fussy eaters, employment status, household size, local authority, home ownership status, and age. Household size was found to be the most important explanatory variable of a households FWG, while household composition was the second most important (38).

2.2.3 Discrete event simulation

DES is an operational research technique that allows managers to determine the efficiency of an existing system (39). In the case of the healthcare industry, hospitals must determine how many patients they can serve in a given amount of time with a limited staff (40). Patient flow is often random, as medical events can happen at any point in time. DES can be used to forecast the impact of changes in the system without modifying the physical system. Therefore, managers can ask 'what if' questions on how resources are best managed (40). If simulation results indicate that resources are better utilized through some change, then the physical change can be implemented to see if the simulation results hold true. Households are like hospitals in that there are usually resources available for consumption, but the time which the resource is needed can be random. In the case of milk consumption, people often drink milk with meals, but not always. DES allows researchers to model household consumption and ask 'what if' questions about household consumption habits. Although all models are a simplification, DES allows for model expansion to include as many variables as are deemed necessary. This modeling technique provides flexibility because additional parameters can be added to the model to increase fidelity. Although the first iteration may be an oversimplification, the model can be refined to provide a closer representation of real life scenarios. Researchers in the U.K. have used DES to simulate household milk consumption. Results from this study found that larger households waste less food, increasing shelf life of milk decreases waste, and better inventory management of milk leads to decreased waste generation.

2.3 Dairy Consumption

2.3.1 Milk Consumption in the U.S.

Although fluid milk consumption in the U.S. has been gradually decreasing over the last 40 years (41), there is still a substantial amount of waste being produced (24). In 2010, there were 54 billion pounds of milk available in the U.S. Approximately 20% of that milk was wasted by consumers, leading to 17 billion pounds of milk wasted each year (41). Consumers waste more milk, 21%, than retailers, 12%, for the reasons listed above. This presents a major concern, as the milk can no longer be saved or used for a value-added process, which leads to a large environmental and societal problem. Waste will be inevitable in such a large complex system, but how much waste is acceptable? Answering this question was one of the goals of this thesis.

CHAPTER 3

DEVELOPMENT OF DISCRETE EVENT SIMULATION MODEL FOR HOUSEHOLD MILK CONSUMPTION

3.1 Introduction

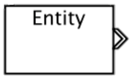
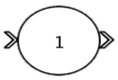
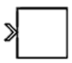
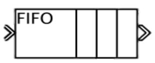
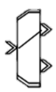
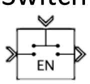
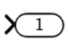
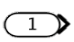
Discrete event simulation (DES) models queuing systems as they progress through time. This method was chosen because consumers purchase and consume at random moments in time. Utilizing the DES method, people's consumption and shopping habits are treated as entities. Entities, or individual items, flow through a series of queues and activities, where they are modified. Attributes are data assigned to entities to represent specific features of that entity. Events are discrete instances in time when changes are made to the system and affect the entities. Therefore, time does not move in a regular fashion within the model, rather it jumps forward when events occur. This type of behavior is ideal when modeling people because consumption or purchases of food can happen at any time.

Entity queues are areas where entities wait to be worked on or serviced. DES models often include randomness within the amount of time that an activity takes, the time that an event occurs, or generation of entities. Randomness within a model allows for the simulation of multiple samples, each with their own assigned random criteria and values (39). There are many software options for modeling discrete event systems; the present model was developed using SimEvents® made by MathWorks® (23). SimEvents® was chosen because it simplifies DES modeling into a series of blocks and provides flexibility to model complicated simulation behavior using custom code. Table 1 and Table 2 indicate each of the different terms and symbols that are used within the SimEvents® (23) software.

Table 2: Common definitions used in discrete event simulation language (DES). Definitions were taken from MathWorks® documentation on DES (23).

Terms	Definitions
Event	An observation of an instantaneous incident that may change a state variable, an output, and/or the occurrence of other events. Events can correspond to changes in the state of an entity.
Entity	Pass through a network of queues, servers, gates, and switches during a simulation. Entities can carry data, known in SimEvents software as attributes.
Intergeneration times for entities	The intergeneration time is the time interval between successive entities that the block generates. You can have a generation process that is: periodic, sampled from a random distribution, and from custom code.
Seed	Value used by the random number generator to generate random numbers within the model.

Table 3: SimEvents® blocks used to develop the model. Definitions for block functions were taken from MathWorks® documentation. Each block is used within the model to represent the consumption of milk within a consumer home (23).

Symbol	**Definition**
 Entity Generator	Generate entities using intergeneration times from dialog or upon arrival of events.
 Entity Server	Serve multiple entities independently for a period and then attempt to output each entity through the output port. If the output port is blocked, the pending entity stays in this block until the port becomes unblocked. You can specify the service time, which is the duration of service.
 Entity Terminator	Accept and destroy entities.
 Entity Queue	Store entities in a queue. The entity at the head of the queue departs when the downstream block is ready to accept it. You can specify the queue capacity and queuing policy.
 Entity Output Switch	Route entities to 1 of the multiple output ports. The port selected for departures can change during the simulation.
 Entity Input Switch	Allows for arrival of multiple entities at its ports. Outputs 1 entity at a time. The selected entity input port can change during the simulation.
 Entity Gate	Controls the flow of entities by opening and closing a gate. Allows 1 entity to advance for each message that arrives on the control port.
 Out 1	Provide an output port for a subsystem or model.
 In 1	Provide an input port for a subsystem or model.

3.2 How the U.S. consumer was modeled using DES

Figure 3 provides a high-level overview of the model used to simulate consumer consumption behavior. The refrigerator system (blue) is modeled in parallel with the consumption event system (green). First (1) consumers must purchase milk from the grocery store (*e.g.*, weekly shopping trips). After purchasing, consumers put milk in their refrigerator (2) and each milk container is assigned with a "use by date", which represents spoilage time.

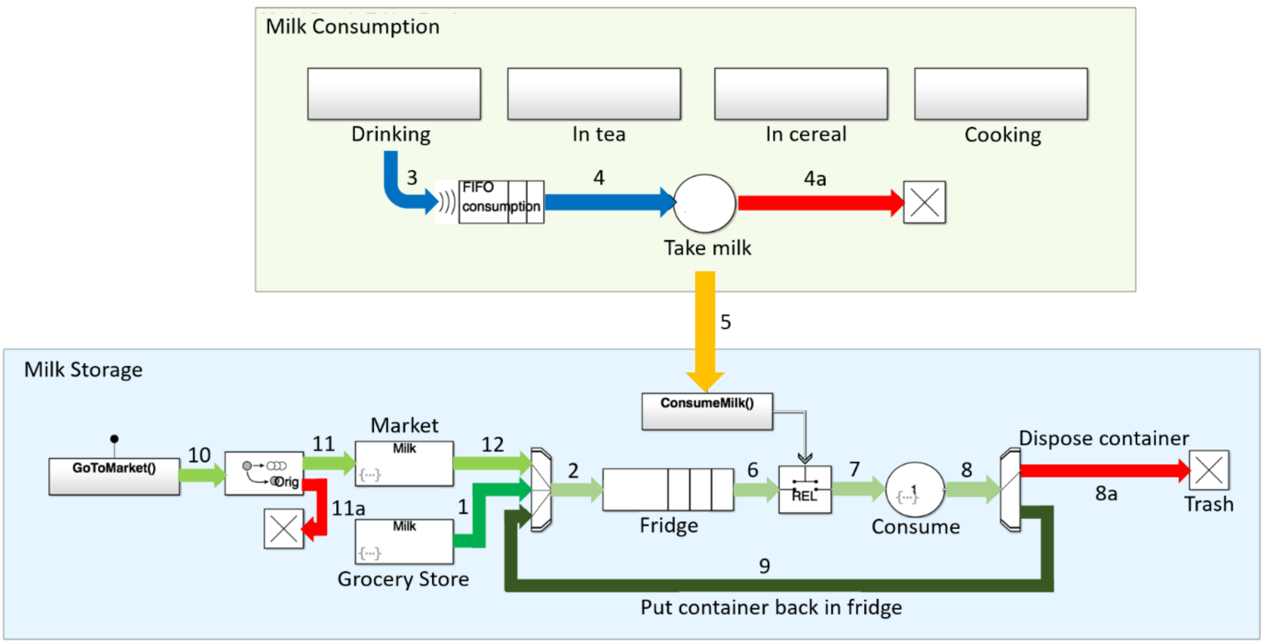


Figure 3: A detailed model output from Matlab® and Simevents®. Consumption is modeled using blocks from the Simevents® software. Arrows and numbers indicate the path that consumption, purchases, and milk containers take within the model. Captions below blocks indicate what the block is simulating, i.e. refrigerator, grocery store…

For example, milk spoils at 14 days after purchase or at 7 days after opening, whichever comes first. Therefore, if milk is opened on day 1, then it expires on day 8, whereas if it is opened on day 13, the milk expires on day 14. To represent variability within milk spoilage, a standard deviation of 2 days was used. Once purchased, milk travels through the gate (2) and enters a sorting queue. Numbers 10, 11 and 12 represent a similar function but instead mimic top-up shop purchases. Containers purchased from the top-up shop are non-periodic purchases that occur on-demand when the consumer runs out of milk. Upon purchase, containers are uniquely identified as shown in Table 4.

Table 4: Entities are assigned values for the following attributes.

Attributes	**Definition**
`ContainerID`	Unique identification number assigned to each container
`ContainerVolume`	Number indicating the amount of milk the container can hold in mL
`MilkVolume`	Number indicating the amount of milk in the container in mL
`UseBy`	Number indicating the use-by date
`IsOpen`	Number used to indicate of the container has been opened (0 = unopened, 1 = opened)
`MilkVolume`	Number indicating the amount of milk in the container in mL
`Path`	Number used to route the entity through the model

The likelihood of someone going top-up shopping is determined by a probability function, as it is assumed consumers do not go top-up shopping each time there is no milk available. For milk to be consumed, milk must be requested (3) via an entity generator. In the example shown in Figure 3, milk is requested to be drunk by the consumer (Block “Drinking”). Consumption events that occur are routed into a first in first out queue (FIFO), Figure 3 (4). The queue keeps consumption events in order and prevents them from disrupting one another. Upon leaving the queue, a consumption event entity enters a server that holds onto the entity and performs some actions. The server checks each event to ensure that the amount of milk requested by the consumer is available in their refrigerator. If there is enough milk in the refrigerator (2), then the request (5) is relayed to the “ConsumeMilk()” Simulink® function and the server triggers the model to remove the requested amount of milk from the refrigerator (2). If the amount requested is greater than the amount available, then a running total is kept of the total amount of milk unavailable. If the probability function for the top-up shop is met, then the consumer will go to top-up shopping. The consumption event entity then exits the server and is terminated from the model (4a).

Next, the REL gate – see Table 3 for SimEvents® blocks description – ensures that milk is being consumed after a container has been taken out of the refrigerator (6). The sorting queue ensures that the oldest milk is used first, before newly purchased milk (2, Refrigerator). The `UseBy` attribute (Table 4) is used to store the use by date for each container entity. Both the consumption request and container enter the "Consume" server, where it is decided whether the milk in the container is spoiled or not. If the milk has spoiled, then it travels through the gate into the trash (8a). If the milk is good, then the amount requested is consumed. The amount consumed is subtracted from the container volume, and then the container travels through the gate (9), where it is put back into the refrigerator.

3.3 Determining model parameters

Four different types of milk consumption events were modeled initially based on U.K. consumer habits and the WRAP Milk Model (22). These include adding milk to coffee or tea, drinking a glass of milk, pouring milk into cereal, and using milk in cooking. Each type of consumption event is defined in the model using three parameters: consumption amount, average consumption frequency, and probability of consumption. Table 5 lists the specific parameter values used for each person in a one, two or four-person household

Table 5: Parameters used to model adults older than 19, children between 2 and 3, and children between 9 and 18. “TD” defines the amount of times per day that the consumption event happens. “Pr” is the probability of consumption for each consumption type. “Amount” specifies the amount of milk consumed on average during each consumption event.

	Child 2-3			**Child 9-18**			**Adult 19+**		
	TD	Pr (%)	Amount (mL)	TD	Pr (%)	Amount (mL)	TD	Pr (%)	Amount (mL)
Coffee/Tea	0	0	0	0	0	0	2	50	20
Drinking	3	50	250	2	35	250	1	35	200
Cereal	1	50	300	1	50	300	1	50	200
Cooking	1	15	300	1	15	300	1	15	600

Detailed data inputs for each consumption type are listed in Figure 4.

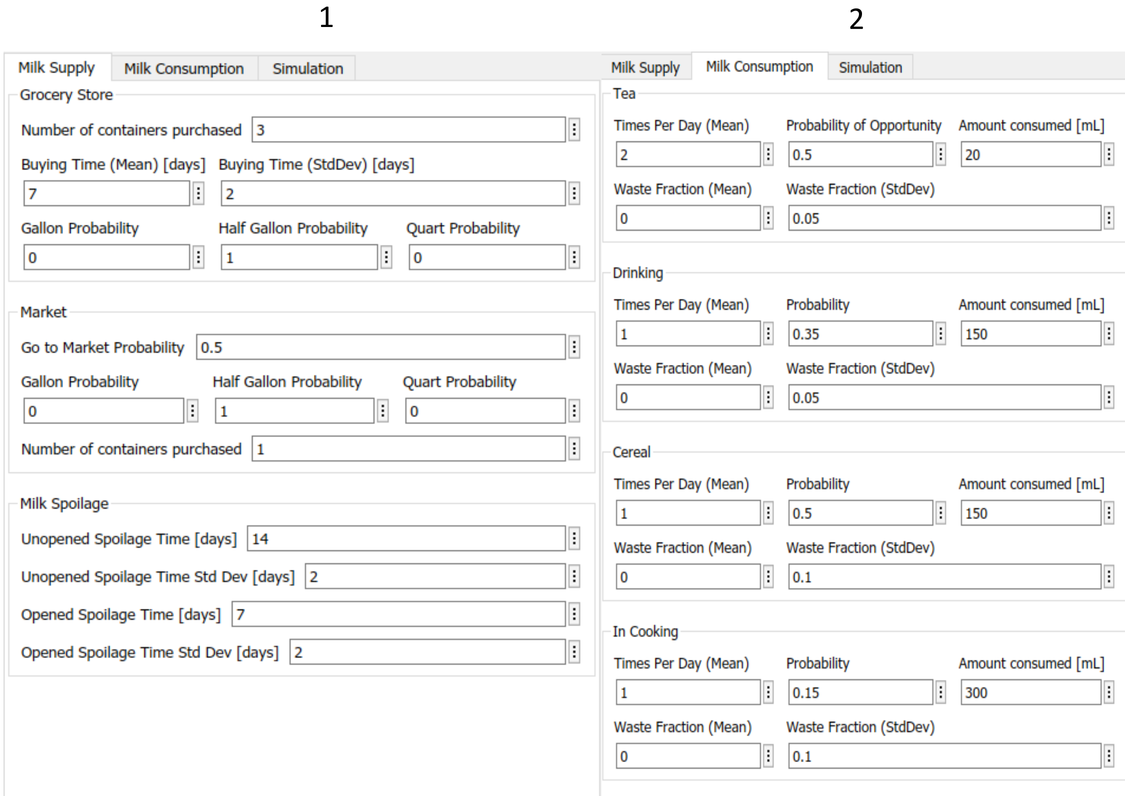


Figure 4: Model inputs dialog boxes. Parameters in the DES model are entered into each of the boxes listed above. Purchasing behavior for grocery stores and top-up shops is specified on the left (1). In addition, spoilage is specified on the bottom left (1). Values for consumption can be specified within the Tea, Drinking, Cereal and In Cooking tabs (2). The box on the right represents the consumption parameters for one adult over the age of 19.

During simulation, *entities* are randomly generated to represent each type of consumption event. The intergeneration time, or time between consecutive entities as described in Table 2, is modeled with an exponential distribution function:

$$\Delta t = -\mu \log(1-\chi) \qquad (1)$$

where χ is an uniformly distributed random number between 0 and 1. The variable μ is the average consumption period, which uses the average times per day value specified for each consumption event, as outlined in Table 5.

$$\mu = (\text{Average times per day})^{-1} \quad (2)$$

When plotting the random seed values using a violin plot, we see that spoilage in households follows a uniform distribution (see Figure 5).

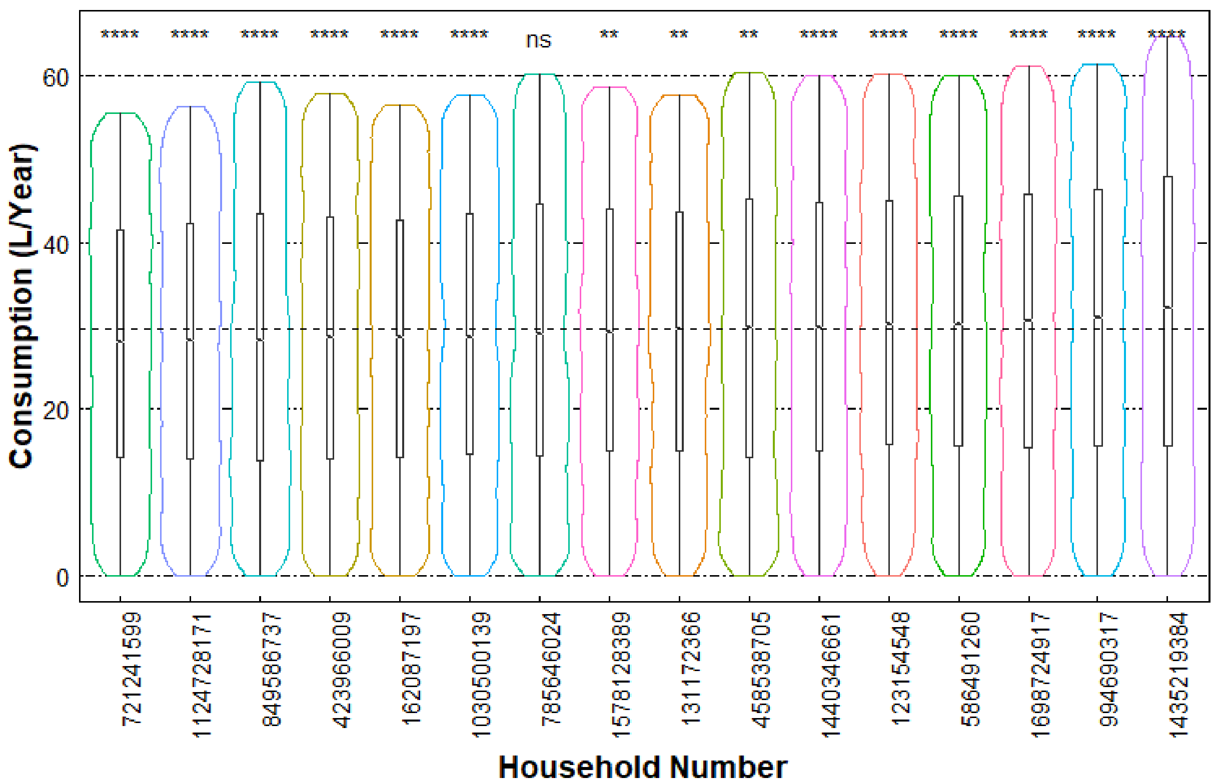


Figure 5: Consumption statistics for 16 1 person households. A violin plot indicates where the largest portion of data is concentrated. The variation within consumption of milk in 1-person households. The dotted line indicates the mean consumption value, and the "*"s indicate whether the household is significantly different from the mean according to an ANOVA ($p<0.05$). Within the data distribution, the boxplot for each household is visible.

After an event is generated, there is a probability associated with whether that specific event occurs or not. Defined as:

$$if\ \chi > P_{Drink} \qquad (3)$$
$$then\ event\ occurs$$

Figure 6 represents the “Drinking” block (“3” in Figure 3), which contains the “ConsumptionEvent” entity generator. Intergeneration time and probability of an event occurring, indicated in equation 3, are executed within the “Drinking” block.

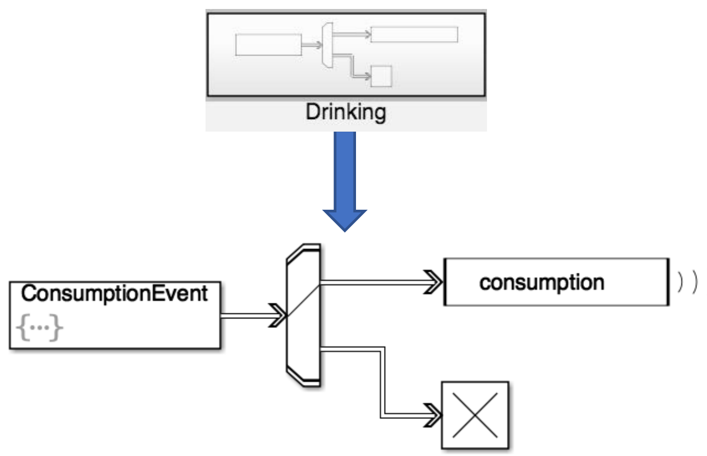


Figure 6: Output from Simevents® representing how drinking events are generated. Within the “Drinking” Block there is a subsystem. The subsystem consists of an entity generator, a gate and a broadcasting signal blocks. Consumption entities that occur travel through path 1 of the gate to the consumption broadcasting signal.

Upon generation of a “ConsumptionEvent” entity, the model generates data with values that are specific to that entity (“consumption” event). This data, known as the entity’s attributes, include:

- `Type` – Number used to indicate the type of consumption event (1 = coffee/tea, 2 = drink, 3 = cereal, 4 = cooking)
- `Amount` – Number to indicate the amount of milk in mL to be consumed
- `Path` – Number used to route the entity through the model

Upon generation of a “ConsumptionEvent” entity, the model determines if that consumption event occurs or not, which depends on a probability (Table 5). If the probability of consumption is met, then milk is consumed, and the entity’s Path attribute is set to 1, as shown in Figure 6. For example, if the probability of drinking milk is 35%, then 35% of the time milk will be drunk and 65% of the time the consumption event will be terminated. Inputs for the probability of consumption events happening is listed in Table 5.

3.4 Representing different household types

Random numbers are used throughout the model to better represent the consumers’ behavior. Each person simulated must be different, this is achieved through randomness within consumption, waste generation, spoilage time, and purchasing of milk. Random numbers are generated based on initial random seed values (a seed represents a consumer). The values of the seed provide a set of numbers that are used by the Matlab® algorithm (mt19937ar) to generate random numbers. When the seed is changed, the random numbers change as well. An indication of how the random numbers change from person to person is portrayed in Figure 7, each color represents a different person.

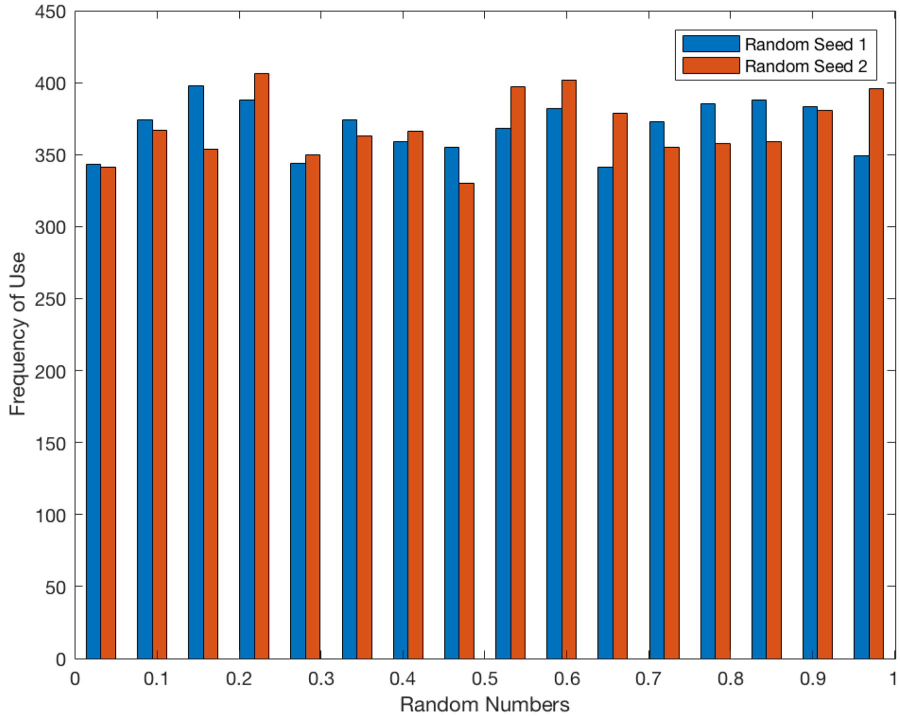


Figure 7: Indication of random generation used to represent different household types. Each random seed number is a different household type. Random numbers were logged for the "Drinking Milk" consumption event. When the seed values were changed, the random numbers generated also changed.

One seed value was assigned to each household type, therefore there were 150 unique seed values used to represent each household. Random numbers follow a uniform distribution (see Figure 5) after repeated sampling over an indefinite amount of time, but when looking at one instance in time the random values generated differ between one another. Thus, when seed values change between simulations, people with different habits are represented. Time between consumption events can be predicted based on the mean consumption events per day and the probability of them occurring as described in equation 4.

$$Predicted\ Intergeneration\ Time = \frac{1}{average\ times/day} * \frac{1}{daily\ probability\ of\ event} \quad (4)$$

whereas average times and daily probabilities of events are defined in Table 5. The observed average time between consumption events is based on results from the model, which may differ from the predicted intergeneration time due to randomness. However, when simulating over a long period, the observed values will asymptote about the predicted average intergeneration time, calculated by equation 4 and shown in Figure 8.

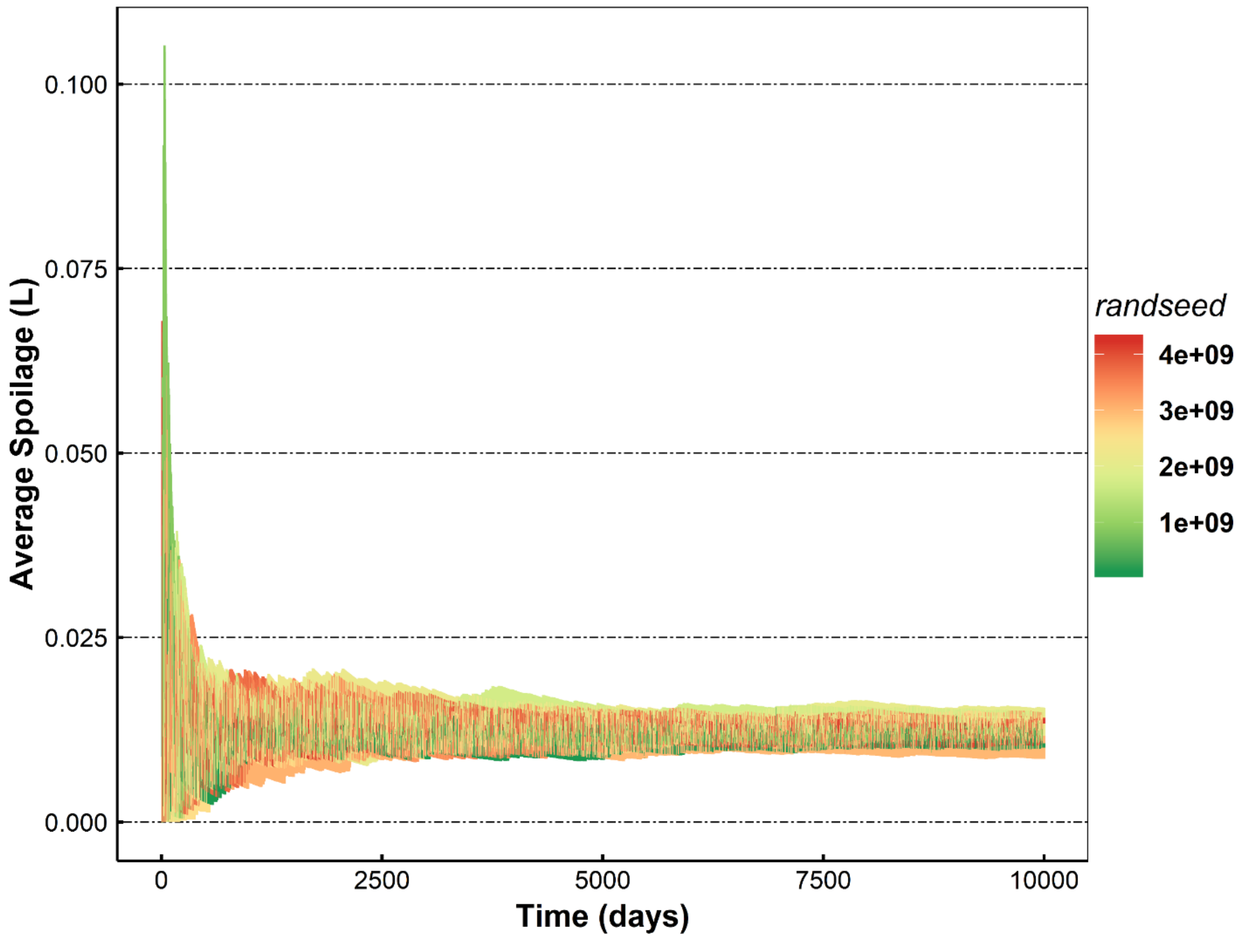


Figure 8: Representation of how variability is generated by the model. Average spoilage from 50 1-person households purchasing 1 quart was plotted over 10,000 days to understand model variability. The legend, “randseed”, represents the different seed values that were used on a gradient scale. Values of average spoilage converge at around 10,000 days.

Like consumption events, buying behavior is also based on a probability of buying a certain size of container. Households are assigned one of three container sizes: a quart, half gallon, and gallon based on a probability, as outlined in Table 6.

Table 6: Probability of buying a certain container type. Probabilities can be adjusted within the model to simulate different scenarios. "1P" (1-person non-family), "2P" (2-person non-family), and "4P" (4-person family) households are depicted with the probability of purchasing a container at a grocery store, versus at a top-up shop.

Container Type	**Probability of Purchase at grocery store (%)**			**Probability of Purchase at top-up shop (%)**		
Household Type	1P	2P	4P	1P	2P	4P
Half Gallon	0	100	0	0	100	100
Gallon	0	0	100	0	0	0
Quart	100	0	0	100	0	0

The frequency of buying from the grocery store in our model is set to every seven days but can be adjusted (Figure 4). Purchases from the top-up shop are only initiated, determined by a probability function, when there is not enough milk available in the refrigerator. For example, an individual can be assigned with a probability of 0.50, meaning that 50% of the time people will go top-up shopping to buy more milk when there is none available (Figure 4). Note that the amount of milk unavailable is recorded when the individual chooses not to go to the top-up shop.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Modeling the American consumer

Modeling consumers can be difficult due to the many variables that affect how people consume food—for example, cooking at home *vs* eating out, number and age of children, and food preferences. When determining how to model consumers, we simplified the process of how food travels through the home (see Figure 9) to understand where waste is being generated.

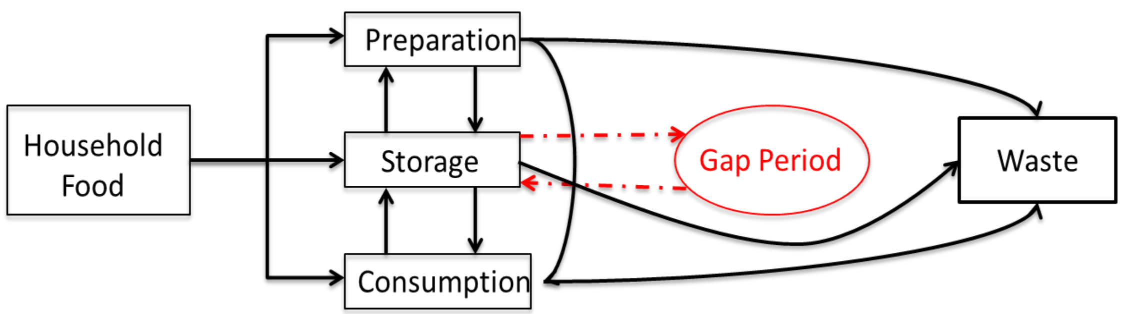


Figure 9: A simple model of how food travels through the home. First food is purchased and enters the household, next it is either stored, prepared or consumed. All three of these blocks generate waste. The gap period during storage is indicative of times when someone may not know what do with a food item, or they decide to go to eat, or leftovers go bad while being stored. It is assumed that during the gap period, most waste generation happens.

It is necessary to determine which of these parameters are most likely to decrease waste by reiterating different combinations of the parameters, similar to what has been done with "fuzzy" modeling (37). DES was chosen in this work to model consumers' consumption due to its extensive use in the health-care industry for assessing resource needs and allocation (40). Like patients needing treatment in a health-care institution at a specific point in time, consumption events are sometimes planned, triggering an event, but not always. Therefore, consumption events are recorded during simulation when they happen at random moments. Household variables—like consumption averages or container sizes—can be modified to answer 'what if' questions on how packaging affects the consumption and spoilage in different household types. To model consumers within the home, many assumptions were made to accurately represent one, two and four-person households. Some basic assumptions that were applied to all three household types included one weekly shopping trip to a large grocery store and milk is assumed to spoil seven days after opening if the expiration date was not reached first. In addition, top-up shopping trips were modeled for times when a household ran out of milk before making their weekly grocery store shopping trip. Households of 1 person bought quart containers, while 2 and 4-person households purchased half gallon containers when top-up shopping for milk (Table 6). Three common U.S. milk package sizes were modeled based on their percentage of market share (Table 7); quart, half gallon, and gallon containers (all made of high-density polyethylene -- HDPE).

Table 7: Market share data for 1 gallon and half gallon containers. Data obtained from the supplementary information in Burek et al. (30).

Container type	Market Share
Monolayer HDPE chilled 1 gallon	65%
Monolayer HDPE chilled 1/2 gallon	10%
Gable Top carton chilled ½ gallon	8%
Monolayer HDPE chilled quart	1.5%
Others*	15.5%

*Note: Others includes stackable HDPE, aseptic bricks, PET, pillow pouches, smaller sizes of gable top cartons, and multilayer HDPE containers.

Milk spoilage was modeled based on three different shelf-lives—7, 14, and 21 days. Previous research indicates high temperature short time (HTST) pasteurized milk in the U.S. has a shelf-life between 17 and 21 days (42). Milk waste from not finishing a bowl of cereal or a glass of milk were not included in this analysis as the amounts wasted were assumed to be miniscule compared to the waste generated from milk spoilage. Therefore, it is assumed that persons within a household consume all the milk that is poured from the carton. In addition, waste due to consumer error, such as leaving milk out for too long or throwing away leftovers with milk in them were not included in the model. Analysis for this paper was mostly focused on a 14-d shelf-life to avoid overestimation of milk spoilage. Families modeled included 1 and 2-person non-family households, and 4-person family households (Table 5). These assumptions were made to streamline modeling. The U.S. Census data indicates that 1 and 2-person non-family households make up most of the non-family household population, while 2, 3, and 4-person households make up most family households (Figure 10) (43).

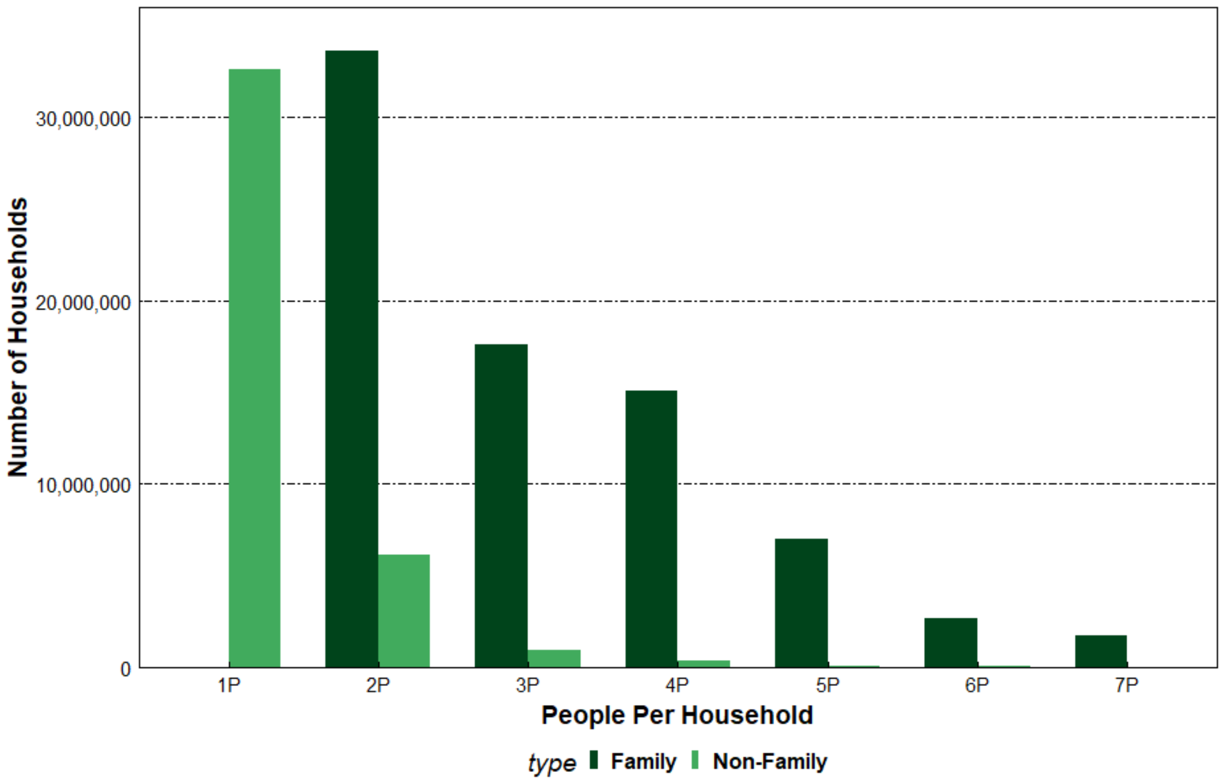


Figure 10: U.S. Census Bureau data for family (dark green) and non-family households (light green), data obtained from the American Community Survey by the U.S. Census Bureau (22).

Family households are generally more diverse, as they can contain children and adults of different ages. For modeling purposes, it was assumed that two-person households are comprised of two adults. Four-person households were assumed to have two adults and two children—child 1 was between 2-3 and child 2 was between 9-18 (44) (Table 5).

4.2 Analyzing large datasets

Simulations were run for 10,000 days for 50 different seed values. To save time on manual labor, a parameter sweep was performed. This means that each combination of the parameters, shown in Figure 11, were performed in one "run". This means that any combination of parameters can be modeled without having to run each parameter individually. Once parameters were determined, simulations were run remotely via a secure shell at MSU's high performance computing center. Analysis was done in R, thus most files are in .Rdata file. These can be converted into other file types if needed. Below are some of the summary data tables that were produced during analysis. Calculations done for the GHG emissions, later shown in Figure 15, were done by taking data on climate change impacts of fluid milk delivery systems from Burek et al (45). To determine the climate change impacts from packaging, container usage had to be first aggregated by type. Containers purchased from the top-up shop were totaled separately than containers bought from regular grocery store shopping trips (Table 8, Table 9, Table 10).

Table 8: Summary statistics in kg of CO_2e for 50 one-person households modeled using different scenarios. Each column represents the emissions generated from containers used in a years' time. Column names with "TP" represent containers that were purchased from the top-up shop, while column names with "wasted" represent containers that were thrown away with milk still inside them. The last three columns represent the emissions from containers that were consumed in full. Three scenarios were tested for one-person households: purchase of a half-gallon container, two-quart containers, and a 1-quart container on weekly grocery shopping trips. Each scenario listed above assumed that consumers purchased 1-quart containers during top-up shopping trips for more milk.

	Cont1QTP1PHG	Cont1QTP1P2Q	Cont1QTP1P1Q	wastedcontHG1P
max	5.37E+06	4.53E+06	3.81E+07	1.42E+08
range	5.37E+06	4.53E+06	3.77E+07	1.50E+07
sum	9.31E+07	6.17E+07	8.24E+08	6.77E+09
median	1.76E+06	1.01E+06	1.52E+07	1.36E+08
mean	1.86E+06	1.23E+06	1.65E+07	1.35E+08
SE.mean	2.21E+05	1.53E+05	1.76E+06	5.13E+05
CI.mean.0.95	4.44E+05	3.08E+05	3.53E+06	1.03E+06
var	2.44E+12	1.17E+12	1.55E+14	1.32E+13
std.dev	1.56E+06	1.08E+06	1.24E+07	3.63E+06

	wastedcont2Q1P	wastedcont1Q1P	contHG1P	cont2Q1P	cont1Q1P
max	2.81E+08	6.19E+07	1.95E+08	4.88E+08	2.43E+08
range	3.66E+07	2.06E+07	5.66E+06	1.54E+07	7.05E+06
sum	1.31E+10	2.59E+09	9.61E+09	2.40E+10	1.20E+10
median	2.62E+08	5.16E+07	1.92E+08	4.79E+08	2.39E+08
mean	2.63E+08	5.18E+07	1.92E+08	4.79E+08	2.39E+08
SE.mean	1.35E+06	6.75E+05	1.84E+05	5.36E+05	2.29E+05
CI.mean.0.95	2.72E+06	1.36E+06	3.69E+05	1.08E+06	4.59E+05
var	9.13E+13	2.28E+13	1.69E+12	1.44E+13	2.61E+12
std.dev	9.56E+06	4.77E+06	1.30E+06	3.79E+06	1.62E+06

Table 9: Summary statistics in kg of CO_2e for 50 two-person households modeled using different scenarios. Each column represents the emissions generated from containers used in a years' time. Column names with "TP" represent containers that were purchased from the top-up shop, while column names with "wasted" represent containers that were thrown away with milk still inside them. The last two columns represent the emissions from containers that were consumed in full. Two scenarios were tested for two-person households: purchase of 2 half gallon containers and 1-gallon container on weekly grocery shopping trips. Each scenario listed above assumed that consumers purchased half gallon containers during top-up shopping trips for more milk.

	contHGTP1G	contHGTP2HG	wastedcontG	wastedcontHG	contG	contHG
min	0.00E+00	0.00E+00	1.01E+07	1.86E+07	2.67E+07	7.11E+07
max	1.76E+06	1.51E+06	1.31E+07	2.33E+07	2.78E+07	7.36E+07
range	1.76E+06	1.51E+06	3.03E+06	4.69E+06	1.09E+06	2.47E+06
sum	3.47E+07	3.12E+07	5.87E+08	1.03E+09	1.36E+09	3.60E+09
median	7.06E+05	5.17E+05	1.18E+07	2.05E+07	2.72E+07	7.21E+07
mean	6.94E+05	6.24E+05	1.17E+07	2.06E+07	2.72E+07	7.21E+07
SE.mean	8.02E+04	6.56E+04	9.03E+04	1.68E+05	3.06E+04	7.29E+04
CI.mean.0.95	1.61E+05	1.32E+05	1.81E+05	3.37E+05	6.16E+04	1.46E+05
var	3.22E+11	2.15E+11	4.07E+11	1.40E+12	4.69E+10	2.66E+11
std.dev	5.67E+05	4.64E+05	6.38E+05	1.19E+06	2.17E+05	5.15E+05

Table 10: Summary statistics in kg of CO_2e for 50 four-person households modeled using different scenarios. Each column represents the emissions generated from containers used in a years' time. Column names with "TP" represent containers that were purchased from the top-up shop, while column names with "wasted" represent containers that were thrown away with milk still inside them. The last three columns represent the emissions from containers that were consumed in full. Three scenarios were tested for four-person households: purchase of 3 half gallon containers, 4 half gallon containers, and 2-gallon containers on weekly grocery shopping trips. Each scenario listed above assumed that consumers purchased half gallon containers during top-up shopping trips for more milk.

	contHGTP4P2G	contHGTP4P3HG	contHGTP4P4HG	wastedcont2G4P	wastedcont3HG4P
min	2.86E+06	1.93E+07	2.92E+06	3.23E+07	1.10E+07
max	8.27E+06	2.77E+07	8.08E+06	4.29E+07	2.08E+07
range	5.41E+06	8.39E+06	5.16E+06	1.07E+07	9.76E+06
sum	2.68E+08	1.16E+09	2.56E+08	1.89E+09	7.67E+08
median	5.41E+06	2.31E+07	5.10E+06	3.77E+07	1.52E+07
mean	5.37E+06	2.32E+07	5.13E+06	3.78E+07	1.53E+07
SE.mean	1.59E+05	2.57E+05	1.60E+05	3.19E+05	2.58E+05
CI.mean.0.95	3.20E+05	5.17E+05	3.22E+05	6.40E+05	5.19E+05
var	1.27E+12	3.31E+12	1.29E+12	5.07E+12	3.34E+12
std.dev	1.13E+06	1.82E+06	1.13E+06	2.25E+06	1.83E+06

	wastedcont4HG4P	cont2G4P	cont3HG4P	cont4HG4P
min	6.79E+07	1.31E+08	2.62E+08	3.47E+08
max	8.78E+07	1.36E+08	2.70E+08	3.62E+08
range	1.99E+07	4.70E+06	8.20E+06	1.49E+07
sum	3.91E+09	6.69E+09	1.33E+10	1.77E+10
median	7.87E+07	1.34E+08	2.66E+08	3.55E+08
mean	7.83E+07	1.34E+08	2.66E+08	3.54E+08
SE.mean	7.45E+05	1.46E+05	2.56E+05	4.55E+05
CI.mean.0.95	1.50E+06	2.93E+05	5.15E+05	9.15E+05
var	2.77E+13	1.06E+12	3.28E+12	1.04E+13
std.dev	5.27E+06	1.03E+06	1.81E+06	3.22E+06

Packages that were thrown away with milk in them were summed separately from containers that were thrown away empty. Once the total amount of containers used in a year's time was determined, population estimates from the U.S. Census Bureau were retrieved via the tidyverse application program interface. These population estimates, shown in Table 11, were multiplied by the GHG emissions for consumption, spoilage, and container waste (Table 12) from Table 8, Table 9, and Table 10

Table 11: Census Bureau data for 4-person family households, and 1 and 2 person non-family households. Data was retrieved using an API key. The "variable" column refers to the Census variable assigned to each household type, while the "estimate" is the number of households of those type. Lastly, the "moe" represents the margin of error, as listed by the U.S. Census Bureau.

Variable Name	NAME	variable	estimate	moe
Four Family Household	United States	B11016_005	15029459	113507
One-person non-family household	United States	B11016_010	32595486	46684
Two-person non-family household	United States	B11016_011	609658	22939

Table 12: Climate change (kg CO2-eq) impacts of gallon, half-gallon, and quart HDPE containers. Data was obtained from Burek et al (45). The last column represents the emissions from consumption, which were determined by subtracting total cradle to grave impacts from container and end of life (EOL) impacts. *Climate change impacts for quart containers were not analyzed in the study, therefore the impact for quart containers was calculated by using data for gallon and half-gallon containers.

Container Type		Raw milk transport	Container	Processing plant	Distribution center	Retail Center	Consumption	EOL	Total Cradle to Grave	Total Emissions from Consumption
Gallon	Climate change (kg CO2-eq)	2.85E+01	6.94E+01	8.58E+01	2.05E+01	1.29E+02	2.40E+02	1.37E+01	2.00E+03	1.92E+03
Half-Gallon		2.85E+01	9.04E+01	8.16E+01	2.27E+01	1.31E+02	2.40E+02	1.96E+01	2.03E+03	1.92E+03
Quart*		2.85E+01	1.11E+02	7.74E+01	2.49E+01	1.33E+02	2.40E+02	2.55E+01	2.06E+03	1.92E+03

4.3 Understanding how packaging affects milk consumption and spoilage

After simulating household consumption for 10,000 days (Figure 8), average yearly consumption was assessed to better understand how people consume based on different package sizes, shelf lives, and probability of top-up shopping. Figure 11 and Figure 12 show how packaging, purchasing behavior and spoilage effect a household's milk consumption.

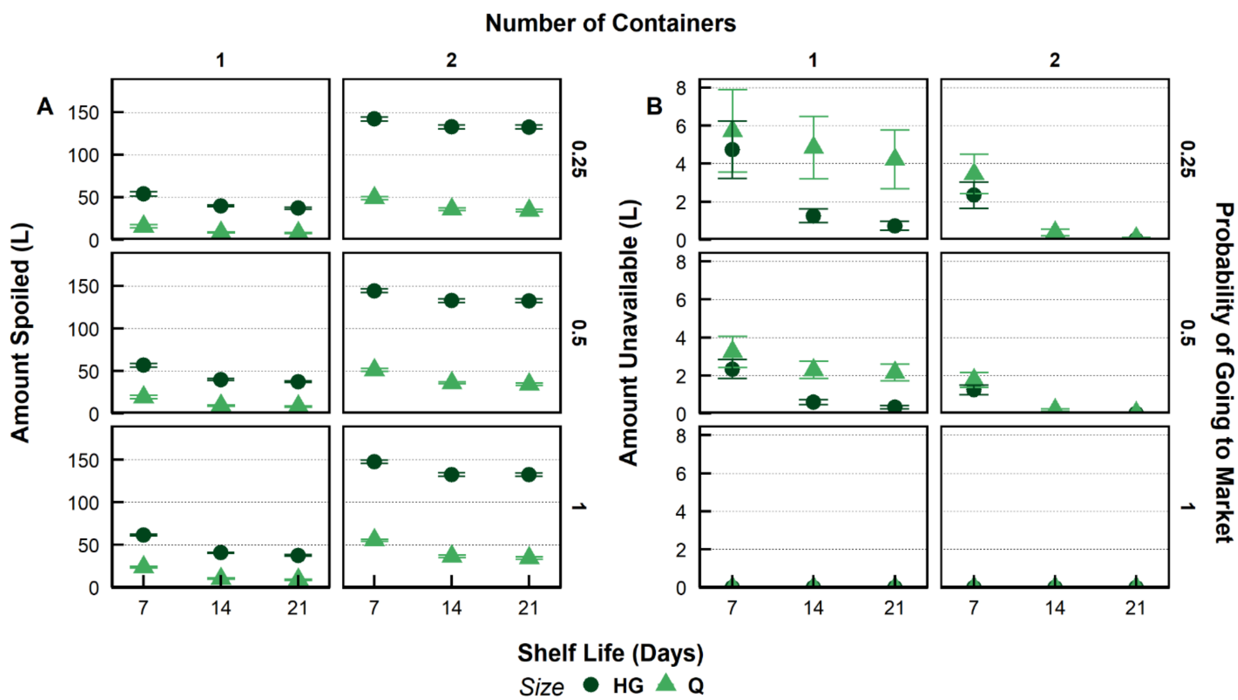


Figure 11: Amount of milk per year, in liters, spoiled (A) and unavailable (B) for a one-person household. Comparison of two different sizes, "Q" indicates a quart container, while "HG" signifies a half-gallon. Centered across the top of the figure are the number of containers purchased by the household on their regular shopping trips. The probability of going to a top-up shop when there is not enough milk available is represented on the right side of the figure. The number of containers purchased is represented on the top of the graph. One-person households purchased 1 or 2 containers of each size.

One-person households saw the greatest reduction in milk waste when they switched from purchasing 1 HG to 1 Q. This indicates that consumers are purchasing too much milk. Even when households purchase two quarts, there was still a large amount of milk being spoiled. Figure 11 indicates that if consumers are willing to go top-up shopping 50% of the time that milk is unavailable to them, they will significantly decrease the amount of wasted milk each year.

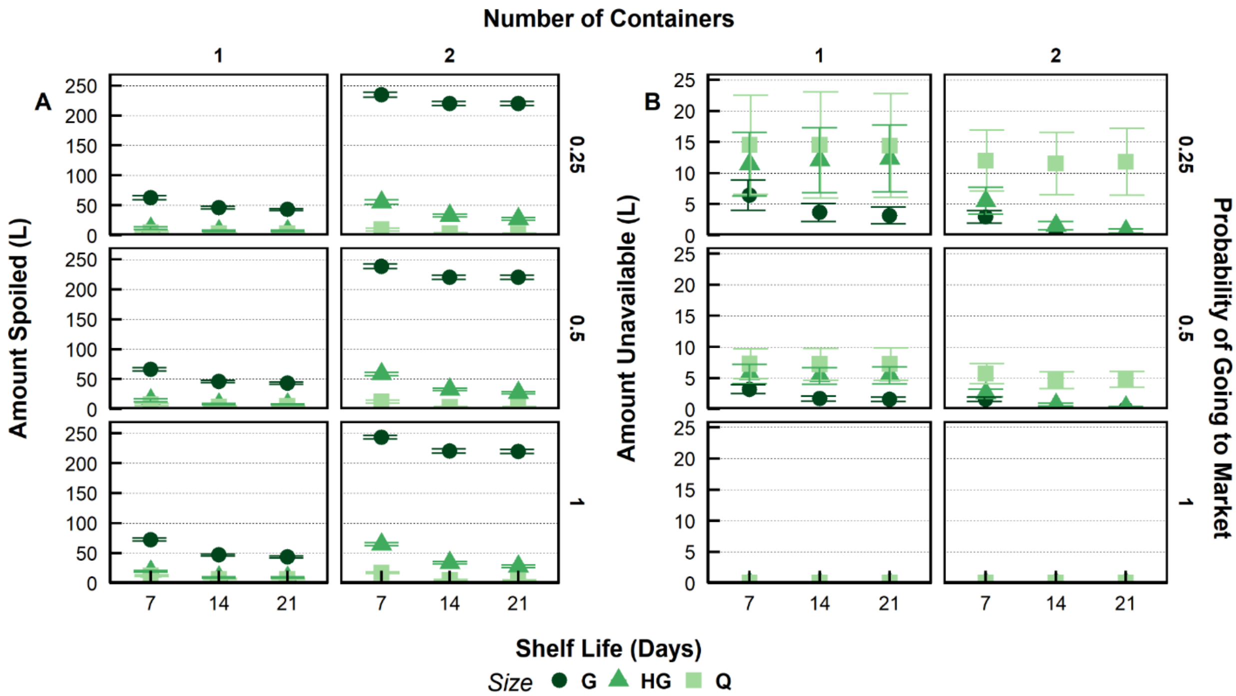


Figure 12: Amount of milk per year, in liters, spoiled (A) and unavailable (B) for a two-person household. Comparison of three different sizes, “G” stands for gallon, “HG” signifies a half-gallon, while “Q” indicates a quart container. Centered across the top of the figure are the number of containers purchased by the household on their regular shopping trips. The probability of going to a top-up shop when there is not enough milk available is represented on the right side of the figure. The number of containers purchased is represented on the top of the graph. One-person households purchased 1 or 2 containers of each size.

Figure 13 illustrates that spoilage increases with the purchase of more milk for four-person households, as expected, while the amount of milk unavailable to the consumer decreases with the purchase of larger containers. Secondly, model results indicate that as the probability of going on a top-up shopping trip increases, the amount of milk unavailable decreases, also as expected.

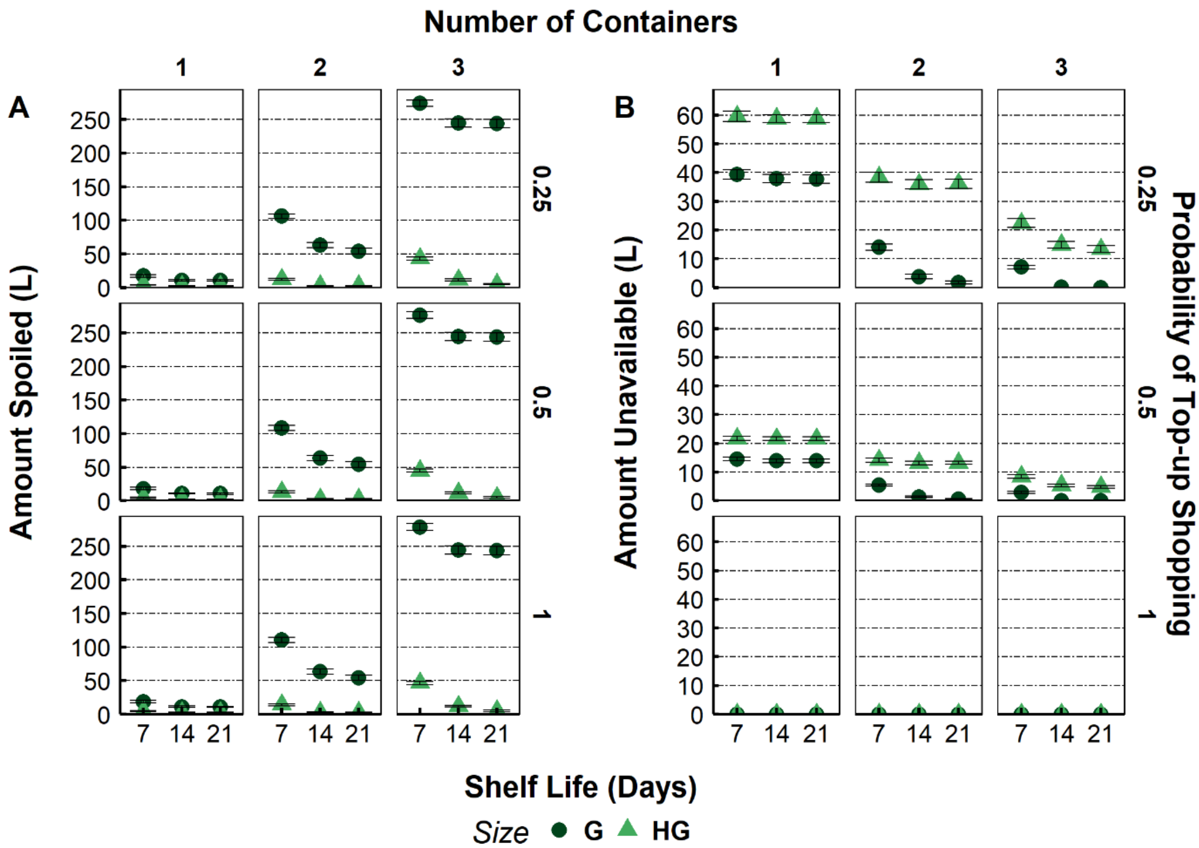


Figure 13: Amount of milk per year, in liters, spoiled (A) and unavailable (B) for a four-person household. Comparison of two different sizes, "G" indicates a gallon container, while "HG" signifies a half-gallon. Centered across the top of the figure are the number of containers purchased by the household on their regular shopping trips. The probability of going to a top-up shop when there is not enough milk available is represented on the right side of the figure. The number of containers purchased is represented on the top of the graph. Households of four purchased 1, 2, or 3 containers of each size.

A shelf-life of seven days was included to exemplify cases in which retailers discount milk at the end of its life. Consumers must then use the milk within seven days to avoid spoilage from expiration. Purchase of milk with a 7-day shelf life increases the amount of spoilage in four-person households when they purchase a gallon container (Figure 13). If consumers want milk that will not spoil within the week, they should always purchase “fresher” containers (i.e., longer than a 7-d shelf-life). One and 4-person households have shown to be the best candidates for changes in purchasing behavior that avoid spoiled milk, as indicated by Figure 14.

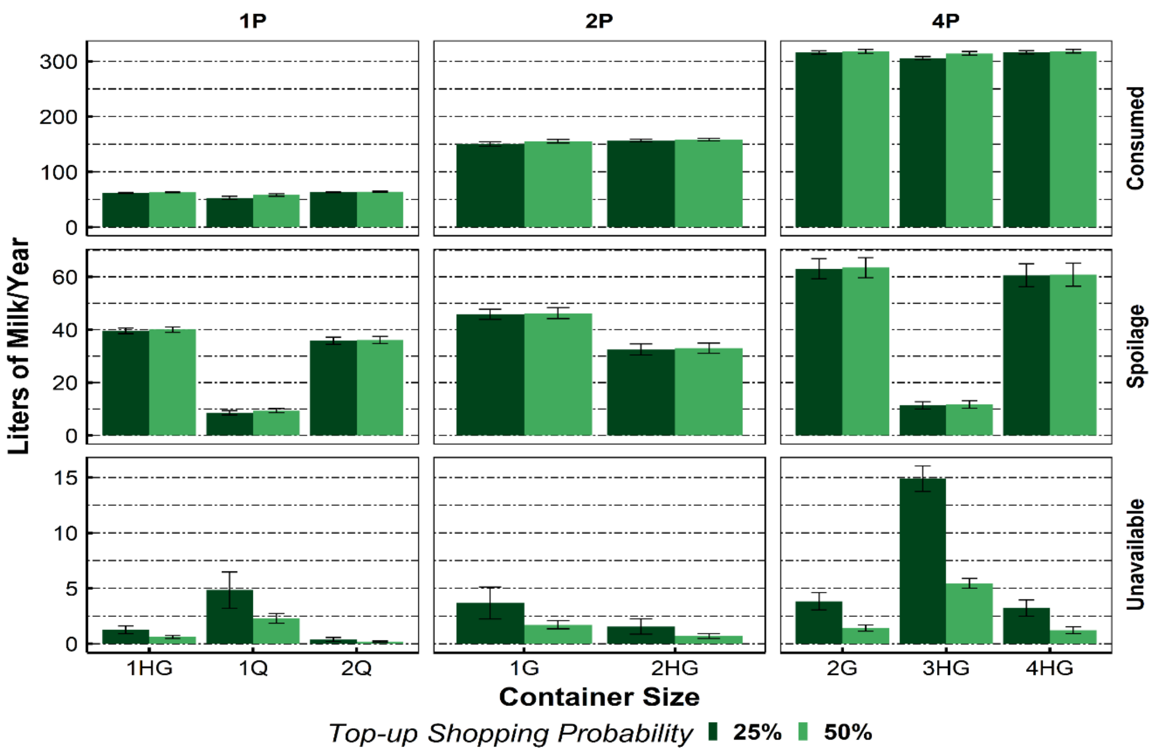


Figure 14: Summary of consumption, spoilage, and amount unavailable for 1 person, 2 person, and 4 person households. The right axis indicates the amount consumed, spoiled, and unavailable milk. Each column represents a different household size, while the colors coordinate with a 25% and 50% chance of going to top-up shopping. Each container size simulated is represented on the x-axis. “Q” indicates a quart size container, “HG” indicates a half-gallon, and “G” signifies a gallon container. Results were averaged over a one-year time frame.

When one and four-person households purchase fewer smaller containers, their milk consumption does not decrease, but their spoilage decreases significantly. The amount of milk unavailable to the consumer decreases when the probability of going top-up shopping increases from 25 to 50%. Spoilage does not increase with increased top-up shopping trips since consumers are purchasing smaller containers when there is not milk available and it is likely consumed right away (Figure 14). Evidence from the model suggests that people should make time for top-up shopping trips to pick up milk if needed, rather than purchase milk in bulk on weekly shopping trips to avoid large spoilage amounts —similar results were found for the U.K. population (19). Two-person households were not simulated for the purchase of 1 HG container as the amount unavailable will be too large. In the case of four-person households, this does not apply because 4 HGs is too much milk for a family of four. Large grocery retailers should consider discounting smaller package sizes, to entice consumers to purchase smaller quantities of milk, as indicated by previous survey results (12, 25). Although previous research claimed that consumers perceive themselves as knowledgeable and engaged about food waste, the DES model suggests that current consumption behavior can be changed to significantly reduce food waste (12). In addition, if consumers are informed about what package sizes they should purchase for their household size, they can avoid guilt associated with throwing food away (26). If consumer fluid milk demand decreases, milk producers could divert fluid milk towards value added products, like cheese and yogurt, which have seen increased demand in the last decade (18).

4.4 Greenhouse Gas Emissions of Milk Consumption, Packaging, and Spoilage

The U.S. Census estimations for 1 (32 million) and 2-person (6 million) non-family households and four-person (15 million) family households were used to assess climate change impacts for three different package delivery systems (23). Packaging impacts were based on the GHG emissions estimated previously for HDPE containers in the U.S. (27), it is assumed that these households are only purchasing containers of this type. HDPE gallon and half-gallon milk containers were targeted, as they make up the largest market share 65 and 10% of total milk sales, respectively (Table S1). Analysis of container purchases was differentiated into three different categories: containers used from regular shopping trips, containers purchased during top-up shopping, and containers thrown away with spoiled milk. Packaging waste was then totaled for a year representing the total GHG emissions for both consumed and spoiled milk and their disposed containers. Figure 15 shows that packaging is the smallest contributor to total GHG emissions, as previously identified by others (12, 19, 20). Packaging accounts for no more than 5% of the total GHGs.

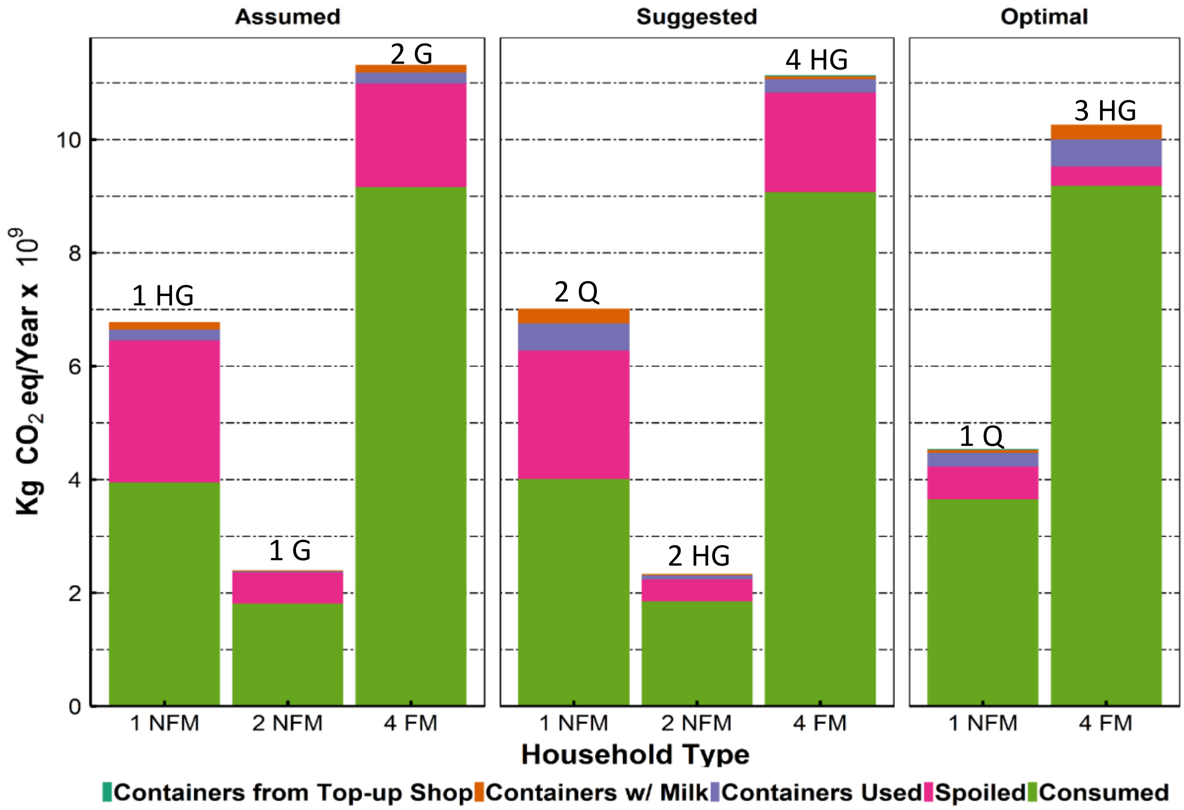


Figure 15: Total GHG emissions of 1 (32 million, 1NFM), 2 (6 million, 2NFM), and 4-person (15 million, 4FM) U.S. households for milk consumption, spoilage and packaging waste. "FM" stands for family, while "NFM" stands the non-family household. Columns are separated by the container size purchased. "Assumed" containers represent what is currently assumed to be purchased by households, new containers were the initially "Suggested" purchasing changes, and "Optimal" represents the optimized container purchase. 1NFM, 2NFM, and 4FM households were assumed to purchase 1HG, 1G, and 2G containers, respectively. 1NFM, 2NFM, and 4FM households were suggested to purchase 2Qs, 2HGs, and 4 HGs, respectively. Lastly, 1NFM and 4FM households were optimized for consumption and spoilage when purchasing 1Q and 3 HGs, respectively.

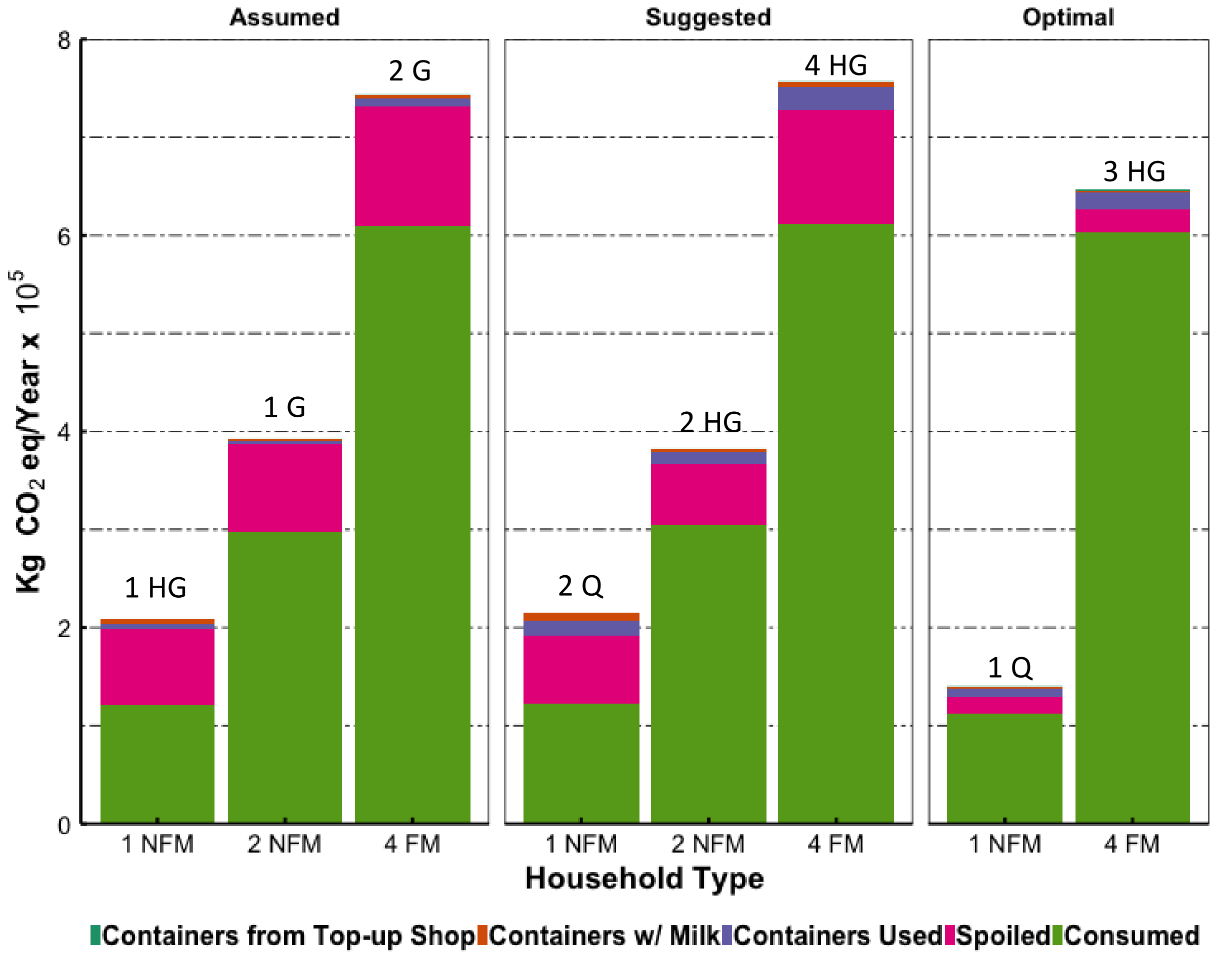


Figure 16: Total GHG emissions of 1000 1 person, 2 person, and 4 person households for milk consumption, spoilage, and packaging waste. Columns are separated by the container size purchased. "Assumed" containers represent what is currently assumed to be purchased by households, new containers were the initially "Suggested" purchasing changes, and "Optimal" represents the optimized container purchase. 1NFM, 2NFM, and 4FM households were assumed to purchase 1HG, 1G, and 2G containers, respectively. 1NFM, 2NFM, and 4FM households were suggested to purchase 2Qs, 2HGs, and 4 HGs, respectively. Lastly, 1NFM and 4FM households were optimized for consumption and spoilage when purchasing 1Q and 3 HGs, respectively.

Figure 15 indicates that when 1-person households purchased a quart of milk, rather than two quarts of milk, their total GHG emissions decreased by 33%. In contrast, purchasing two quarts, rather than 1 half gallon, produced a larger impact due to increased packaging, and minimal reduction in milk spoilage. Figure 16 shows the impact of different household types when the population is standardized to 1000 people, while Figure 15 shows GHG emissions based on population data. When looking at the amount of milk spoiled between these three scenarios, decreasing the amount of milk purchased significantly reduced spoilage without a considerable increase in the amount of milk unavailable (See Figure 14); thus, the GHG emissions from a one-person household can be decreased with increased top-up shopping trips. GHG emissions associated with increased transportation were not included in this analysis since this purchase can easily be done during other needed trips, such as returning from work. Previous research has indicated that shopping and planning routines are two of the most important factors in food waste reduction (27), while the EPA and WRAP determined that increased shopping trips lead to less waste (28, 29). If consumers are willing to have better milk inventory management and make more top-up shopping trips for milk when they run out, then they will likely decrease their total GHG emissions for milk consumption. The trend in family households of four was similar to that of 1-person households. When purchasing 2 gallons or 4 half gallons of milk, spoilage was approximately the same. In contrast, when 4-person households purchased 3 half gallon containers, their total spoilage decreased significantly, thus decreasing their total GHG emissions without increasing the amount of unavailable milk (see Figure 14). For 1-person non-family households and 4-person family households, spoilage reductions were large enough to justify the purchase of less milk in smaller containers. Model results indicate that consumers are purchasing too much milk, leading to overconsumption (8). Non-family households of two use most of the milk that is available to them regardless of the container size, but when purchasing 2 half-gallons, the extension of shelf-life leads to decreased spoilage due to increased time for milk consumption.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Packaging has been placed under the spotlight recently due to environmental concerns, but it is important to understand the whole food-packaging system to reduce the GHG emissions of a food product (8, 18). This model was created as a tool for simulating household food consumption behavior for other food products. To the best of the authors' knowledge, DES provides the best method for modeling U.S. consumers household food consumption habits. Ultimately, a household's food consumption could be modeled to optimize packaging and food waste. Evidence from DES modeling could then be used to educate consumers on what package sizes they should purchase based on their household type. The simulations provide a framework for future researchers to extrapolate how changes in consumption and purchasing behavior effect expenditure on food, nutritional requirements, and a household's total environmental footprint. This tool provides researchers with the ability to model other common household foods with a high environmental impact and a short shelf life, such as meat products. Researchers are provided with a full life cycle perspective of a product, including packaging, giving a more holistic approach to understand food waste generation within the home. Although this model does not provide verified food waste data, it does provide estimates of where large portions of waste generation are coming from. This tool allows researchers to simulate different scenarios before performing field experiments, saving both time and money. In addition, this model pays special attention to packaging and behavior, which have often been ignored in other environmental food studies.

5.2 Recommendations

In this work, Matlab® was used to create the model due to its simplicity and ease of use compared to other methods. It is recommended that the model should be built using an open source software language such as Python. This would enable users to have more control over the code that is being implemented into the model. In addition, it would allow researchers to share their work more easily as Python is accessible to anyone. Data analysis for this work was done using R, but it is recommended that future work use Python as it provides the same functionality as R. This would ensure that all code is reproducible and easily read. Producing data in Matlab® proved to be a challenge when data analysis needed to be done. R and Python provide packages that are more intuitive for data analysis when compared to Matlab®. In addition, running simulations on the HPCC proved to be a difficult task due to licensing issues. Personalized modules had to be created on the HPCC in order to run the SimEvents® software. When the HPCC was updated, the simulations did not run properly due to conflicts between licenses.

Future researchers should model more household types to understand how their consumption could be optimized through packaging and purchasing behavior. Currently only one, two and four-person households were modeled. The household types were also very specific as to represent each household type accurately. Future research should conduct more simulations on households composed of different age groups, such as more children and senior citizens.

Based on the literature conducted in this work, it is recommended that future researchers focus on optimizing food costs for consumers. Survey results have shown that people are most enticed to reduce waste if there is a cost benefit (33). If a cost comparison could be implemented into the model, then potential cost savings could be extrapolated from model results. This type of modeling would provide more evidence as to why consumers should choose one package over another.

Finally, it is recommended that student's collaborate with students within the computer science field. Much of computational modeling knowledge was self-taught. If students were to work with someone with more programming experience, they may be able to achieve more in a shorter amount of time. The focus then could be on extrapolating results to further environmental indicators, and not just greenhouse gas emissions. Results could also further focus on recommendations for consumers on how they could optimize their consumption. Ideally, future work will incorporate all food categories and provide an application for consumer's to monitor their total household food wastage.

BIBLIOGRAPHY

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1. Food and Agriculture Organisaton (2014) *Food and Nutrition in Numbers 2014* doi:10.1017/S0001972000039334.

2. Mandyck JM, Schultz EB (2015) *Food Foolish: The Hidden Connection Between Food Waste, Hunger and Climate Change* (Carrier Corp.). 1st Ed.

3. Buzby JC, Wells HF, Hyman J *The Estimated Amount, Value, and Calories of Postharvest Food Losses at the Retail and Consumer Levels in the United States* doi:10.2139/ssrn.2501659.

4. Buzby JC, Farah-Wells H, Hyman J (2014) *The Estimated Amount, Value, and Calories of Postharvest Food Losses at the Retail and Consumer Levels in the United States* doi:10.2139/ssrn.2501659.

5. Bigelow PD, Borchers A (2017) *Major Uses of Land in the United States* doi:10.1097/00010694-195403000-00015.

6. Toth JD, Dou Z (2016) Wasted Food, Wasted Resources: Land, Irrigation Water, and Nutrients Associated with Food Wastage in the U.S. *Food Waste Across the Supply Chain: A US Perspective On a Global Problem*, eds Dou Z, et al. (Council for Agricultural Science and Technology, Ames, Iowa), pp 57–71. 1st Ed.

7. Clune S, Crossin E, Verghese K (2017) Systematic review of greenhouse gas emissions for different fresh food categories. *J Clean Prod* 140:766–783.

8. Williams H, Wikström F (2011) Environmental impact of packaging and food losses in a life cycle perspective: A comparative analysis of five food items. *J Clean Prod* 19(1):43–48.

9. Schmidt K, Matthies E (2018) Where to start fighting the food waste problem? Identifying most promising entry points for intervention programs to reduce household food waste and overconsumption of food. *Resour Conserv Recycl* 139(May):1–14.

10. Aschemann-witzel J, Hooge I De, Amani P, Bech-larsen T, Oostindjer M (2015) Consumer-Related Food Waste: Causes and Potential for Action. *Sustainability* 7(May):6457–6477.

11. Thoma G, et al. (2013) Greenhouse gas emissions from milk production and consumption in the United States: A cradle-to-grave life cycle assessment circa 2008. *Int Dairy J* 31(1):S3–S14.

12. Hebrok M, Boks C (2017) Household food waste: Drivers and potential intervention points for design – An extensive review. *J Clean Prod* 151:380–392.

13. Neff RA, Spiker ML, Truant PL (2015) Wasted food: U.S. consumers' reported awareness, attitudes, and behaviors. *PLoS One* 10(6). doi:10.1371/journal.pone.0127881.

14. Karli V, Helen L, Simon L, Helen W (2013) *The role of packaging in minimising food waste in the*

supply chain of the future doi:10.13140/2.1.4188.5443.

15. Wilson NLWW, Rickard BJ, Saputo R, Ho ST (2017) Food waste : The role of date labels , package size , and product category. *Food Qual Prefer* 55(August):35–44.

16. Williams H, Wikström F, Otterbring T, Löfgren M, Gustafsson A (2012) Reasons for household food waste with special attention to packaging. *J Clean Prod* 24:141–148.

17. Schanes K, Dobernig K, Gözet B (2018) Food waste matters - A systematic review of household food waste practices and their policy implications. *J Clean Prod*. doi:10.1016/j.jclepro.2018.02.030.

18. Licciardello F (2017) Packaging, blessing in disguise. Review on its diverse contribution to food sustainability. *Trends Food Sci Technol* 65:32–39.

19. Molina-Besch K, Wikström F, Williams H (2019) The environmental impact of packaging in food supply chains—does life cycle assessment of food provide the full picture? *Int J Life Cycle Assess* 24(1):37–50.

20. Wikström F, Williams H, Venkatesh G (2016) The influence of packaging attributes on recycling and food waste behaviour – An environmental comparison of two packaging alternatives. *J Clean Prod* 137:895–902.

21. Williams H, Wikström F (2011) Environmental impact of packaging and food losses in a life cycle perspective: a comparative analysis of five food items. *J Clean Prod* 19(1):43–48.

22. Quested T (2013) *The Milk Model : Simulating Food Waste in the Home* (Banbury).

23. MATLAB and Simulink Toolbox R2018a, The MathWorks, Inc., Natick, Massachusetts, United States.

24. R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.

25. Jan O, et al. (2013) *Food wastage footprint* doi:ISBN 978-92-5-107752-8.

26. Gustavsson J, Cederberg C, Sonesson U, Meybeck A, Otterdijk R van (2011) *Global Food Losses and Food Waste* (FOOD AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS, Rome).

27. Qi D, Roe BE (2016) Household food waste: Multivariate regression and principal components analyses of awareness and attitudes among u.s. consumers. *PLoS One* 11(7):1–19.

28. Aschemann-Witzel J, de Hooge I, Amani P, Bech-larsen T, Gustavsson J (2015) *Consumers and food waste – a review of research approaches and findings on point of purchase and in-household consumer behaviour* (Naples, Italy).

29. Parizeau K, von Massow M, Martin R (2015) Household-level dynamics of food waste production and related beliefs, attitudes, and behaviours in Guelph, Ontario. *Waste Manag* 35:207–217.

30. Schanes K, Dobernig K, Gözet B (2018) Food waste matters - A systematic review of household food waste practices and their policy implications. *J Clean Prod* 182(182):978–991.

31. Block LG, et al. (2016) The Squander Sequence : Understanding Food Waste at Each Stage of the Consumer. *J Public Policy Mark* 35(2):292–304.

32. Visschers VHM, Wickli N, Siegrist M (2016) Sorting out food waste behaviour: A survey on the motivators and barriers of self-reported amounts of food waste in households. *J Environ Psychol* 45:66–78.

33. Neff RA, Spiker ML, Truant PL (2015) Wasted food: U.S. consumers' reported awareness, attitudes, and behaviors. *PLoS One* 10(6):1–16.

34. Silvenius F, et al. (2014) The role of household food waste in comparing environmental impacts of packaging alternatives. *Packag Technol Sci* 27:277–292.

35. Wikström F, Williams H, Verghese K, Clune S (2014) The influence of packaging attributes on consumer behaviour in food-packaging life cycle assessment studies - a neglected topic. *J Clean Prod* 73:100–108.

36. Kosko B (1986) Fuzzy cognitive maps. 65–75.

37. Morone P, Falcone PM, Lopolito A (2018) How to promote a new and sustainable food consumption model: A fuzzy cognitive map study. *J Clean Prod* 208:563–574.

38. Grainger MJ, et al. (2018) Model selection and averaging in the assessment of the drivers of household food waste to reduce the probability of false positives. *PLoS One* 13(2):1–17.

39. Robinson S (2014) Discrete-event simulation : A primer. *Discrete-Event Simulation and System Dynamics for Management Decision Making*, eds Brailsford S, Churilov L, Dangerfield B (John Wiley & Sons, Ltd., Loughborough), pp 10–25. First Edit.

40. Jun JB, Jacobson SH, Swisher JR (1999) Application of Discrete-Event Simulation in Health Care Clinics: A Survey. *J Oper Res Soc* 50(2):109–123.

41. Buzby JC, Hyman J (2012) Total and per capita value of food loss in the United States. *Food Policy* 37:561–570.

42. Barbano DM (2017) A 100-Year Review: The production of fluid (market) milk. *J Dairy Sci* 100(12):9894–9902.

43. American Community Survey 5-Year Detailed Tables (2016) Available at: https://api.census.gov/data/2016/acs/acs5/tags/household.html [Accessed February 27, 2019].

44. Average Daily Servings of Dairy Foods by Ethnicity and Age Group (NHANES 2011-2014) (2014).

45. Burek J, et al. (2017) Environmental Sustainability of Fluid Milk Delivery Systems in the United States. *J Ind Ecol* 22(1):180–195.