2016

Hybrid simulation modeling for regional food systems

Anuj Mittal
Iowa State University

Hybrid simulation modeling for regional food systems

by

Anuj Mittal

A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Industrial Engineering

Program of Study Committee:
Caroline C. Krejci, Major Professor
Michael C. Dorneich
Richard T. Stone
David E. Cantor

Iowa State University

Ames, Iowa

2016

DEDICATION

I would like to dedicate this thesis to my parents for their continuous support and motivation.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

DES	Discrete Event Simulation
ABM	Agent-Based Model
SD	System Dynamics
RFSC	Regional Food Supply Chains

ACKNOWLEDGMENTS

First and foremost, I would like to thank my major professor Dr. Caroline C. Krejci for her continuous encouragement and confidence in me. She has been a great help in making me learn on how to prioritize work in life. I would sincerely like to express my respect and gratitude to her for inspiring me from time to time and making my first research experience really enjoyable.

I would also like to thank my committee members, Dr. Michael C. Dorneich, Dr. Richard T. Stone and Dr. David E. Cantor for their guidance and support throughout the course of this research. I want to specially thank them for providing their valuable inputs and guidance in designing and conducting the survey for this research study.

I would also like to thank my great friend Akshit Peer for his help and suggestions while writing this thesis. A special thanks to Gary Huber for his contribution towards his thesis and making my research smooth. I would also like to thank Leopold Center for Sustainable Agriculture for partially funding this research.

In addition, I would also like to thank my friends at Iowa State, colleagues, Hardik Bora and Teri Craven, the department faculty and staff for making my time at Iowa State University a wonderful experience. I want to also offer my appreciation to those who were willing to participate in my surveys and observations, without whom, this thesis would not have been possible.

Finally, a big thank you to Dr. Saurabh, Dr. Surabhi, Sarthak, Samarth, Alisha and Ankur for their encouragement, patience and love.

ABSTRACT

In response to concerns regarding the serious environmental and social issues associated with conventional food distribution systems, consumer demand for regionally-produced food is growing. Regional food hubs are playing a critical role in meeting this growing demand. Food hubs aggregate, distribute, and market regionally-produced food, with a goal of promoting and supporting environmental and social sustainability. They provide an alternative distribution channel through which small and mid-sized producers can access wholesale markets, and they improve consumer access to regional food at competitive prices. Despite the benefits they provide, food hubs struggle to maintain profitability, and they face many challenges to growth and success. In particular, they are often unable to achieve the logistical and operational efficiencies that characterize conventional large-scale food distribution. This is partly due to a lack of implementation of efficiency-enhancing conventional supply chain practices in food hub operations. One possible method of improving food hub efficiency targets their inbound logistics operations. This thesis studies the inbound operations of a regional food hub in Iowa, with a focus on the scheduling of producers' deliveries to the food hub.

This thesis proposes a hybrid simulation modeling framework to show how the advantages of both discrete event simulation (DES) and agent-based model (ABM) can be leveraged to address socio-technical problems in regional food supply chains. The usefulness of this hybrid methodology is demonstrated through the development of an empirically-based hybrid simulation model of the inbound logistics operations of a food hub in Iowa. ABM was used to model the decision-making process of producers for scheduling their deliveries. DES was used to model the inbound operations of the food hub, including the receiving and storing of the goods brought by the producers. Four different versions of the hybrid simulation model are used to examine the effectiveness of various policies in encouraging producers to schedule their deliveries, as well as the impacts of producer scheduling on food hub efficiency and effectiveness. Experimental results suggest that different incentives vary in their degree of effectiveness, and increasing the percentage of producers who schedule their deliveries is unlikely to improve overall system operations by itself – in order for all participants to benefit, the food hub manager must also adjust the hub's inbound operations to account for producers who refuse to schedule. This hybrid model will help guide policy recommendations to food hub managers to make their inbound operations more efficient and effective.

CHAPTER 1

INTRODUCTION

Regional Food

The demand for regionally-produced food has seen sharp growth over the last decade, due to its perceived social, environmental, and economic benefits. Increasingly, consumers are choosing food that is produced in the same region in which they live, rather than food from the conventional food supply system. Regionally-produced food sales via both direct-to-consumer and intermediated marketing channels are increasing: from 2006 to 2014, the number of farmers' markets, school districts with farm-to-school programs, and regional food hubs in the United States have increased by 180%, 430%, and 288%, respectively (Low, et al., 2015). According to the National Grocery Association, 87.2% of consumers regard the availability of locally-grown produce and other locally-produced food as being important in their grocery shopping decisions (Tropp, 2014). Locally-grown and organic food is not only in high demand at the farmers' market and natural food retailers but also in conventional markets (Farnsworth, McCown, Miller, & Pfeiffer, 2009). Consumers' reasons for preferring regionally-produced food vary widely, including: ensuring the nutrition, quality, freshness, and safety of their food, saving money, health concerns, environmental consequences of globalized and industrialized agriculture, farm animal welfare, fair trade, food security, concerns over the environment and the treatment of farm workers, a desire to support the local economy and build a connection with the person who produced their food (Brown A. , 2002; Brown C. , 2003; Wolf, Spittler, & Ahern, 2005).

Traditionally, the most common market channel for the regional food produced by small- and medium-scale producers has been direct-to-consumer. Producers typically get better prices at the farmers' market than through wholesale outlets (Myers, 2011), and farmers' markets are ideal venues for producers who have limited quantities of a large variety of products. However, these direct-to-consumer outlets are highly labor intensive and are not very profitable for producers on average (Tropp, 2014). This is because of low sales volumes, competition from multiple sellers, and high transportation and marketing costs (LeRoux, Schmit, Roth, & Streeter, 2010). To avoid the challenges associated with direct-to-consumer sales, many small- and medium-scale producers would prefer to sell to large-scale institutional customers (e.g., grocery stores, restaurants, schools), either directly or through a distributor. Many of these institutional customers are also interested in developing a connection with local producers, in order to fulfill growing demand for local food. However, producers face many obstacles. In particular, individual farm operators often lack individual capacity to meet buyer requirements for product volume, quality, consistency, variety or extended availability. They are also challenged by a lack of distribution, processing, and marketing infrastructures that would give them wider access to larger-volume customers (Tropp, 2014). High logistics and transportation costs also limit producers' ability to tap into wholesale markets (Bosona, Gebresenbet, Nordmark, & Ljungberg, 2011; Diamond & Barham, 2012)

Regional food hubs

Intermediated marketing channels provide producers an alternative to farmers' markets and other direct-to-consumer channels, potentially reducing marketing and transportation costs for the participating producers (Low, et al., 2015). One type of intermediated channel that has experienced tremendous recent growth in popularity is the *regional food hub*. The USDA defines a food hub as "a business or organization that actively manages the aggregation, distribution and marketing of source-identified food products primary from local and regional producers to strengthen its ability to satisfy wholesale, retail and institutional demand" (Barham, et al., 2012). Food hubs act as regional aggregation points for producers, facilitating logistics for wholesale channels and offering non-direct-marketing services for their products. Unlike farmers' markets, food hubs give producers the opportunity to access comparatively larger-volume markets by providing them with a convenient drop-off point for their food to be distributed to multiple customers, which may include individual consumers, restaurants, and/or institutions (e.g., hospitals, universities, schools). They can play an instrumental role in increasing small producers' operations.

In many ways, food hub operations are quite similar to those in conventional food supply chains. Acting as an aggregator and distributor, a food hub must be expert and efficient at handling and transporting highly perishable goods. It must manage the procurement of products from multiple farmers and ensure on-time arrivals to the warehouse. Internally, the food hub's operations include correct product placement in inventory locations, inventory tracking, processing and repackaging as necessary, order picking, and loading orders onto delivery trucks for distribution to customers.

However, conventional food distributors' focus mostly on profit, and producers are typically exploited with short-term contracts where only they bear the risks and do not get an equal share of the profits. Relationships between buyers and suppliers are constructed as competitive and even adversarial (Stevenson & Pirog, 2013). By contrast, local and regional food supply chains focus on both financial performance and the well-being of all stakeholders. In fact, one a food hub's primary objectives is to strengthen local producers' capacity and increase their access to markets (Farm Credit East; Wallace Center at Winrock International; Morse Marketing Connections; Farm Credit Council, 2013). Unlike conventional food distributors, they strive to provide fair pricing and increased market access to their producers, and they often offer them development services, such as training and assistance with crop planning, business and farm management, quality control techniques, and insurance (Moraghan & Vanderburgh-Wertz, 2014). Food hubs try to ensure that profits are shared fairly with the producers, who are treated as strategic partners with rights and responsibilities and are involved in decision-making processes (Rogoff, 2014; LeBlanc, Conner, McRae, & Darby, 2014). Food hubs are also committed to purchasing goods from small and mid-sized local growers and consider them to be partners, rather than suppliers (Woods, Velandia, Holcomb, Dunning, & Bendfeldt, 2013). Food hubs also aim to provide exceedingly high levels of quality, variety, and food traceability to their customers. Because of the significant differences in their objectives and inherent supply chain structures, adopting the efficiency-enhancing operations and logistics methods of the conventional system can be challenging and even counterproductive for food hubs.

Challenges

Despite the benefits that food hubs can provide to an RFSC, a 2013 national food hub survey indicated that food hubs are not profitable on an average (Fischer, et al., 2013). Food hubs in the United States typically operate at a close to break-even level. The financial data of 48 food hubs surveyed across United States indicates that the highest performing (i.e., top 25%) food hubs earn only a 4% profit with an average of -2%. The typical food hub operates at a close to break-even level with a gross margin of only 14.5% to cover profit and overhead expenses (Farm Credit East; Wallace Center at Winrock International; Morse Marketing Connections; Farm Credit Council, 2013). This data suggests that there is a need for a better understanding of food hub practices in order to increase their overall operational efficiency (Fischer, et al., 2013). Innovations in conventional food supply chains related to quality assurance, distribution efficiency, food traceability, market information management, and product development have been recommended for adoption by RFSCs for their long-term growth and sustainability (Rogoff, 2014). Such methods could help food hubs reduce their warehousing and transportation costs, which have proven to be difficult for many food hubs to manage (Mittal, Zugg, & Krejci, 2016). In particular, food hubs could greatly benefit from the application of traditional supply chain management techniques to their inbound operations. Inbound operations at a warehouse include receiving goods, performing quality inspection checks, and storing goods at the desired inventory storage locations.

One critical component of efficient and effective inbound operations is scheduling the deliveries of goods to the warehouse. Knowing in advance what is coming into the warehouse allows managers to preplan receiving activities for the day, enabling better warehouse labor utilization and allowing sufficient time for quality inspections of received material. Conventional supply chains typically have a large number of suppliers with enormous volumes, and unscheduled deliveries would create a huge burden on warehouse receiving operations, as well as long queues for the suppliers waiting for service. A study conducted on the inbound operations of retailers in Sweden mentions the need for fixed supplier arrival times as their first priority (Ljungberg & Gebresenbet, 2004). This helps them to plan their receiving operations in advance, enabling better labor utilization and allowing more time for quality inspections of received material, thereby benefiting customers. Without this information, managers face random delivery arrivals, which can result in inefficiencies and long queue times for carriers.

Regional food hubs, which have comparatively smaller operations, do not typically assign fixed delivery times to their suppliers (Mittal & Krejci, 2015). Requiring producers to schedule their deliveries is often viewed by food hub managers as an unnecessary burden on the producers, since they are known to highly value their autonomy (Krejci & Beamon, 2015) and prefer to deliver according to their convenience. Fixing producer arrival times could also potentially affect their transportation costs if they are unable to schedule at their preferred time, as they might be combining their deliveries to the food hub with other deliveries in the area for better resource utilization and reduced overall travel distance and time.

However, unscheduled deliveries can negatively impact the food hub. As a consequence of the unscheduled and irregular delivery times, preventative quality checks and proper inventory put-away procedures are often curtailed in an effort to speed up the receiving process and reduce producer queue time at the warehouse. One of the major challenges faced by food hubs in Iowa is that many of their producers often arrive for delivery simultaneously, typically at the end of the day, rather than spreading delivery times uniformly throughout the delivery period (Huber, 2015). As a result, queues form and producers must wait for service from food hub personnel. This is inconvenient for the producers who must wait, but it is also problematic for the food hub operations. As the queue length increases, service time tends to decrease, thereby negatively affecting the quality of service (Anand, Pac, & Veeraraghavan, 2011). For a food hub, "quality of service" is related to the quality check and inventory placement of delivered goods. Unscheduled deliveries force food hub personnel to speed up their receiving process, leaving less time for quality checks and inventory put-away, which increases the likelihood of errors in product placement in storage locations.

Another result of unscheduled deliveries is ineffective labor utilization. As per a 2013 national food hub survey, employee salaries occupied the second largest expense for most hubs, at an average of 23% of total revenues (Fischer, et al., 2013). Almost all of the food hubs in United States use some volunteer labor for carrying out their operations. While volunteer labor can help save on labor costs, using volunteers can also have drawbacks related to efficiency and consistency (Matson, Thayer, & Shaw, 2015). This can lead to customer dissatisfaction if poor-quality or incorrect products leave the warehouse undetected (Huber, 2015; Grimm, 2015). Therefore, food hubs should try to manage an effective balance between their paid and volunteer labor.

Given these potential problems, one might expect that food hub managers would require producers to schedule their deliveries. However, since meeting the needs of producers is one of the major objectives of a food hub, a food hub manager may choose not to enforce a delivery schedule in an effort to support the producers. For example, the Iowa Food Cooperative (based in Des Moines, Iowa) has given its producers the option of scheduling their deliveries online in advance by selecting preferred delivery time slots. However, very few producers actually participate. In one typical example, out of 57 producers, only 14 opted to schedule their deliveries, and few among those producers actually delivered in the time window they indicated on the schedule (Huber, 2015). Similar observations have been made by the Iowa Valley Food Cooperative (Grimm, 2015).

It would be valuable for food hub managers to have a better understanding of the conditions that would encourage producers to schedule their deliveries to the food hub, as well as the impacts of scheduling on food hub performance. This would help them to make good strategic decisions to improve their inbound operations.

Evaluating Supply Chain Performance

Evaluating supply chain performance can facilitate better understanding of the supply chain and increase its overall performance (Chen & Paulraj, 2004; Shepherd & Günter, 2011).

Supply chain performance is typically measuredin terms of cost and customer responsiveness (Beamon 1999). Costs include inventory and operational costs, while customer responsiveness includes lead time, stockout probability and fill rate. There are different ways to evaluate supply chain performance. Chen and Paulraj (2004) surveyed the supply chain management literature and identified three kinds of studies aimed at the improvement of supply chain performance:

1) *Operation studies* focus on the development of mathematical models
2) *Design studies* focus on the development of deterministic analytical models, stochastic analytical model, and simulation models
3) *Strategic studies* evaluate how to align the supply chain as per a firm's strategic objectives

Modeling is a way to recreate and experiment with a real system on a computer when experimenting with the real system is expensive or difficult (Borshchev & Filippov, 2004). There are various methods used to model supply chain systems. Beamon (1998) identified four different modeling methods to evaluate supply chain performance:

1) *Deteministic analytical models* - Variables are known and specified
2) *Stochastic analytical models* - At least one variable is unknown and is assumed to follow a particular probability distribution
3) *Economic models*
4) *Simulation models*

Analytical techniques and optimization approaches have limits in evaluating complex supply chains (Owen, 2013). Closed form solutions do not always exist or can be very difficult to find (Borshchev & Filippov, 2004). In contrast, simulation allows for systematic testing and investigation of supply chain performance by performing various experiments without intervening with the real system (Van der Vorst, Tromp, & Zee, 2009; Schieritz & Grobler, 2003). Three of the most popular simulation techniques used to model supply chains are (Owen, 2013):

1) Discrete-event simulation (DES)
2) Agent-based model (ABM)
3) System dynamics (SD)

However, most of the simulation techniques in the area of supply chain management and logistics have been used in isolation (Mustafee, et al., 2015). Hybrid simulation (i.e., combining one or more simulation techniques) can be used to develop models of complex real-life problems in logistics and supply chain management in a more realistic way than by using a single modeling methodology.

Motivation for This Study

There are three key aspects that motivate this research:

1) Need for structured research to address challenges in RFSCs
2) Lack of models in the existing literature to address RFSC management policies
3) Need of a hybrid simulation framework to better understand the complex nature of supply chains

The growing emergence of local food indicates the need for developing alternate logistics and supply chain management techniques to improve the performance of RFSCs (Gebresenbet, Ljungberg, Nordmark, & Cardoso, 2013). Many researchers have mentioned that food supply chains in general and regional food supply chains specifically are not as developed as the supply chain systems of automotive or electronic industries (Ahumada & Villalobos, 2009). This is because moving niche products from farm to market is more complex and expensive than moving conventional farm products. The smaller volumes handled and the need to keep niche products separate from bulk commodities add to the cost of handling and shipping (Vanwechel, Vachal, & Berwick, 2009). Stroink (2013) mentions that lack of systematic supply chain management structures, and numerous false starts and experiments are the reasons for failures of many food hubs. Therefore in such multi-layered complex supply chains, there is a need for structured methodology to address challenges in RFSCs (Ting, Tse, Ho, Chung, & Pang, 2014). Also as RFSCs are relatively new, their logistics experience is still being developed, and they have significant room for further performance improvement. Nearly one-third (of N=106) of the food hubs in the United States began their operations within the last 2 years, and most had been in operation for 5 years or less (66 hubs, or 62%) (Fischer, et al., 2013).

There are few state-of-the-art models for RFSC management, and there is a need for more research in this area in order for them to be on par with the conventional supply chains (Ahumada & Villalobos, 2009). The literature suggests that very few models have been developed for the management of shipping and receiving operations of a warehouse, and most of the literature available in this area addresses strategies for cross docking warehouses. Therefore, case studies and computational tools for warehouse design and operations will help to bridge the significant gap between academic research and practical application, and therefore, represent a key need for the future (Gu, Goetschalckx, & McGinnis, 2007).

Simulation is still the most widely used technique for warehouse performance evaluation (Gu, Goetschalckx, & McGinnis, 2007). However, these simulation techniques have been used in isolation. Hybrid simulation can be used to better understand complex supply chains by leveraging the advantages of multiple simulation modeling paradigms. The research presented in this thesis bridges this gap by developing an empirical hybrid simulation model of inbound operations of a food hub, which is validated using the real outputs from the food hub's operational database.

A flowchart representing the logic supporting the motivation and research direction in this thesis is shown in Figure 1.

Thesis Organization

Chapter 2 describes advantages and limitations of different simulation techniques to evaluate supply chain performance, followed by advantages and limitations of hybrid simulation models. Then, previous work on the development of empirical simulation models is discussed, followed by a discussion of the existing research on evaluating regional food supply chains. In Chapter 3, four versions of an empirical hybrid simulation model are described in detail. Chapter 4 describes the verification and validation of the simulation model with the actual conditions of the system under study. This is followed by descriptions of key experimental results. In Chapter 5, conclusions from this research are presented, limitations of this study are explained, and the need for future work is identified.

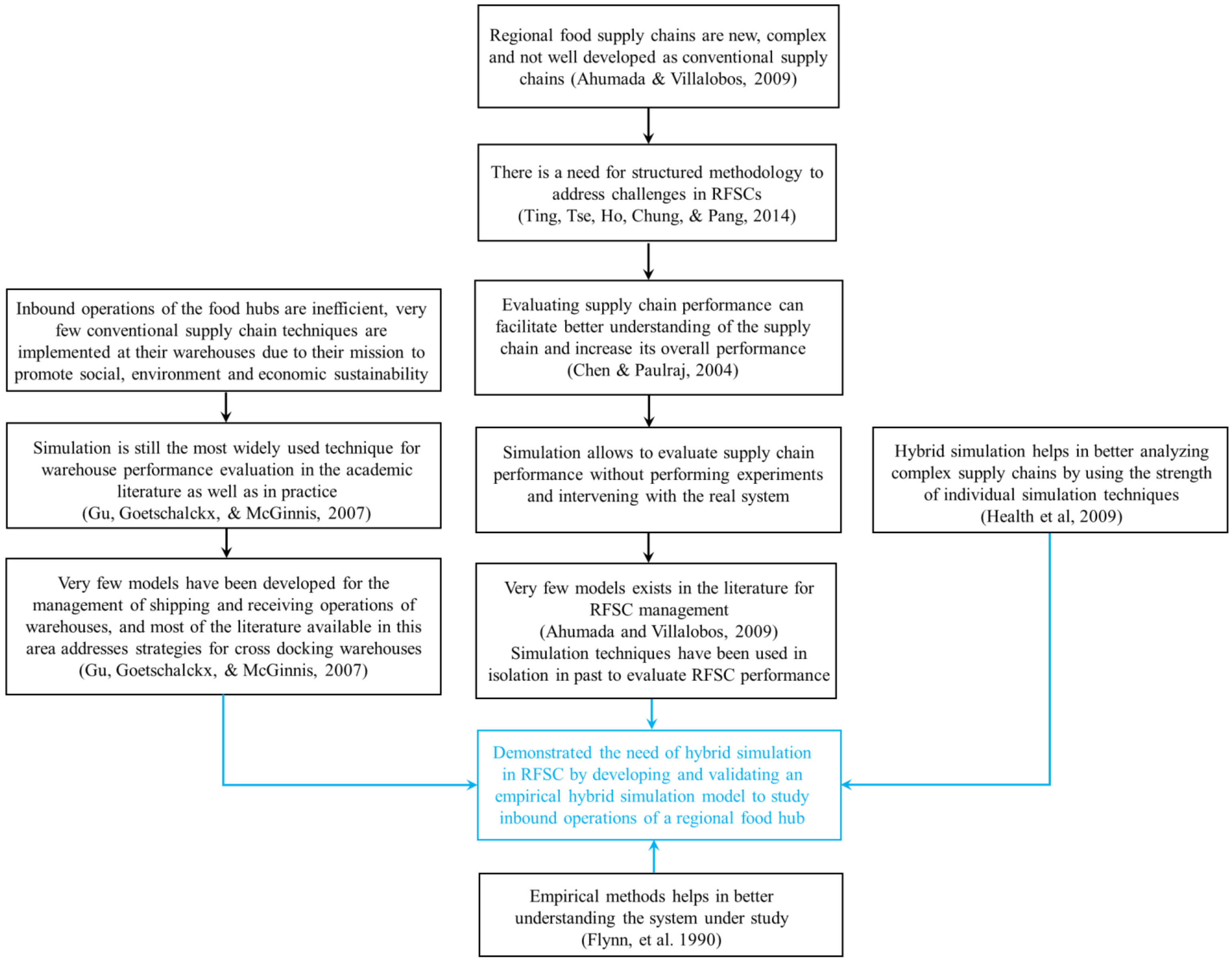

Figure 1. *Flowchart of research motivation.*

References

Ahumada, O., & Villalobos, J. R. (2009). Application of planning models in the agri-food supply chain: A review. *European Journal of Operational Research, 196(1),* 1-20.

Anand, K. S., Pac, M. F., & Veeraraghavan, S. (2011). Quality-speed conundrum: trade-offs in customer-intensive services. *Management Science, 57(1),* 40-56.

Barham, J., Tropp, D., Enterline, K., Farbman, J., Fisk, J., & Kiraly, S. (2012). *Regional Food Hub Resource Guide.* USDA - Agriculture Marketing Service.

Beamon, B. M. (1998). Supply chain design and analysis:: Models and methods. *International journal of production economics, 55(3),* 281-294.

Beamon, B. M. (1999). Measuring supply chain performance. *International Journal of Operations & Production Management, 19(3),* 275-292.

Borshchev, A., & Filippov, A. (2004). From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. *In Proceedings of the 22nd international conference of the system dynamics society, 22.*

Bosona, T., Gebresenbet, G., Nordmark, I., & Ljungberg, D. (2011). Box-scheme based delivery system of locally produced organic food: evaluation of logistics performance. *Journal of Service Science and Management, 4(03),* 357.

Brown, A. (2002). Farmers' market research 1940–2000: An inventory and review. *American Journal of Alternative Agriculture, 17(04),* 167-176.

Brown, C. (2003). Consumers' preferences for locally produced food: A study in southeast Missouri. *American Journal of Alternative Agriculture, 18(04),* 213-224.

Chen, I. J., & Paulraj, A. (2004). Understanding supply chain management: critical research and a theoretical framework. *International Journal of Production Research, 42(1),* 131-163.

Diamond, A., & Barham, J. (2012). *Moving Food Along the Value Chain: Innovations in Regional Food Distribution.* USDA - Agriculture Marketing Service.

Farm Credit East; Wallace Center at Winrock International; Morse Marketing Connections; Farm Credit Council. (2013). *Counting Values - Food Hub Financial Benchmarking Study.* NGFN.

Farnsworth, L. D., McCown, B., Miller, M., & Pfeiffer, A. (2009). *Scaling up : meeting the demand for local food.*

Fischer, M., Hamm, M., Pirog, R., Fisk, J., Farbman, J., & Kiraly, S. (2013). *Findings of the 2013 National Food Hub Survey.* Michigan State University & Wallace Center at Winrock International.

Flynn, B. B., Sakakibara, S., Schroeder, R. G., Bates, K. A., & Flynn, E. J. (1990). Empirical research methods in operations management. *Journal of operations management, 9(2)*, 250-284.

Gebresenbet, G., Ljungberg, D., Nordmark, I., & Cardoso, M. (2013). Local Food Producers and Their Supply and Marketing Channels in Sweden. *13th World Conference on Transportation Research.*

Grimm, J. (2015, March). Iowa Valley Food Co-op, Cedar Rapids, Iowa. (C. Krejci, Interviewer)

Gu, J., Goetschalckx, M., & McGinnis, L. F. (2007). Research on warehouse operation: A comprehensive review. *European journal of operational research, 177.1*, 1-21.

Heath, S. K., Dolk, D., Lappi, E., Sheldon, B., & Yu, L. (2009). Investigating the use of simulation tools for mass casualty disaster response. *Proceedings and Bulletin of the International Data Farming Community, 6*, pp. 22-25.

Huber, G. (2015, February). Iowa Food Cooperative, Des Moines, Iowa. (A. Mittal, & C. Krejci, Interviewers)

Krejci, C. C., & Beamon, B. (2015). Impacts of Farmer Coordination Decisions on Food Supply Chain Structure. *Journal of Artificial Societies and Social Simulation, 18(2)*, 19.

LeBlanc, J. R., Conner, D., McRae, G., & Darby, H. (2014). Building resilience in nonprofit food hubs. *Journal of Agriculture, Food Systems, and Community Development, 4(3)*, 1-15.

LeRoux, M. N., Schmit, T. M., Roth, M., & Streeter, D. H. (2010). Evaluating Marketing Channel Options for Small-Scale Fruit and Vegetable Producers. *Renewable Agriculture and Food Syste, 25(01)*, 16-23.

Ljungberg, D., & Gebresenbet, G. (2004). Mapping out the potential for coordinated goods distribution in city centres: The case of Uppsala. *International Journal of Transport Management, 2(3)*, 161-172.

Low, S. A., Adalja, A., Beaulieu, E., Key, N., Martinez, S., Melton, A., . . . Jablonski, B. B. (2015). *Trends in U . S . Local and Regional Food Systems Report to Congress.* USDA.

Matson, J., Thayer, J., & Shaw, J. (2015). *Running a food hub - A business operations guide (Vol 2).* USDA.

Mittal, A., & Krejci, C. C. (2015). A hybrid simulation model of inbound logistics operations in regional food supply systems. *Proceedings of the 2015 Winter Simulation Conference* (pp. 1549-1560). IEEE Press.

Mittal, A., Zugg, M., & Krejci, C. C. (2016). Improving Regional Food Hub Operational Efficiency with Lean Practices. *Paper to be presented at the 2015 Industrial & Systems Engineering Research Conference.* Anaheim: IIE.

Moraghan, M. R., & Vanderburgh-Wertz, D. (2014). *Food Hub Business Assessement Toolkit.* Wholesome Wave.

Mustafee, N., Sahnoun, M., Smart, A., Godsiff, P., Baudry, D., & Louis, A. (2015). Investigating Execution Strategies for Hybrid Models developed using Multiple M&S Methodologies. *Spring Simulation Multi-Conference.*

Myers, G. S. (2011). *Ag Marketing - News Update, University of Maryland Extension.* Retrieved from https://extension.umd.edu/learn/booth-farmers-market-profit-or-loss

Owen, C. (2013). Selection of simulation tools for improving supply chain performance. *Doctoral dissertation*. Aston University.

Rogoff, J. (2014). *Improving Systems of Distribution and Logistics for Regional Food Hubs.*

Schieritz, N., & Grobler, A. (2003). Emergent structures in supply chains-a study integrating agent-based and system dynamics modeling. *In System Sciences, 2003. Proceedings of the 36th Annual Hawaii International Conference* (pp. 9-pp). IEEE.

Shepherd, C., & Günter, H. (2011). Measuring supply chain performance: current research and future directions. In *Behavioral Operations in Planning and Scheduling* (pp. 105-121). Springer Berlin Heidelberg.

Stevenson, G. W., & Pirog, R. (2013). *Values-Based Food Supply Chains: Strategies for Agri-Food Enterprises-of-the-Middle.*

Stroink, M. L. (2013). Complexity and food hubs: five case studies from Northern Ontario. *Local Environment, 18(5)*, 620-635.

Ting, S. L., Tse, Y. K., Ho, G. T., Chung, S. H., & Pang, G. (2014). Mining logistics data to assure the quality in a sustainable food supply chain: A case in the red wine industry. *International Journal of Production Economics, 152*, 200-209.

Tropp, D. (2014). Why Local Food Matters: The Rising Importance of Locally-Grown Food in the U.S. Food System. *Presentation at National Association of Counties Legislative Conference, March 2, 2014*.

Van der Vorst, J. G., Tromp, S.-O., & Zee, D.-J. V. (2009). Simulation modelling for food supply chain redesign : integrated decision making on product quality, sustainability and logistics. *International Journal of Production Research, 47(23)*, 6611- 6631.

Vanwechel, T., Vachal, K., & Berwick, M. (2009). *Supply Chain Basics: Niche Agricultural Marketing, The Logistics.* United States Department of Agriculture, Agricultural Marketing Service, Transportation and Marketing Program.

Wolf, M. M., Spittler, A., & Ahern, J. (2005). A profile of farmers' market consumers and the perceived advantages of produce sold at farmers' markets. *Journal of Food Distribution Research, 36(1)*, 192-201.

Woods, T., Velandia, M., Holcomb, R., Dunning, R., & Bendfeldt, E. (2013). *Local Food Systems Markets and Supply Chains.*

CHAPTER 2

LITERATURE REVIEW

Supply Chain Management

There are a number of definitions of supply chain management that exist in the literature. (Beamon, 1998) defined supply chain management as an integration between different entities to achieve common predefined goals: “A supply chain may be defined as an integrated process wherein a number of various business entities (i.e., suppliers, manufacturers, distributors, and retailers) work together in an effort to: (1) acquire raw materials, (2) convert these raw materials into specified final products, and (3) deliver these final products to retailers.” Similarly, (Chopra & Meindl, 2007) state: “A supply chain consists of all parties involved, directly or indirectly, in fulfilling a customer request. The supply chain includes not only the manufacturer and suppliers, but also transporters, warehouses, retailers, and even customers themselves.” Modern supply chains are very complex and are composed of multiple stages, including manufacturers, suppliers, distributors, and consumers. Each of these stages can be further broken down into sub-systems. For example, a manufacturer contains many sub-systems, such as warehouses, production lines, and material handling systems. These stages and their constituent sub-systems are physically and socially interconnected (Behdani, 2012). Physical connections include the flow of goods (e.g., transportation of material from a supplier to manufacturer via trucks), as well as the flow of information (e.g., a manufacturer sharing its inventory status with its suppliers). Socially connections include the connections between supply chain stages through contracts and agreements. Thus supply chains can be viewed as socio-technical systems (Behdani, 2012).

Supply chain stages and sub-systems are heterogeneous - they have different needs, objectives, and decision-making behaviors (Behdani, 2012). They also have different geographic locations, unique cultures, and different technological capabilities (Behdani, 2012). Figure 2 illustrates the structure of a typical supply chain.

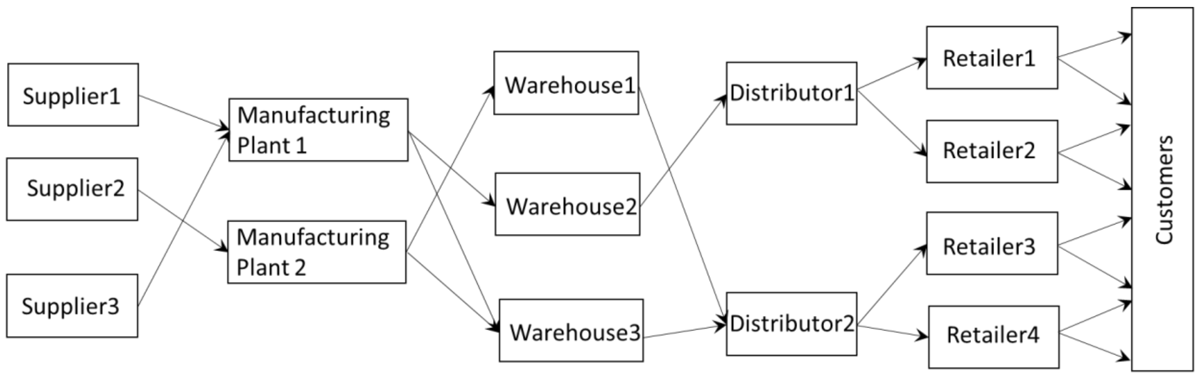

Figure 2. *A typical supply chain structure (derived from Chang and Makatsoris 2001).*

Supply chains also have a process-oriented structure, including loading and unloading activities at warehouse docks, complex processes at different stations on production lines, and queuing systems. Thus the overall performance of a supply chain is the resultant output behavior of physical and social interactions that occur between its various interconnected and heterogeneous stages and subsystems, as well as the processes that occur within each individual stage and sub-system.

Simulation in supply chain management

Three most popular simulation modeling techniques used to model supply chains are DES (Discrete Event Simulation), ABM (Agent-Based Model) and SD (System Dynamics) (Owen, 2013). The following section describes each of these techniques and their advantages and limitations with respect to supply chain management.

Discrete event simulation

Discrete event simulation (DES) is the most widely used simulation technique in the operations research literature for modeling systems which can be viewed as queuing networks (Moradi, Nasirzadeh, & Golkhoo, 2015). DES is used to model stochastic and dynamic systems where system state variables change at discrete points in time (known as an "events") (Heath, Buss, Brailsford, & Macal, 2011). DES has been classified into two major "worldviews": one is process-oriented and the other is event-oriented (Heath, Buss, Brailsford, & Macal, 2011; Behdani, 2012). In the process-oriented worldview, passive entities move through various system processes, where each process requires a certain amount of time (usually stochastic). In the event-oriented worldview, the state of an entity at any given time is a function of its initial state values along with the sequence of events assigned to that entity that have occurred by that time (Heath, Buss, Brailsford, & Macal, 2011). In both the approaches, the entities are passive objects, and their behaviors are predefined by the modeler (Behdani, 2012; Heath, Buss, Brailsford, & Macal, 2011). The process-oriented framework is the most commonly used DES framework, and most commercial software uses this framework. Figure 3 shows the basic process-oriented DES approach, with entity *e* entering a queue (Q) to wait for service, followed by processing at Process A, and finally exiting the system.

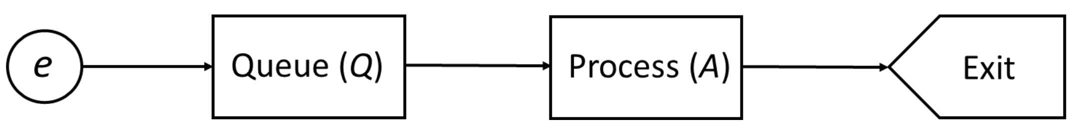

Figure 3. *Process-oriented approach of DES.*

Many studies using DES have been conducted in the domain of supply chain management (Terzi & Cavalieri, 2004), including food supply chains. DES is also the dominant simulation technique used to evaluate the performance of manufacturing systems (Helal, 2007).

DES has been used to study warehouse operations, which involves loading, unloading, and other warehouse-specific activities (Liong & Loo, 2009; Deshpande, Yalcin, Zayas-Castro, & Herrera, 2007). Liong and Loo (2009) used DES to develop a strategy to optimize the residence time of delivery trucks at warehouses and found that the truck drivers have to wait in long queues when there is no scheduling of arrivals. The simulation results show that scheduling the truck arrivals reduces drivers' wait times and average time in the system.

One strength of DES is its capability of modeling heterogeneous entities (Behdani, 2012). DES is an excellent modeling technique for simulating networks of queuing systems in which the processes are very well predefined (Siebers, Macal, Garnett, Buxton, & Pidd, 2010). Also, DES tools can provide excellent visualization and animation, which is a powerful way to verify, validate, and explain the simulation model. Despite these many advantages, DES also has limitations. DES does not provide good-quality approximations of continuous behaviors in systems, thereby limiting its accuracy (Helal, 2007; Lee, Cho, Kim, & Kim, 2002). Additionally, the entities in a DES are passive objects whose behavior is governed by rules and flowcharts that are predefined by the modeler (Borshchev & Filippov, 2004). Finally, DES models are very data-intensive, and multiple replications of a simulation must be performed to understand the actual behavior of the system, which can potentially lead to long runtimes (Viana, Brailsford, Harindra, & Harper, 2014).

Agent-based simulation

Real-time decision making by an individual supply chain actor is difficult to incorporate into a DES model, because very strict assumptions pertaining to human choices need to be made in order to accommodate human behavior in a DES (Dubiel & Tsimhoni, 2005). By contrast, ABM is well-suited to modeling complex systems involving decision making among autonomous and interacting entities. An agent is a uniquely defined autonomous and self-directed entity which exists in an environment (North & Macal, 2007; Brailsford S. , 2014). In ABM, agents interact with each other and with their environment directly or indirectly as per their behavioral rules, which are defined by the modeler at an individual level (Figure 4).

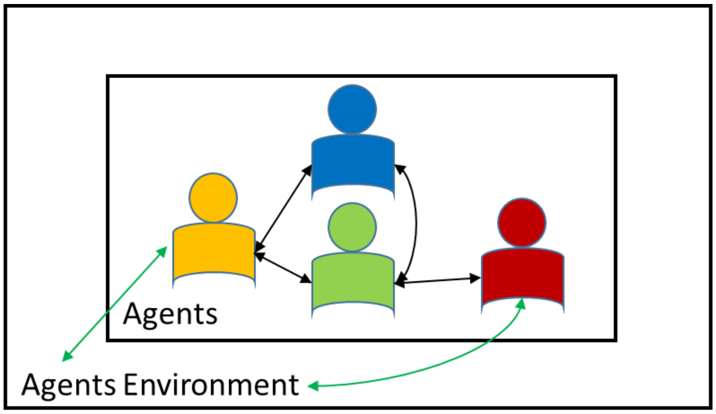

Figure 4. *Heterogeneous agents interacting with each other and with the environment in a typical ABM.*

In ABM, autonomous agents make decisions and take action to achieve their objectives. They are able to observe the outcomes of these decisions, compare these outcomes with the intended results, and take corrective action as needed. The nonlinear interactions of these decisions, actions, and adaptations among many agents within the same system can result in overall system-wide behavior that emerges over time (Huanhuan, Yuelin, & Meilin, 2013). Such emergent system behavior can be difficult to predict without the use of an ABM. The interactions among heterogeneous actors in a supply chain make ABM a particularly suitable technique for modeling supply chains (Schieritz & Grobler, 2003; Janssen & Ostrom, 2006). ABM has been used in the field of logistics and transportation management, including proposing new strategies in courier services (Knaak, 2006) and in the areas of air and road traffic management (Davidsson, Henesey, Ramstedt, Törnquist, & Wernstedt, 2005).

One disadvantage of ABM is its high computational requirements (Scerri, 2010). Also, if there is insufficient empirical data to accurately model a real-life system, the resulting ABM may misrepresent the system and yield inaccurate and misleading outputs (Siebers, Macal, Garnett, Buxton, & Pidd, 2010). As with DES, ABM must be run multiple times, as a single run of the model might not provide sufficient statistical information to the modeler (North & Macal, 2007).

System dynamics

System dynamics (SD) is defined as "the study of information-feedback characteristics of industrial activity to show how organizational structure, amplification (in policies), and time delays (in decisions and actions) interact to influence the success of the enterprise" (Forrester J. , 1958; Forrester, 1961). In system dynamics, aggregate entity behaviors are represented by interacting feedback loops and are assumed to describe the behavior of a system (Borshchev & Filippov, 2004). System dynamics model are best described as stock and flow models. Stocks are used to represent the state of the system, and flows indicate the rate of increase or decrease in the levels of the stocks. The dynamic state of the system arises from the effects of positive and negative feedback loops. If it is given that variable X affects a variable Y; a positive feedback means that if the value of X increases, so does the value of Y, whereas a negative feedback means that as the value of X increases, Y decreases. Hence, the overall net effect of all the feedback loops cannot be identified from the causal loop or influence diagram, as the same system belongs to several feedback loops and it is very difficult to identify which feedback loop drives the system behavior (Heath, Buss, Brailsford, & Macal, 2011). A system dynamics model showing the influence diagram from (Borshchev & Filippov, 2004; Sterman, 2000) is shown in Figure 5.

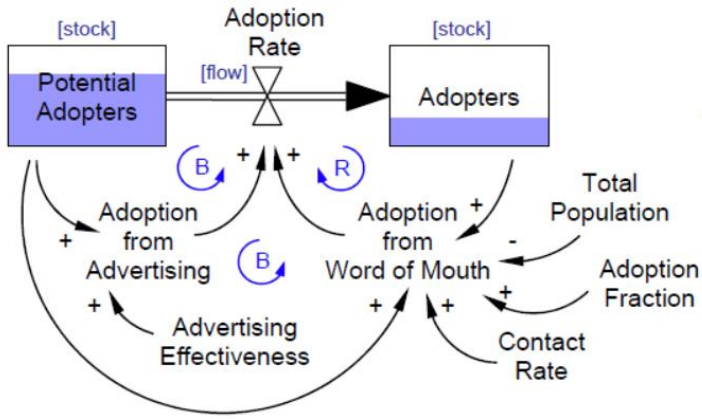

Figure 5. *A system dynamics model of "product diffusion" in the form of a stock and flow diagram (Borshchev & Filippov, 2004).*

In Figure 5, "Potential Adopters" become "Adopters" at an "Adoption Rate" that depends upon the rate of promotion of "word of mouth" and through "advertising". The total "Adoption Rate" is the sum of "advertising" effectiveness (i.e., the rate at which potential adopters convert to adopters) and the adoption rate due to "word of mouth" (i.e., the contact rate at which potential adopters come into contact with the adopters). The main disadvantage of this type modeling is that items in the individual stocks are indistinguishable. Thus heterogeneous entities can't be modeled. In reality, every entity in the system might have different adoption rates due to "advertisement". Also, the "word of mouth" adoption rate might differ between two different adopters. Therefore, aggregating the adopters into one or a reasonably finite number of stocks can distort the results (Borshchev & Filippov, 2004). Another drawback of system dynamics is that the structure of the supply chain is predetermined, which is not generally applicable to real supply chains and especially to RFSCs (Schieritz & Grobler, 2003).

However, SD has advantages if the modeling is to be done at a system level. SD simulation has been used in supply chain management to support strategic decision making in the areas of inventory management, demand amplification, supply chain redesign and in international supply chain management (Angerhofer & Angelides, 2000). System dynamics has also been used to identify effective policies and optimal parameters to make strategic decisions in a food supply chain (Georgiadis, Vlachos, & Iakovou, 2005). The authors implemented the developed methodology for transportation capacity planning in a major Greek fast-food restaurant supply chain. There is often insufficient data available to model manufacturing systems in detail, and SD can be very useful to support strategic decisions. However, the quality of the simulation results is inadequate for modeling systems at an operational level (Helal, 2007).

ABM vs DES – A long Controversy

There has been a long controversy in the literature regarding whether ABM can be modeled as DES models and vice versa, and if there is really a need for both the simulation methodologies. This section describes this controversy and argues that both of these simulation methodologies are necessary to model complex supply chains.

ABM and DES are both discrete time simulations. It is possible to model queuing systems using ABM (Pugh, 2006; Borshchev & Filippov, 2004), but queuing systems of any significant complexity are difficult to model in the agent-based environment, due to high computational requirements (Pugh, 2006). Agent actions can be modeled as events in a DES, and agent interactions can be represented via the arrival, service, and exiting processes. However, doing so will exponentially increase the number of events in the DES, making the model inefficient and hard to analyze (Chan, Son, & Macal, 2010).

To compare the two methodologies, DES model and ABM have been developed in parallel to study the fitting room operations of a retailer in the U.K. The study found that both models performed equally well but concluded that the DES model was easier to build and validate than an equivalent ABM (Majid, Aickelin, & Siebers, 2009). The emergent behavior of an ABM could be incorporated in DES using timed triggers or probabilities, but this requires an iterative approach, with a couple of cycles of using results of one model to improve the other model. Also, making any significant changes to the modeled system would require updating both models, thus repeating the iterative movement (Heath, Buss, Brailsford, & Macal, 2011).

There is significant evidence from the literature to support the need for both ABM and DES. Siebers, et al. (2010) concluded that true ABM in OR doesn't exist. Therefore, they developed a hybrid ABM-DES model in which a process-oriented framework was represented using a DES model, and the passive entities of the DES were replaced by the active agents of the ABM. Behdani (2012) mentions that DES is appropriate if the focus of the model is on the logistics of order fulfillment and delivery. However, modeling interactions between the customers and manufacturers is beyond the fundamental concepts and standard procedures of discrete event modeling. The author also concluded that although efforts have been made to include active entities in DES models, if the active entities are required, ABM may be conceptually more appropriate. Heath et al. (2011) suggests that in DES, once an entitiy begins processing, it is difficult to interrupt that processing if there are any changes in the environment after the processing has begun. Also, it is easy to model queuing behavior as well as the processing of entities that require multiple sources in DES. In some ABM toolkits, it is really difficult to model this type of behavior (Heath, Dolk, Lappi, Sheldon, & Yu, 2009). The authors recommend using a two-model approach, rather than trying to construct a single model with both ABM and DES attributes. In this approach two models are built using two different software packages (one for DES and the other for ABM), and use these models to inform each other. This will enable the modeler to leverage the strength of both modeling paradigms. Table 1 summarizes the important differences between the three simulation techniques described above in relation to a supply chain context ((Behdani, 2012; Heath, Buss, Brailsford, & Macal, 2011;

Schieritz & Grobler, 2003; Helal, 2007; Moradi, Nasirzadeh, & Golkhoo, 2015; Sumari, Ibrahim, Zakaria, & Ab Hamid, 2013).

Table 1. *Comparison of three most popular simulation techniques in supply chain management.*

	Basis of comparison	**System Dynamics**	**Discrete Event Simulation**	**Agent Based Simulation**	**Comments**
1	Purpose	Strategic decision making at a system level	Optimize, precise prediction and comparing scenarios	Study emergent behavior of the system due to interacting autonmous agents	
2	Problem scope	Strategic level as it is a top down approach and modelling is done at a system level	Operational level to capture more details	Operational level to capture more details	SD is used mainly at strategic level to evaluate policies, whereas DES and ABM is used for decision making at operational level
3	Modeling approach	Top down approach	Bottom up approach	Bottom up approach	
4	Unit of analysis	Structure of the system	Rules assigned to entitities	Rules assigned to agents	
5	Model components	Feedback loops	Queues, activities and processes	Agents and environment	
6	Control parameters	Flow rate	Time of queue	Agents interaction	
7	Nature of model	Deterministic	Stochastic	Stochastic	
8	Amount of data required	Low	High	High	That's why DES and ABM are more accurate, but if there is inadequate data and the decisions are to be made at the system level, SD is preferred over DES and ABM.
9	Accuracy	Low	High	High	Accuracy is low in SD due to aggregate behavior of entities
10	Predictabality	Low	High	High	
11	Structure of the system	Fixed	Not fixed (Process is fixed)	Not fixed	
12	Hetrogenity	No distinctive entities, aggragate behavior of the entities is assumed	Distinctive and hetrogenous entities	Distinctive and hetrogenous entities	SD has no micro level entities, whereas in DES microlevel entities are passive and in ABS microlevel entities are active agents which interacts with each other and the environment (Strength of ABM
13	Entitiy behavior	Active entities	Passive entities	Active - autonomous entities (agents)	Strength of ABS over DES

Table 1. *(Continued)*

	Basis of comparison	System Dynamics	Discrete Event Simulation	Agent Based Simulation	Comments
14	Interactions	Average value of interactions are modeled	Interactions possible at physical level (for example: manufacturing lines connected to the warehouse)	Interactions possible at physical and social level (social level includes formal and informal interactions among the agents)	Strength of ABS over DES and SD
15	Adaptiveness	No adaptiveness at individual level	No adaptiveness at individual level	Adaptiveness at individual level	Memories of entities and agents to learn and adapt their behaviors based on experience
16	Time steps	Continuous	Discrete	Discrete	
17	Nestedness	Hard to present	Not usually presented	Straightforward to present	
18	Emergence	Debatable because lack of modeling of one system lvel	Debatable because of pre-defined system properties	Capable to capture because modeling is done at two distinct level, agent and environment	The system level behavior in a complex system which emergence from the behavior of individual components and their interactions
19	Self-organizaton	Hard to capture due to aggregate behavior of the entities	Hard to capture due to passive entities	Capable to captue because of modeling autonomous agents	Self organization means emergence of the system due to only local interactions among the agents and entities in the system and without any presence of external factors
20	Co-evolution	Hard to capture as system structure is fixed	Hard to capture as the processes are fixed	Capable as the network structure is modified by agents interactions	Co-evolution corresponds to change in the states of entities and agents due to their adaptive nature along with change in the physical
21	Path dependency	Debatable as no explicit consideration of history to determine future state	Debatable as no explicit consideration of history to determine future state	Capable to capture because current and future state can be explicitly defined based on system history	Path dependency means, current and future states and decision in a complex system depend upon previous states, actions or decisions, rather thean simple on current
22	Animations and graphics	System behavior is difficult to be identified from graphics and animations	Easy to understand with the help of animations and graphics	System behavior is difficult to be identified from graphics and animations	Graphical representation sometimes helps the modeler to verify and validate the model
23	Experimentation in the model	Experimentation done by changing the system structure	Experimentaion done by changing the process structure	Experimentation done by changing the agent rules and system structure	

Hybrid Simulation

To integrate human decision making and behavior with the capabilities of DES, researchers have combined DES with ABM to form hybrid simulations (Huanhuan, Yuelin, & Meilin, 2013). Hybrid simulation enables researchers to leverage each individual methodology's strengths and analyze systems that could not be realistically modeled using a single approach (Powell & Mustafee, 2014; Zulkepli, Eldabi, & Mustafee, 2012). The literature suggests that hybrid simulation modeling is a growing trend, but the concept is still in the early stages of development (Eldabi, et al., 2008).

Hybrid simulation has been used to simulate transportation evacuation and disaster response systems (Zhang, Chan, & Ukkusuri, 2011). ABM was integrated with DES to simulate the movement of people in a theme park, in which people interact with other people and objects in the park to reach their destination (Dubiel & Tsimhoni, 2005). A hybrid (DES-ABM) model of patients in a clinic in the United Kingdom incorporated patient interactions into the clinic's fundamental queuing problem (Viana, Rossiter, Channon, Brailsford, & Lotery, 2012; Brailsford, Viana, Rossiter, Channon, & Lotery, 2013). The authors mention that in order to incorporate the social care side (i.e., patient interactions) with the fundamental queuing problem of the clinic, using a hybrid methodology was a desirable option. This enabled them to realistically capture the actual system, which could not have been easily done using a single simulation technique. A similar model for the treatment of chlamydia was developed (Viana, 2011). In this system, many patients book appointments, but due to long wait times, patients may leave the clinic without getting tested, and the infection spreads. This further increases the proportion of infected people in the community and the demand for the clinic. In this case the queuing behavior is captured by a DES model (built using Simul8), and the effect of spreading infection leading to increased demand of clinic is captured by an SD model (built using Vensim). Although hybrid simulations leverage the strengths of different simulation methodologies, they require much more effort to develop and are computationally difficult to execute (Heath, Buss, Brailsford, & Macal, 2011; Moradi, Nasirzadeh, & Golkhoo, 2015). Also, the increased complexity that results from using multiple methodologies means that hybrid models are difficult to validate, since simpler models are generally easier to validate (Barton, Bryan, & Robinson, 2004).

Execution strategies for hybrid simulation

Mustafee, et al. (2015) mention three different execution strategies for hybrid simulation models. The first strategy involves two different modeling packages for different simulation techniques, with the output of one serving as the input to the other, and the operation is done manually. This methodology has been applied by (Zulkepli, Eldabi, & Mustafee, 2012) to develop and run a hybrid DES-SD model of an Integrated Care system in healthcare. The second strategy also involves two modeling packages, but the integration between them is automated. Examples include the use of Excel to link a DES-SD model (Viana, Brailsford, Harindra, & Harper, 2014) and the use of a distributed simulation system to link an ABM-DES model (Mustafee, Sahnoun, Smart, Baudry, & Louis, 2015). The third approach to hybrid simulation model execution is through the use of a single modeling package that supports multiple modeling paradigms. For example, the hospital workflow model (a combination of ABM, DES, and SD methodologies) and an ABM-DES model of a material handling process in an assembly line were both developed and run using AnyLogic (Djanatliev & German, 2013; Hao & Shen, 2008).

Empirical Simulation Models

The use of empirical research methods in operations management supports the development of theory (Filippini, 1997). Empirical research also provides a strong foundation for making realistic assumptions in simulation modeling and enables a better understanding of the system under study (Flynn, Sakakibara, Schroeder, Bates, & Flynn, 1990). Although much of the existing research on ABM is theoretical and abstract, there has been an increasing trend of combining ABM with empirical data (Janssen & Ostrom, 2006). Providing input values to ABM variables and parameters through social survey data demonstrates a strong empirical foundation for the development of these models (Sopha, Klöckner, & Hertwich, 2013). In particular, integrating ABM with empirical research can lead to a better representation of the human decision-making process. For example, an ABM was developed to study the diffusion of water-saving innovations in households in Southern Germany (Schwarz & Ernst, 2009). The information on the household agents was gathered through a telephonic survey. Brown and Robinson (2006) developed an empirical ABM to study the selection of residential locations within an urban system in southeastern Michigan. The authors used a survey to collect information on residents' preferences, and the survey data was used to inform the ABM.

Evaluating RFSC Performance

Many analytical methods have been adopted to evaluate RFSCs. Route and load optimization methodologies using analytical software (e.g., GIS and Route LogiX) have been proposed for regional food distribution systems (Bosona & Gebresenbet, 2011; Bosona T. , Gebresenbet, Nordmark, & Ljungberg, 2011). Craven, Mittal and Krejci (2016) proposed a coordinated transportation system among the four food hubs in Iowa to help them better meet the supply and demand of local food and reduce their overall distribution costs. Nordmark, et al. (2012) used empirical and analytical methods to study the impact of internet-based systems and evaluate environmental and economic impacts due to transportation optimization in local food supply chains. Demir and Demir (2014) developed an integer programming model to evaluate the transportation performance of 62 organic fresh produce farmers in Istanbul.

Using simulation is cost-effective and can enable useful investigations and system improvement implementations without experimenting with the real world systems (Schieritz & Grobler, 2003; Towill, Naim, & Wikner, 1992). However, a literature survey done by (Soysal, Bloemhof-Ruwaard, Meuwissen, & van der Vorst, 2012), suggests that very few simulation models have been developed in sustainable food logistics management. Jansen, et al. (2001) developed a DES model to analyze the implementation of a multi-compartment distribution system in a catering supply chain in the Netherlands. DES has been used to evaluate the performance of a supply chain for chilled food products (Van der Vorst, Beulens and van Beek 2000), as well as comparing different transport modes in terms of logistics cost, energy use, CO_2 emissions, and product quality decay (Van der Vorst, Tromp and Zee 2009). Vorst (1998) developed a computer simulation model to study the effect of uncertanitites on food supply chain performance. Krejci and Beamon (2015) used ABM to study the impacts of the farmer coordination on the emergence of different types of RFSC structures over time. Their model captures price negotiations between farmer and distributor agents. Bora and Krejci (2015) used ABM to evaluate various supplier selection policies in RFSCs.

We are unaware of any simulation models in the existing literature that address RFSC management policies. This thesis proposes and demonstrates the need for hybrid simulation to evaluate RFSCs through the development of an empirically-based hybrid simulation model to study the inbound logistics operations of a regional food hub in Iowa.

References

Angerhofer, B. J., & Angelides, M. C. (2000). System dynamics modelling in supply chain management: research review. *Proceedings of the 2000 Winter Simulation Conference* (pp. 342-351). IEEE.

Barton, P., Bryan, S., & Robinson, S. (2004). Modelling in the economic evaluation of health care: selecting the appropriate approach. *Journal of health service research policy, 9(2),* 110-118.

Beamon, B. M. (1998). Supply chain design and analysis: Models and methods. *International journal of production economics, 55(3),* 281-294.

Behdani, B. (2012). Evaluation of paradigms for modeling supply chains as complex socio-technical systems. *Proceedings of the 2012 Winter Simulation Conference* (pp. 1-15). IEEE.

Bora, H., & Krejci, C. C. (2015). Multi-agent simulation modelling of supplier selection for local food systems. *Industrial and Systems Engineering Research Sessions (ISERC).*

Borshchev, A., & Filippov, A. (2004). From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. *Proceedings of the 22nd international conference of the system dynamics society*, *22.*

Bosona, T. G., & Gebresenbet, G. (2011). Cluster building and logistics network integration of local food supply chain. Biosystems engineering. *Biosystems engineering, 108(4),* 293-302.

Bosona, T., Gebresenbet, G., Nordmark, I., & Ljungberg, D. (2011). Box-scheme based delivery system of locally produced organic food: evaluation of logistics performance. *Journal of Service Science and Management*, *4(03)*, 357.

Brailsford, S. (2014). Discrete-event simulation is alive and kicking! *Journal of Simulation, 8(1)*, 1-8.

Brailsford, S. C., Viana, J., Rossiter, S., Channon, A., & Lotery, A. J. (2013). Hybrid simulation for health and social care: The way forward, or more trouble than it's worth? *In Proceedings of the 2013 Winter Simulation Conference* (pp. 258-269). IEEE.

Brown, D. G., & Robinson, D. T. (2006). Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl. *Ecology and society*, *11(1)*, 46.

Chan, W. K., Son, Y. J., & Macal, C. M. (2010). Agent-based simulation tutorial-simulation of emergent behavior and differences between agent-based simulation and discrete-event simulation. *Proceedings of the 2010 Winter Simulation Conference*, (pp. 135-150).

Chang, Y., & Makatsoris, H. (2001). Supply chain modeling using simulation. *International Journal of simulation, 2(1)*, 24-30.

Chopra, S., & Meindl, P. (2007). *Supply chain management. Strategy, planning & operation.* Gabler.

Craven, T., Mittal, A., & Krejci, C. C. (2016). Effective Coordination in Regional Food Supply Chains. Paper to be presented at the 2016 *Industrial & Systems Engineering Research Conference.* Anaheim: IIE.

Davidsson, P., Henesey, L., Ramstedt, L., Törnquist, J., & Wernstedt, F. (2005). An analysis of agent-based approaches to transport logistics. *Transportation Research part C: emerging technologies, 13(4)*, 255-271.

Demir, A. Y., & Demir, M. C. (2014). Vehicle Routing Solution Reduces Transportation Costs for Organic Farmers Serving the Domestic Market in Turkey. *International Journal of Applied, 4(6).*

Deshpande, P. J., Yalcin, A., Zayas-Castro, J., & Herrera, L. E. (2007). Simulating less-than-truckload terminal operations. *Benchmarking: An international journal, 14(1)*, 92-101.

Djanatliev, A., & German, R. (2013). Prospective healthcare decision-making by combined system dynamics, discrete-event and agent-based simulation. *Proceedings of the 2013 Winter Simulation Conference* (pp. 270-281). IEEE.

Dubiel, B., & Tsimhoni, O. (2005). Integrating agent based modeling into a discrete event simulation. *Proceedings of the 2005 Winter Simulation Conference* (pp. 9 - pp). IEEE.

Eldabi, T., Jahangirian, M., Naseer, A., Stergioulas, L., Young, T., & Mustafee, N. (2008). A survey of simulation techniques in commerce and defence. *Proceedings of the 4th Simulation Workshop.*

Filippini, R. (1997). Operations management research: some reflections on evolution, models and empirical studies in OM. *International Journal of Operations & Production Management, 17(7)*, 655-670.

Flynn, B. B., Sakakibara, S., Schroeder, R. G., Bates, K. A., & Flynn, E. J. (1990). Empirical research methods in operations management. *Journal of operations management, 9(2)*, 250-284.

Forrester. (1961). *Industrial Dynamics.* MIT Press.

Forrester, J. (1958). Industrial Dynamics: A Major Breakthrough for Decision Makers. *Harvard Business Review, 36(4)*, 37-66.

Georgiadis, P., Vlachos, D., & Iakovou, E. (2005). A system dynamics modeling framework for the strategic supply chain management of food chains. *Journal of food engineering, 70(3)*, 351-364.

Hao, Q., & Shen, W. (2008). Implementing a hybrid simulation model for a Kanban-based material handling system. *Robotics and Computer-Integrated Manufacturing, 24(5)*, 635-646.

Heath, S. K., Buss, A., Brailsford, S. C., & Macal, C. M. (2011). Cross-paradigm simulation modeling: challenges and successes. *In Proceedings of the 2011 Winter Simulation Conference*, (pp. 2788-2802).

Heath, S. K., Dolk, D., Lappi, E., Sheldon, B., & Yu, L. (2009). Investigating the use of simulation tools for mass casualty disaster response. *Proceedings and Bulletin of the International Data Farming Community, 6*, pp. 22-25.

Helal, M. R. (2007). A methodology for integrating and synchronizing the system dynamics and discrete event simulation paradigms. *In Proceedings of the 25th international conference of the system dynamics society, 3(3)*, pp. 1-24.

Huanhuan, W., Yuelin, Z., & Meilin, Z. (2013). A framework for integrating discrete event simulation with agent-based modeling. *Innovation Management and Industrial Engineering (ICIII), 2013 6th International Conference. 3*, pp. 176-180. IEEE.

Jansen, D. R., Van Weert, A., Beulens, A. J., & Huirne, R. B. (2001). Simulation model of multi-compartment distribution in the catering supply chain. *European Journal of Operational Research, 133(1)*, 210-224.

Janssen, M. A., & Ostrom, E. (2006). Empirically based, agent-based models. *Ecology and Society, 11(2)*, 37.

Knaak, N. K. (2006). An agent-based simulation tool for modelling sustainable logistics systems. *Proceedings of the iEMSs Third Biennial Meeting: Summit on Environmental Modelling and Software.* . International Environmental Modelling and Software Society.

Krejci, C., & Beamon, B. (2015). Impacts of Farmer Coordination Decisions on Food Supply Chain Structure. *Journal of Artificial Societies and Social Simulation, 18(2)*, 19.

Lee, Y. H., Cho, M. K., Kim, S. J., & Kim, Y. B. (2002). Supply chain simulation with discrete–continuous combined modeling. *Computers & Industrial Engineering, 43(1)*, 375-392.

Liong, C. Y., & Loo, C. S. (2009). A simulation study of warehouse loading and unloading systems using Arena. *Journal of Quality Measurement and Analysis, 5(2)*, 45-56.

Majid, M. A., Aickelin, U., & Siebers, P. O. (2009). Comparing simulation output accuracy of discrete event and agent based models: a quantitative approach. *Proceedings of the 2009 Summer Computer Simulation Conference* (pp. 177-184). Society for Modeling & Simulation International.

Moradi, S., Nasirzadeh, F., & Golkhoo, F. (2015). A hybrid SD–DES simulation approach to model construction projects. *Construction Innovation, 15(1)*, 66-83.

Mustafee, N., Sahnoun, M. H., Smart, A. G., Baudry, D., & Louis, A. (2015). Investigating Execution Strategies for Hybrid Models developed using Multiple M&S Methodologies. *2015 Sprind SImulation Multi-Conference.*

Nordmark, I., Ljungberg, D., Gebresenbet, G., Bosona, T., & Jüriado, R. (2012). Integrated logistics network for the supply chain of locally produced food, Part II: Assessment of E-trade, economic benefit and environmental impact. *Journal of Service Science and Management, 5(3)*, 249-262.

North, M. J., & Macal, C. M. (2007). *Managing business complexity: discovering strategic solutions with agent-based modeling and simulation.* Oxford University Press.

Owen, C. (2013). Selection of simulation tools for improving supply chain performance. *Doctoral dissertation*. Aston University.

Powell, J., & Mustafee, N. (2014). Soft or approaches in problem formulation stage of a hybrid M&S study. *Proceedings of the 2014 Winter Simulation Conference* (pp. 1664-1675). IEEE Press.

Pugh, G. A. (2006). Agent-Based Simulation of discrete-event systems. *Proceedings of the 2006 Illinois-Indiana and North Central Joint Section Conferences.*

Scerri, D. D. (2010). An architecture for modular distributed simulation with agent-based models. *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems*, *1*, pp. 541-548.

Schieritz, N., & Grobler, A. (2003). Emergent structures in supply chains-a study integrating agent-based and system dynamics modeling. *In System Sciences, 2003. Proceedings of the 36th Annual Hawaii International Conference* (pp. 9-pp). IEEE.

Schwarz, N., & Ernst, A. (2009). Agent-based modeling of the diffusion of environmental innovations—an empirical approach. *Technological forecasting and social change, 76(4)*, 497-511.

Siebers, P. O., Macal, C. M., Garnett, J., Buxton, D., & Pidd, M. (2010). Discrete-event simulation is dead, long live agent-based simulation! *Journal of Simulation, 4(3),* 204-210.

Sopha, B. M., Klöckner, C. A., & Hertwich, E. G. (2013). Adoption and diffusion of heating systems in Norway: coupling agent-based modeling with empirical research. *Environmental Innovation and Societal Transitions*, *8*, 42-61.

Soysal, M., Bloemhof-Ruwaard, J. M., Meuwissen, M. P., & van der Vorst, J. G. (2012). A review on quantitative models for sustainable food logistics management. *International Journal on Food System Dynamics, 3(2),* 136-155.

Sterman, J. (2000). *Business Dynamics: Systems Thinking and Modeling for a Complex World.* McGraw Hill.

Sumari, S., Ibrahim, R., Zakaria, N. H., & Ab Hamid, A. H. (2013). Comparing three simulation model using taxonomy: system dynamic simulation, discrete event simulation and agent based simulation. *International Journal of Management Excellence, 1(3)*, 54-59.

Terzi, S., & Cavalieri, S. (2004). Simulation in the supply chain context. *Computers in industry, 53(1)*, 3-16.

Towill, D. R., Naim, M. M., & Wikner, J. (1992). Industrial dynamics simulation models in the design of supply chains. *International Journal of Physial Distribution & Logistics Management, 22(5)*, 3-13.

Van der Vorst, J. G., Beulens, A. J., & van Beek, P. (2000). Modelling and simulating multi-echelon food systems. *European Journal of Operational Research, 122(2)*, 354-366.

Van der Vorst, J. G., Tromp, S. O., & Zee, D. J. (2009). Simulation modelling for food supply chain redesign : integrated decision making on product quality, sustainability and logistics. *International Journal of Production Research, 47(23)*, 6611- 6631.

Viana, J. (2011). The development of a combined simulation approach in a sexual health context - combining discrete event and system dynamics simulation to form a composite model. *Doctrol dissertation*. University of Southampton.

Viana, J., Brailsford, S. C., Harindra, V., & Harper, P. R. (2014). Combining discrete-event simulation and system dynamics in a healthcare setting: A composite model for Chlamydia infection. *European Journal of Operational Research, 237(1)*, 196-206.

Viana, J., Rossiter, S., Channon, A. A., Brailsford, S. C., & Lotery, A. (2012). A multi-paradigm, whole system view of health and social care for age-related macular degeneration. *Proceedings of the 2012 Winter Simulation Conference* (p. 95). IEEE.

Vorst, J. G. (1998). Supply chain management in food chains: Improving performance by reducing uncertainty. *International Transactions in Operational Research, 5(6)*, 487-499.

Zhang, B., Chan, W. K., & Ukkusuri, S. V. (2011). Agent-based discrete-event hybrid space modeling approach for transportation evacuation simulation. *Proceedings of the 2011 Winter Simulation Conference* (pp. 199-209). IEEE.

Zulkepli, J., Eldabi, T., & Mustafee, N. (2012). Hybrid simulation for modelling large systems: An example of integrated care model. *Proceedings of the 2012 Winter Simulation Conference* (pp. 1-12). IEEE.

CHAPTER 3

HYBRID SIMULATION MODEL

This section describes a hybrid simulation model of inbound operations at a regional food hub in Iowa. The food hub operates as an online grocery store and sell products directly to its customers. The food hub has two order cycles per month. An order cycle consists of the four stages described below:

1) *Inventory listing* – Producers list the products that they are willing to sell in the current order cycle on the food hub webpage.
2) *Shopping period* – Every order cycle has a "cart open" period of six days, in the week prior to the distribution week. Throughout this period, food hub members may add products to their online shopping carts via the food hub webpage.
3) *Receiving process* – As per the customer orders, each producer delivers products to the food hub warehouse. The producers may either deliver their products on the day prior to the distribution day (i.e., the day that products are distributed to customers) or on the distribution day. The volunteers at the food hub inspect the products to ensure that the delivered items and quantities match the orders, and that the quality of the products is acceptable. The volunteers then place the products in the appropriate storage locations by product category.
4) *Delivery process* – After all of the products have been received, the food hub sorts and delivers the products to multiple distribution points throughout central Iowa, where the customers pick up their orders.

The timeline diagram of the food hub describing all four stages of an order cycle is shown in Figure 6.

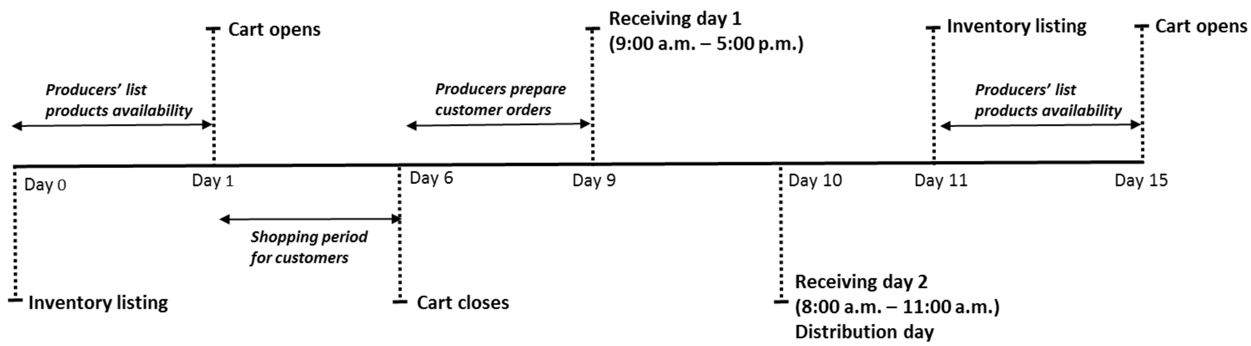

Figure 6. *Timeline diagram describing four stages in an order cycle at the food hub.*

The hybrid simulation model described in this section is focused on the receiving process at the food hub, which includes the arrival of the food hub producers to the hub, the quantity check and quality inspection by the volunteers, and the placement of the goods in storage. The food hub considered in this study has enabled its producers to schedule the dates and times of their deliveries via an online on the day prior to the distribution day and three on the distribution day) for their delivery to the food hub. However, as described in Chapter 1, small and mid-sized producers highly value their autonomy. As a result, only approximately 25% of the producers schedule their deliveries in advance, and only a few of those who use the schedule actually show up in their chosen time slot (Huber, 2015). Unscheduled deliveries result in speeding up the receiving process by the food hub personnel due to many producers arriving at the same time, thus leaving less time for quality checks and inventory put-away. This increases the likelihood of errors in product placement in storage locations and leads to customer dissatisfaction, due to poor quality of products, or wrong delivery.

This thesis describes a hybrid simulation (DES-ABM) model that employs an ABM to capture food hub producers' delivery scheduling decisions and behaviors and a DES model to represent the food hub's receiving process, with the DES model providing feedback to the ABM. These models run in a sequence as shown in Figure 7. In Stage 1, the ABM (created using *NetLogo 5.1.0*) determines the producer agents' scheduling decisions and generates the arrival times of the producers at the food hub warehouse according to these decisions. These arrival times become the input to Stage 2, which is a DES model (developed using *Arena 14.7*) of inbound operations at the warehouse. This model generates the queue time of each producer as he waits his turn to be served by a volunteer for receiving. The queue time serves as an input to the producer agents in the ABM. The data exchange between these two separate models is performed manually, using the read/write functions of both software platforms.

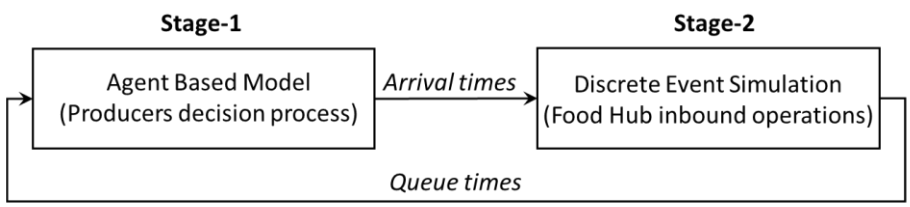

Figure 7. *Hybrid simulation (ABM-DES) model overview.*

Agent-Based Model

As described in Chapter 1, agent-based modeling (ABM) is well-suited to modeling heterogeneous components in a supply chain. In a regional food supply chain that is intermediated by a food hub, these components may include producers, the food hub, consumers, and the volunteers who work at the food hub. However, in the ABM described in this thesis, only one of these components is represented as an agent: the producers.

This ABM is used to analyze producers' decisions to schedule their deliveries before arriving to the food hub. These decisions are often influenced by multiple factors. For example, producers often like to combine multiple deliveries in the same area, coordinate their deliveries with other activities, and coordinate and share deliveries with other producers. The decision to schedule is also subject to the producers' desire to maintain their autonomy and flexibility. Small and mid-sized producers associated with the food hub (i.e., farmers) are known to highly value their autonomy, and they are often willing to make significant sacrifices to maintain it (Krejci & Beamon, 2015). However, one of the main incentives for selling products through a food hub is the convenience of avoiding multiple direct-to-consumer transactions.

This thesis describes an empirical ABM that was developed using data from a survey of the producers associated with the Iowa Food Cooperative (a food hub based in Des Moines, Iowa) and informal interviews with the food hub manager. The producer survey questionnaire targets behavioral components that include different factors affecting producers' decisions to schedule their deliveries. The detailed survey questionnaire and its explanation is provided in Appendix A.

Parameterization of the ABM

The main strength of ABM is its ability to implement human decision-making processes. The agent attributes and behavioral response functions in an ABM require knowledge from empirical sources (Smajgl, Brown, Valbuena, & Huigen, 2011). In the development of an empirical ABM, two fundamental steps are required: development of appropriate behavioral categories, and scaling the real-world sample to the whole ABM population level. The population size (i.e., the total number of agents in the ABM) can be anywhere from 20 to many millions, and therefore it becomes necessary to collect empirical data from a sample of the real-world population, which will represent the agents in the ABM (Smajgl, Brown, Valbuena, & Huigen, 2011). Therefore, the first step in the parameterization framework includes collecting the empirical data from the sample of population under study. However, it is important that the agent population appropriately reflects the actual heterogeneity of the real-world objects that it represents (Brown & Robinson, 2006). In order to identify the potential factors that affect producers' decision to schedule their deliveries, the relevant literature (including journal articles, case studies published by the U.S. Department of Agriculture and the National Good Food Network, and manuals published by food hubs in United States) was reviewed, and informal interviews with two subject matter experts (i.e., food hub managers in Iowa) were conducted (Huber, 2015; Grimm, 2015). This was followed by a survey of 25 producers, which was conducted during the delivery process of one of the order cycles at the Iowa Food Cooperative. Social surveys can serve as the source of information about the heterogeneity present in agents that are being represented in ABM, provided that the survey questions relate directly to the agent attributes in the model (Brown & Robinson, 2006). Due to missing values of key parameters for one of the respondents, the responses of 24 of these producers were used to develop the empirical ABM. The survey data was used to develop producer agent attributes, thereby providing input parameters for the simulation.

Based on the literature and the discussions with the food hub managers, six factors were initially identified as the potential reasons which might affect producers' decisions to schedule their deliveries before arriving to the food hub:

1) Producers may combine their deliveries with other activities and other deliveries in the area near the food hub.

2) Producers may combine their deliveries with other producers located near their farm.
3) Producers may be affected by their harvesting schedule, if they harvest on the day of delivery to the food hub.
4) Producers may value flexibility in delivery times to avoid placing any constraints on their schedules.
5) Access to the internet (which is required to schedule a delivery) may be inconvenient for a producer.
6) Producers may value reductions in in queue time at the food hub while waiting for service from volunteers.

These factors informed the design of the producer survey. The objective of the survey was to gather information on how the six factors described above impact producers' scheduling decision. The survey also consisted of questions related to producers' current level of satisfaction of doing business with the food hub, their geographical locations, how their behavior to schedule will change if the food hub provides certain incentives and other potential factors which are not listed in the survey but play a significant role in their scheduling decision. At the end, every producer was asked to rank all the factors (including those when food hub provides incentives to the producers for scheduling the delivery) in the decreasing order of their importance in their scheduling decision.

All the survey respondents were producers associated with the food hub and all but one were aware that the food hub gives an option to schedule their delivery online. Two of the six factors that were hypothesized to affect producers' delivery scheduling decisions (internet access and combining deliveries with other producers) were rarely mentioned by the surveyed producers. Therefore, these two factors were removed from further analysis. Some of the other factors which came from the responses that affected producers' scheduling decision and were not included in the producer survey included weather conditions, ignorance, volunteering at the food hub, delivering freshest products to the customers and family commitments. We have not considered these factors in our model as they were not applicable on all the producer population. The detailed survey results corresponding to different attributes of the ABM and DES models have been included in the respective model descriptions.

The second step in the ABM parameterization framework involves scaling up the empirical data to the entire population of agents. To accomplish this, cluster analysis was performed on the survey data to identify sample agents with similar behavioral patterns (Yim & Ramdeena, 2015). Only those variables associated with the behavioral attributes of agents in the ABM were considered in the cluster analysis (Sopha, Klöckner, & Hertwich, 2013). Behavioral attributes were derived from the producers' responses to the following survey questions, where the response was given on a 5-point Likert scale (1 as "not likely" and 5 as "highly likely").

1) How likely is it that combining your deliveries with other activities and other deliveries in the area near the food hub affects your decision to schedule the delivery?
2) How likely is it that your harvesting and packing schedule affects your decision to schedule the delivery?
3) On scale of 1 to 5 (1 is "least satisfied" and 5 as "most satisfied") what will be your satisfaction level for the different waiting times to have your products inspected and checked in by the IFC volunteers? (Refer Appendix A, question number 9, for the different waiting times included in the survey)

4) If the food hub offers you a priority delivery option (i.e. go to the front of the line for receiving) as an incentive to schedule, how likely is it that you would be scheduling your delivery?
5) How will your decision to schedule the delivery change for the different monetary incentive levels provided by the food hub? (Refer Appendix A, question number 14, for the different monetary incentive levels included in the survey)
6) If you interact with other producers, how often do you share the experiences you have with the food hub?

Hierarchical clustering analysis (Ward's Method) was used to identify different clusters (Punj & Stewart, 1983; Krejci, Stone, Dorneich, & Gilbert, 2015). The sample data was not standardized before clustering, since all responses were on a same scale. Squared Euclidean distance was used to generate the agglomerative schedule (Appendix B) to determine the coefficient values (i.e., the distance between two combined clusters) at each stage of hierarchical clustering. The increase in coefficient values indicates that the clusters that are combined at any given stage are more heterogeneous than the previous combinations (Yim & Ramdeena, 2015). The agglomerative schedule shows that the first notable increase in the coefficient value occurs at stage 20. Therefore the 24 surveyed producers were grouped into four clusters and were identified from a unique producer id by visually inspecting the dendrogram as shown in Figure 8.

Table 2 provides a summary of the responses to the six behavioral survey questions for each of the four clusters. For all the questions, higher the average response values, higher is the impact, but for the queue time, it is vice versa. If the average value of the responses is 1, then it has been assumed that the particular factor doesn't affect producers' scheduling decision. The value for these average responses for each cluster on the scale of 1 through 5 (1 as “low impact” and 5 as “impact”) are also indicated in Table 2.

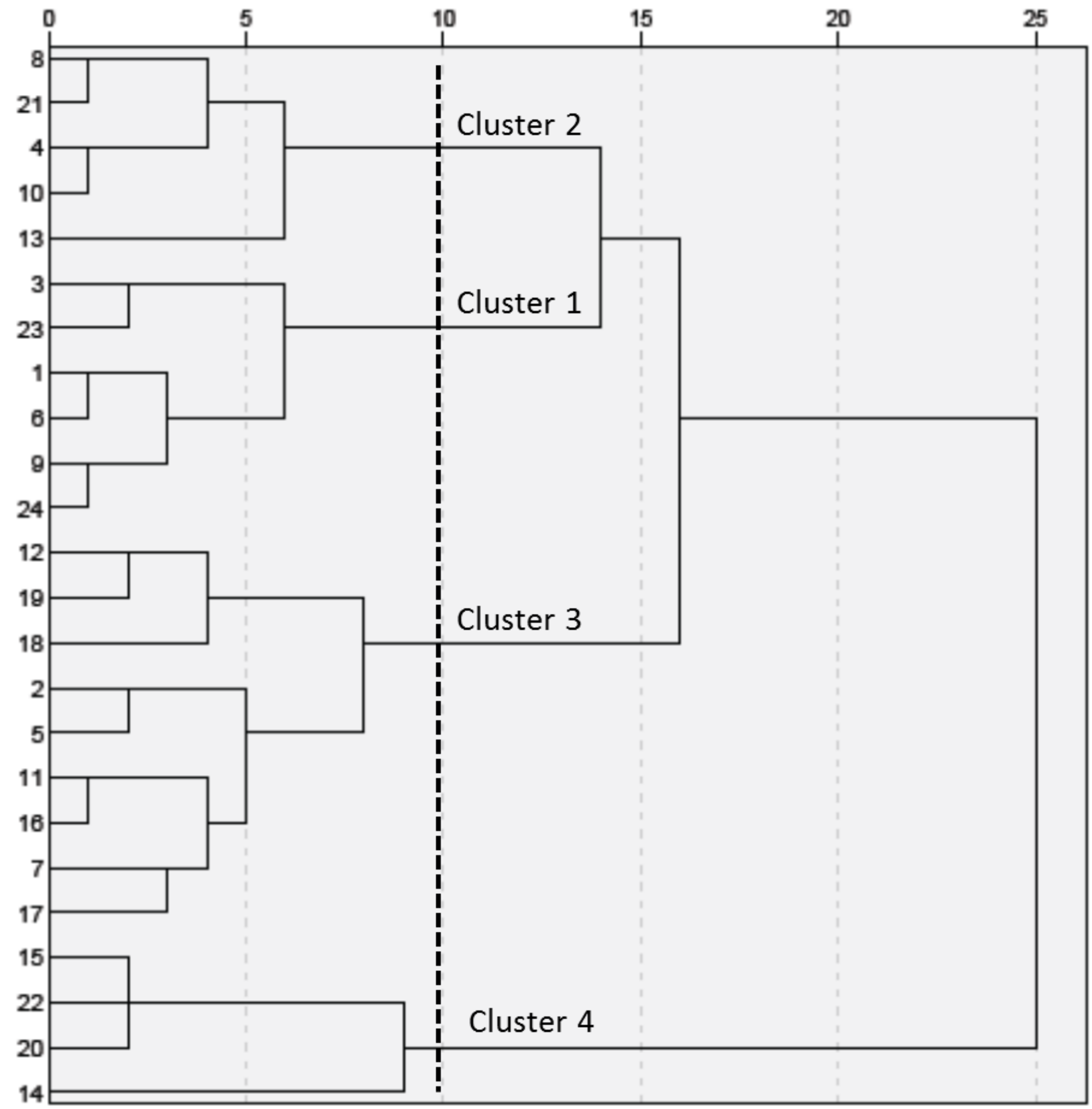

Figure 8. *Dendrogram for hierarchical cluster analysis from producers’ survey data.*

The producers in Cluster 1 consist of 6 producers. They consider waiting time and priority delivery option by the food hub as moderately important in their scheduling decision. However, other activities and deliveries in the area near to the food hub highly drives their decision to schedule the delivery. Harvesting schedule is less important in their decision making. They would highly consider scheduling the delivery if the food hub provides monetary incentives and are moderately expressive with respect to sharing their business experiences with the other food hub producers.

There were 5 producers in Cluster 2. Waiting time at the food hub, priority delivery option and monetary incentives have moderate impact while other activities in the area have high impact on their scheduling decision. These producers don’t harvest and pack their products on the day of the delivery therefore this factor doesn’t impact their scheduling decision at all. They also don’t communicate much and don’t share their business experiences with the other food hub producers.

Cluster 3 comprised majority of the respondents. Waiting time moderately affects their scheduling decision, but if they have been provided with priority queue option for scheduling, they would highly consider scheduling the delivery. Their scheduling decision is moderately driven by other deliveries and activities near the food hub area and harvesting schedule moderately affects their scheduling decision. They would be moderately affected by the monetary incentives option and the likelihood of sharing their experiences with the other producers is very less.

Cluster 4 consisted of 4 producers who are highly satisfied with their business with the food hub. It’s only the waiting time which has a very less impact on their scheduling decision, and no other factor is responsible in their decision making to schedule the delivery. Their scheduling behavior will not be affected much due to monetary incentives provided by the food hub, and they moderately share their positive or negative experiences with the other food hub producers.

Table 2. *Behavioral response of four clusters to six attributes.*

Cluster #	Queue time	Priority delivery	Other activities	Harvesting schedule	Monetary incentive	Sharing experience	Description
Cluster 1 (N = 6, 25%)	2.76	3.00	5.00	1.33	4.00	3.33	Queue time at the food hub is moderately important, priority delivery will moderately impact their scheduling decision, other activities in the area highly impact their scheduling decision, harvesting schedule impact on their scheduling decision is very less, high impact of monetary incentive on scheduling decision, likelihood of sharing experience with other producers is moderate
Cluster 2 (N = 5, 20.8%)	2.37	3.40	4.80	1.00	1.80	2.20	Queue time at the food hub and priority delivery will moderately impact their scheduling decision,other activities in the area high impact their scheduling decision, harvesting schedule doesn't impact their scheduling decision, moderate impact of monetary incentive on scheduling decision, likelihood of sharing experience with other producers is low
Cluster 3 (N = 9, 37.5%)	3.14	3.89	2.67	3.67	3.00	2.33	Queue time at the food hub is moderately important, priority delivery will highly impact their scheduling decision, other activities in the area moderately impact their scheduling decision, harvesting schedule moderately impact their scheduling decision, moderate impact of monetary incentive on scheduling decision, likelihood of sharing experience with other producers is low
Cluster 4 (N = 4, 16.7%)	3.50	1.00	1.00	1.00	1.25	3.00	Queue time at the food hub is less important, priority delivery will not impact their scheduling decision, other activities in the area doesn't impact their scheduling decision, harvesting schedule doesn't impact their scheduling decision, low impact of monetary incentive on scheduling decision, likelihood of sharing experience with other producers is moderate

After clustering, the sample data was translated into behavioral representations for the whole population using the method called up-scaling. Up-scaling can be done in two ways (Smajgl, Brown, Valbuena, & Huigen, 2011; Berger & Schreinemachers, 2006):

1) *Proportionately* – Assumes the sample is representative of the whole population.

2) *Disproportionally* – If the sample can't be assumed to be correct representation of the whole population, alternative approaches (e.g., Monte Carlo Approach, using census and GIS data) are employed.

According to its historical sales data, the food hub considered in this study is doing business with an average of 70 producers per order cycle. The ABM includes 72 producer agents who are delivering products in every order cycle to the food hub. In order to up-scale the data from 24 agents to the model population size of 72, the strategy of Schreinemachers et al. (2009) was adopted, wherein proportional cloning was used to scale the sample data to agent population. The number of agents in this study was equal to the number of Thai farm households in reality. They surveyed around a quarter of farm households, and used sampling weights (inverse probability of selection) to multiply households inside the ABM. Therefore each farm household appeared about four times in the model. The average of the 24 responses to the six behavioral questions were up-scaled proportionally by cluster to 72 producer agents in the ABM. Therefore each cluster appeared three times in the ABM.

ABM Overview

Each of the 72 producer agents in the ABM decides in each time-step whether or not they will schedule their delivery to the food hub. This decision is informed by factors that are either 1) indirectly related to the food hub or 2) directly related to the food hub. Indirect factors include the producer's preference to combine their food hub delivery with other activities/deliveries in the area and their harvesting schedule. These two factors were ranked as the most important by the most of the surveyed producers. Each producer agent is assigned a probability that their decision to schedule their delivery will be affected by these indirect factors in a given time-step. The value of this probability is based on survey responses. The probability has been assigned based on average value of the responses to these factors within each cluster. Higher the average response value for a cluster, higher is the probability that the factor will affect producers' scheduling decision. It has been assumed that the probability decreases linearly from 0.8 to 0, if the response value decreases from 5 to 1. 3 out of 24 respondents in the survey mentioned that they don't combine their delivery with other deliveries and activities in the area near the food hub. Figure 9 shows the response of 21 producers in the survey on how their decision to schedule the delivery gets affected due to this factor. The response was taken on a 5 point Likert scale with 1 as "not likely and 5 as "highly likely".

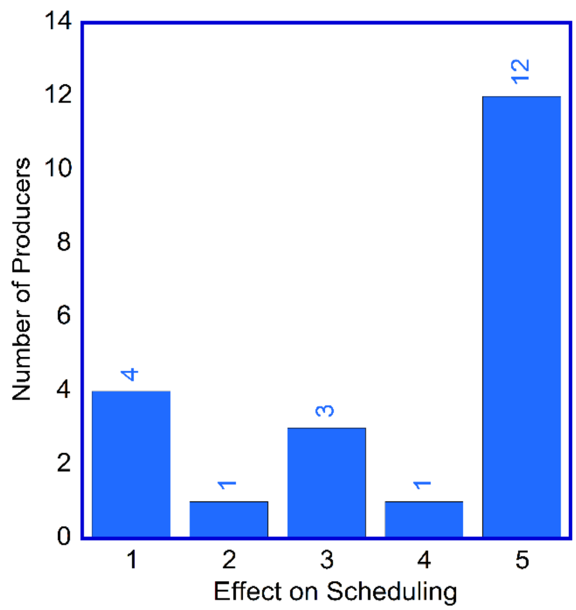

Figure 9. *Survey data showing the effect of other deliveries and activities in the area near to the food hub on producers' decision to schedule the delivery.*

Also, 12 out of 24 survey respondents mention that they don't harvest, pack or label their products on the day of the delivery. Figure 10 shows the response of the remaining 12 producers' on how their decision to schedule affects based on their harvesting schedule. The response was taken on a 5 point Likert scale with 1 as "not likely" and 5 as "highly likely".

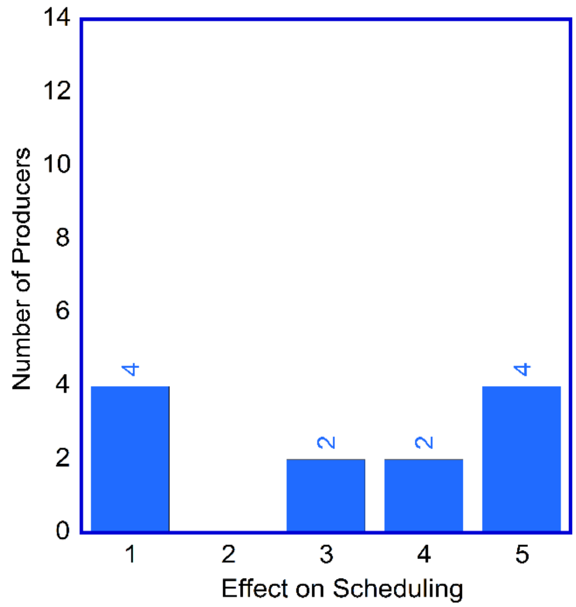

Figure 10. *Survey data showing the effect of harvesting schedule on producers' decision to schedule the delivery.*

If a producer's decision in any given cycle is not affected by these indirect factors, then it will be influenced by factors that are directly related to the producer's previous experiences with the food hub. Specifically, the producer recalls whether he was satisfied with his scheduling decision in the previous cycle or not. His level of satisfaction is based on two different components: autonomy (i.e., flexibility in delivery) and convenience. In the model, it is assumed that the degree of autonomy that a producer experiences depends upon the flexibility he has in choosing times to deliver goods to the food hub. The level of convenience that a producer agent experiences depends upon the amount of time that he spends waiting in a queue to receive service from personnel at the food hub during a delivery.

Every producer has a time preference for delivering their goods to the food hub. The food hub currently offers 11 one-hour time slots in its online schedule from which the producers can choose to deliver their goods. These time slots are available between 9:00 am to 5:00 pm on the day prior to the distribution day and from 8:00 am to 11:00 am on the distribution day in every order cycle. The surveyed producers were asked about their preferences for each of the 11 time slots, on a scale of 1 to 5, where 5 is most satisfied and 1 is least satisfied. Figure 11 shows the satisfaction level of the 24 producers surveyed for each of the 11 time slots (1 – 8 represents receiving day 1 time slots, 9 – 11 represents receiving day 2 time slots). On delivery day 1, slot number 2 and 6 are highly preferred by the producers to deliver their products. While on delivery day 2, most of the producers preferred to deliver in the last two time slots.

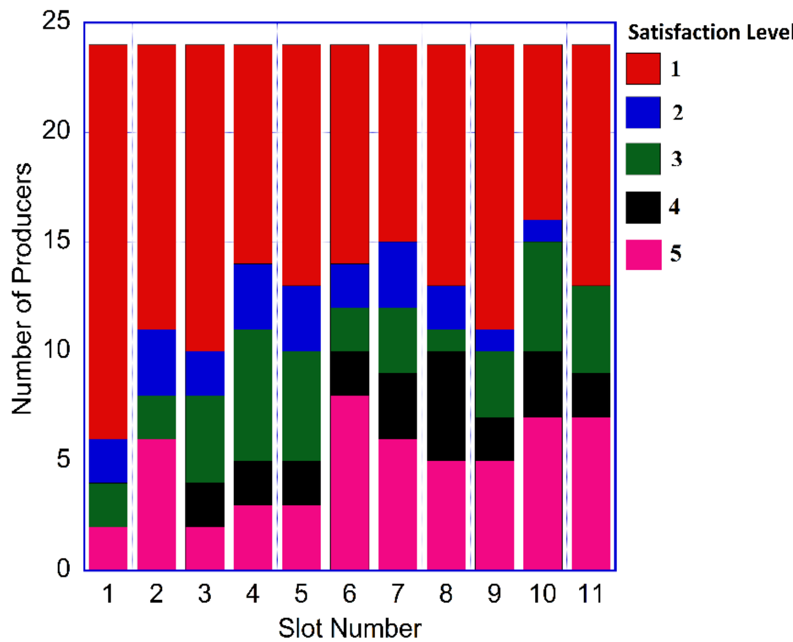

Figure 11. *Satisfaction level of 24 survey respondents to deliver the products in 11 time slots.*

It is assumed that this preference does not change over the course of a simulation run. The slots are assumed to be filled on a first-come-first-served basis, and it is assumed that if a producer schedules his delivery in a given time slot, he is guaranteed to arrive at the food hub in that time slot.

The utility that a producer gains from autonomy in each delivery cycle depends upon his ability to schedule his delivery for his preferred time slot, or better yet, to avoid scheduling altogether. The producer's utility due to autonomy (U_A) is defined on a scale from 0 to1 (where 0 and 1 represent the worst and best possible outcomes, respectively). U_A is assigned a value of 1 if the producer doesn't schedule his delivery. If a producer decides to schedule his delivery, he will first check the availability of his most-preferred time slot. If the slot is not full (i.e., it has not reached its maximum capacity), he will schedule his delivery for this time. If the time slot is full, he will check for availability in his second most-preferred time slot, and so on, until he is able to successfully schedule. This is because, all the 24 producers responded in the survey, that if there most preferred time slot is not available, they will schedule the delivery in their next preferred time slot. In this case U_A decreases linearly from 0.8 to 0, with a value of 0.8 when he get his most-preferred time slot and 0 if he get his least-preferred time slot.

A producer agent's utility due to convenience (U_C) is a function of producer queue time (Q) at the food hub. Previous research has shown that an inversely proportional relationship exists between customer waiting time in queue and customer satisfaction (Davis & Heineke, 1998). However, for producers that are supplying food to regional food hubs, this is not necessarily the case – for a variety of reasons, not all producers are concerned about the time they have to wait in queue for their products to get checked in. For example, some of the producers spend time volunteering at the food hub when they come to drop of their products, so waiting time in queue doesn't affect their satisfaction level at all. In the survey, producers were asked about their satisfaction level on a scale from 1 to 5 for 7 different wait time ranges (where 5 is "most satisfied" and 1 is "least satisfied"). Figure 12 shows the producers' response to satisfaction level in the survey corresponding to 7 different ranges of waiting times with 1 as "least satisfied" and 5 as "most satisfied".

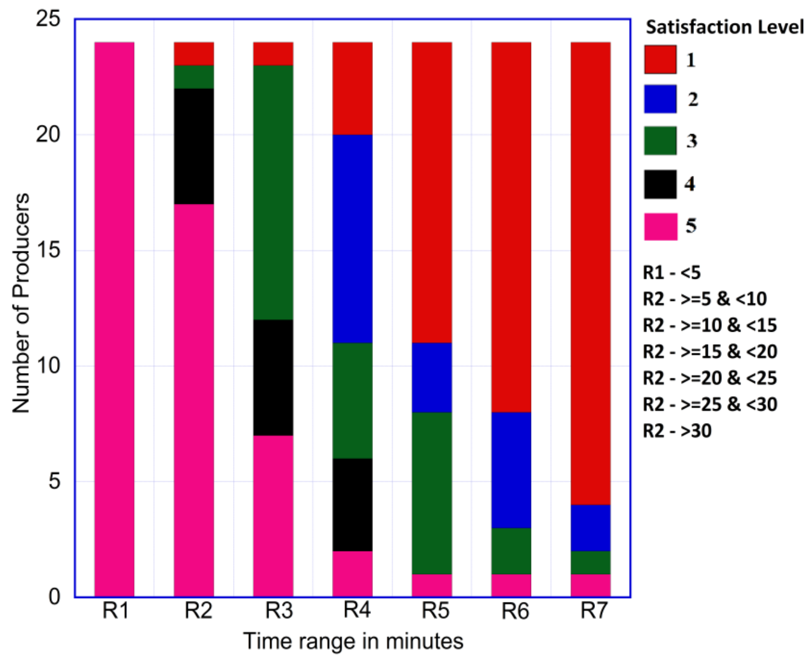

Figure 12. *Survey data showing satisfaction level of 24 producers for the 7 different waiting times range at the food hub.*

Utility due to convenience (U_C) is defined on a scale of 0.2 to 1. U_C is assigned a value of 1 if the producer's queue time (Q) yields the highest satisfaction level (i.e., 5), and it decreases linearly to a value of 0.2 if the queue time results in the minimum satisfaction level (i.e., 1). Figure 13 shows how U_C varies for each cluster as the waiting time increases based on the producers' responses in the survey.

The overall utility (U) of a producer's decision is a weighted combination of U_A and U_C, given by: $U = W_AU_A + W_CU_C$, where W_A and W_C are measures of the producer's relative preference for autonomy and convenience, respectively. Every producer has a satisfaction threshold, and if his scheduling decision yields a level of satisfaction that falls below this threshold, he will update his decision-making strategy in an attempt to improve it. To define this satisfaction in terms of utility, every producer is assigned a constant threshold utility value (U_T) of 0.88, below which a producer will be dissatisfied. It is calculated by assuming that a producer will be satisfied if he gets at least his most-preferred time slot for scheduling the delivery ($U_A = 0.8$) and his wait time in the queue is in the range of highest satisfaction level ($U_C = 1$), with $W_A = 0.6$ and $W_C = 0.4$. Table 3 and Table 4 summarize all of the variables and parameters used to describe the state of a producer agent in the ABM.

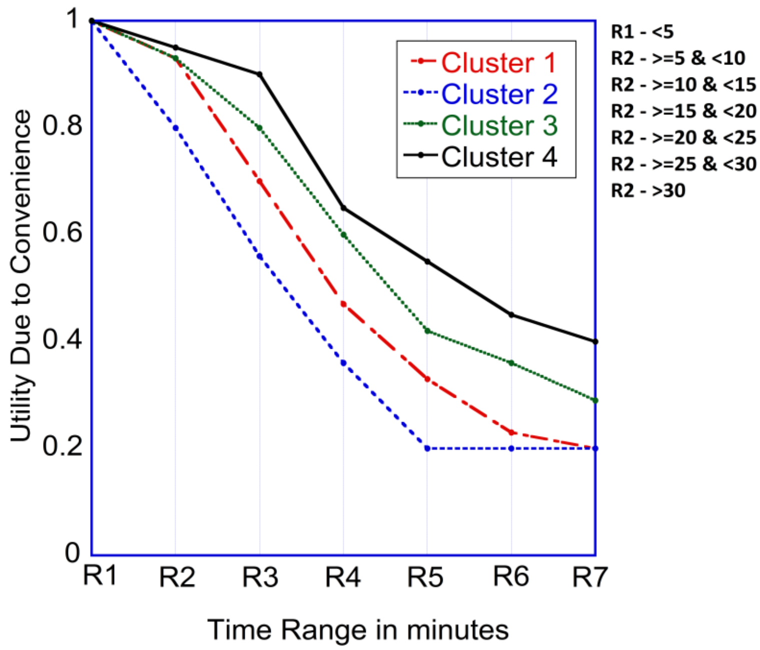

Figure 13. *Variation of U_C vs waiting time for each cluster.*

Table 3. *ABM variables.*

#	Variable	Description	Source	Possible values
1	producer_combine_delivery	Producer combine his delivery with other deliveries and activities in the area in an order cycle	Producer survey	1 – if yes 0 – if no
2	producer_harvest	Producer harvest on the day of the delivery in an order cycle	Producer survey	1 – if yes 0 – if no
3	producer_schedule_delivery	Producer decision to schedule the delivery	ABM	1 – if yes 0 – if no
4	producer_slot_number	Time slot number in which the producer decides to deliver the products at the food hub	ABM	1 - 8 (day prior to distribution day) 9 – 11 (on distribution day)

Table 3. *(Continued)*

#	Variable	Description	Source	Possible values
5	producer_delivery_day	Arrival day of the producer	ABM	1 – day prior to distribution day 2 – distribution day
6	producer_arrival_time	Arrival time of the producer in the chosen time slot on a given delivery day	ABM	-
7	producer_queue_time (Q)	Time spent by the producer in queue waiting for his turn to get the products checked in	DES	-
8	producer_utility_queue_time (U_C)	Utility gain by a producer due to waiting time in an order cycle	DES-ABM	0.2 to 1
9	producer_utility_autonomy (U_A)	Utility gain by a producer due to his decision to schedule the delivery and availability of his preferred time slots	ABM	0 to 1
10	producer_overall_utility (U)	Weighted utility of a producer	ABM	0 to 1

Table 4. *ABM parameters.*

#	Parameter	Description	Source	Possible values
1	producer_number	Unique number assigned to each producer agent in ABM	-	1 - 72
2	producer_combine_probability	Probability that the producer will not schedule the delivery if he combine it with other activities and other deliveries	Producer survey	0 to 1
3	producer_harvest_probability	Probability that the producer will not schedule the delivery if they harvest on the same day	Producer survey	0 to 1
4	producer_time_slot_satisfaction	Satisfaction level of producers to deliver in each of the 11 time slots	Producer survey	1 to 5 (1 as least satisfied and 5 as most satisfied)
5	weight_queue_time (W_C)	Weight of queue time in the aggregate utility function in the decision making process of the producer	Experimental	0 to 1
6	weight_autonomy (W_A)	Weight of autonomy in the aggregate utility function in the decision making process of the producer	Experimental	0 to 1

Table 4. *(Continued)*

#	Variable	Description	Source	Possible values
7	producer_threshold_utility (U_T)	Utility below which the producer will not be satisfied with the decision	Experimental	0 to 1
8	max_slot_capacity	Maximum number of producers allowed to choose a particular time slot for scheduling their delivery	Experimental	6 – 18

Discrete Event Simulation (DES)

DES model captures the activities of the inbound receiving operations in the food hub, including quality inspection and storage of the goods brought by the producers. The receiving process of the food hub considered in this thesis is shown in Figure 14. The entities in the DES model represent the producer agents of the ABM. The four attributes of these entities are the quantity and the category of the goods they are selling through the food hub in every order cycle, and their arrival times and waiting times at the food hub. The receiving operations are divided into four stages in the DES: the arrival of producers at the food hub, queuing for service, receiving service from the food hub personnel, and exiting the food hub.

Figure 14. *Receiving process at the food hub.*

Producer arrival times that are determined by their scheduling decisions. Upon arrival, if there are unoccupied receiving personnel available, an arriving producer will immediately be served; otherwise, the producer will wait in a queue for service. Receiving time is known to be dependent upon product attributes. For example, milk will have a different receiving time than an equivalent volume of vegetables/meat. It is necessary for the receiving personnel to count the quantity and types of milk containers and ensure that these match the values on the producer's invoice, as well as inspecting the products' expiry dates. Vegetable deliveries must be reconciled to the producer's invoice, but they also undergo a quality inspection. For example, every bag of potatoes must be carefully inspected for sprouted or green potatoes, which is a very time-consuming process. Therefore, quality inspection and product placement time are a function of both the quantity delivered and the product category. The food hub in this study has categorized the products sold by its producers into four different categories, which are summarized in Table 5.

Table 5. *Four different types of product categories at the food hub.*

Serial #	Product Type	Description
1	NON	Shelf-stable goods
2	FROZ	Frozen goods
3	REF	Refrigerated goods
4	PLANTS & INVENTORY	Plants and dry goods kept as inventory at the food hub

The probability distributions that define the receiving times of products in the DES model depend on the quantity of goods sold by the producers in each of the four different categories. The storage strategies adopted by the food hub for each of the four product categories are described below.

NON – Shelf-stable goods

"NON" includes the shelf-stable goods (e.g., salsa, flour, potatoes) sold by the producers that do not require refrigeration. "NON" goods are stored on shelves in the food hub warehouse according to customer member identification numbers. Figure 15 schematically illustrates how the products in the "NON" category of the food hub considered in this study are stored. The receiving time for "NON" goods depends on the number of customer orders for these items.

Figure 15. *Storage of "NON" goods at the food hub.*

FROZ – Frozen goods

"FROZ" includes frozen meat products and other frozen goods (e.g., ice cream), which are stored in freezers in the food hub warehouse. The goods of each producer are stored at a unique location in the freezer, which is labeled by the producer's name. Customer orders are stored in order of increasing identification number, with the smallest number in the front of the freezer and largest at the back. Figure 16 shows how "FROZ" products are stored at the food hub. The receiving time of the frozen goods depends on the number of customer orders within a producer's delivery.

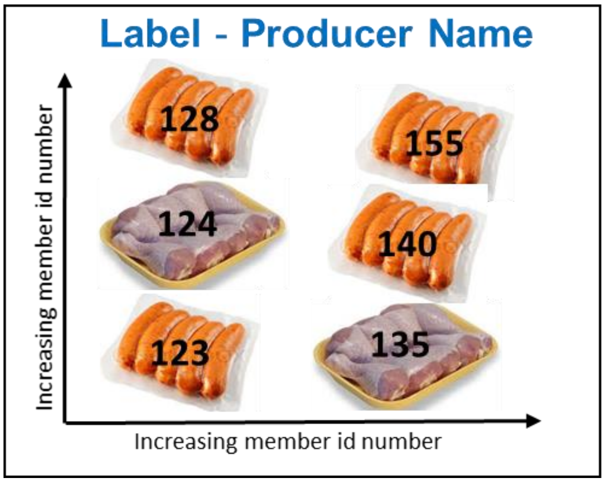

Figure 16. *Storage of "FROZ" goods at the food hub.*

REF – Refrigerated goods

"REF" includes all the vegetables, fruit, and dairy products. These items are stored according to the producer in refrigerators in the food hub warehouse. This storage scheme is similar to that of the "FROZ" products, but the refrigerated items are not arranged according to customer identification number. Figure 17 shows the typical storage strategy of "REF" products for one particular producer at the food hub.

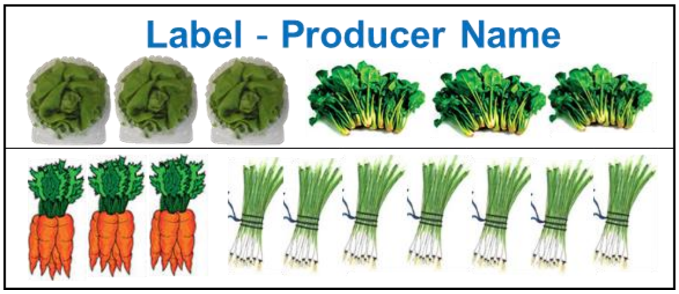

Figure 17. *Storage of "REF" goods at the food hub.*

Plants and inventory goods

The inventory goods are stored in a similar way as that of "REF" products, but as they are shelf-stable goods they are stored on shelves that are designated to each individual producer. The plants are also stored according to their producer and are arranged in the order of increasing customer identification number, as with the "FROZ" products. The overall layout of the food hub warehouse under study is shown in Figure 18. The layout shows the arrangement of refrigerators, freezers, dry good shelves, and inventory storage area.

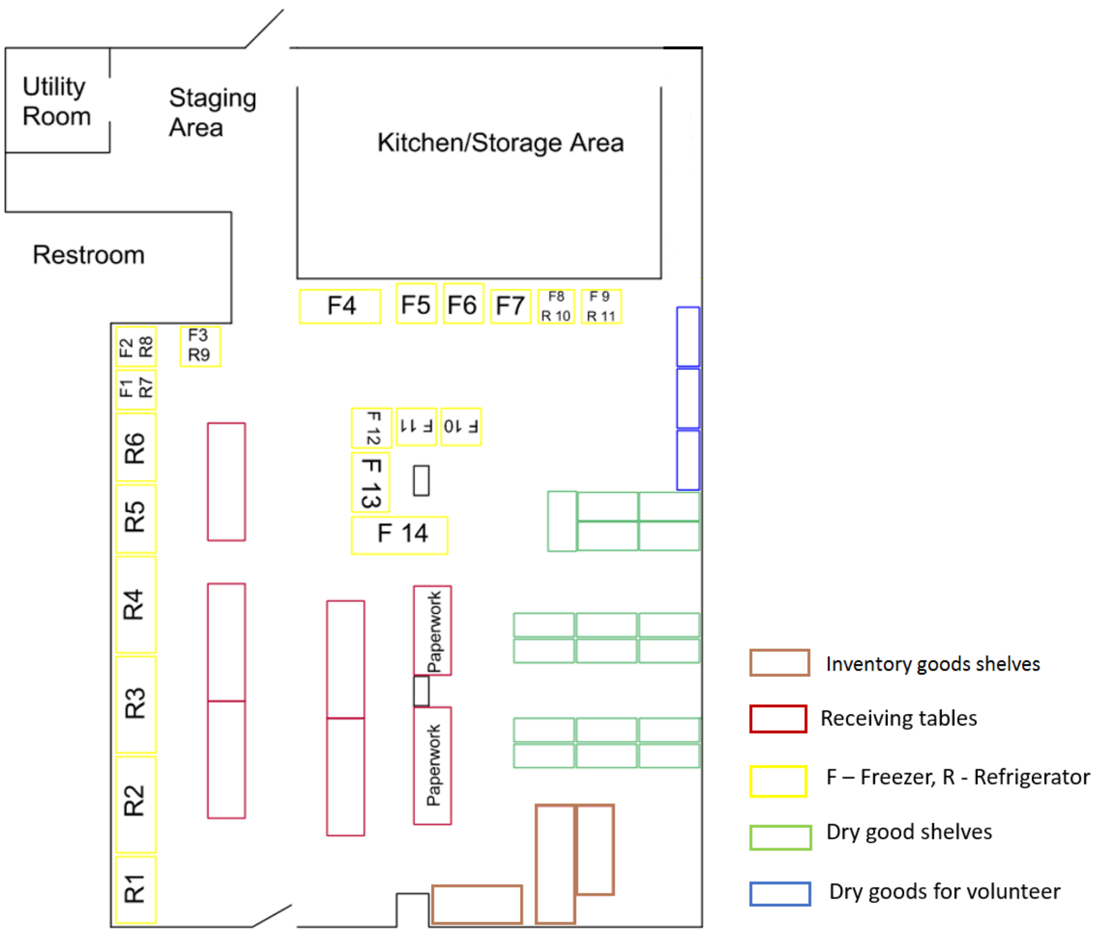

Figure 18. *Facility layout of the food hub.*

Data collection

The volume of products sold in each of the four product categories in the past year was identified for each of the 24 producers surveyed using the food hub's sales database. Table 6 describes this data for one order cycle. This data was up-scaled to 72 producer agents using the hierarchical cluster analysis described previously.

Table 6. *Description of data for each of the four product categories.*

Serial #	**Product Type**	**Data Description**
1	NON	Total number of individual packages brought by the producer labelled as "NON"
2	FROZ	Total number of customers served by a producer
3	REF	Total number of individual packages of "REF" products
4	PLANTS & INVENTORY	Total counts of plants and inventory goods brought by the producer

The data acquired for receiving time at the food hub per unit of each product type is based on a time study conducted at the food hub. The time-study was conducted by capturing the minimum and maximum time taken to receive and store the products for a sample of producers in each product category. This time-study data was then used to assign the receiving time for each product category based on the data type as mentioned in Table 5. The range of receiving times for each of the four product categories is shown in Table 7. In the DES model the receiving time for per unit in each of the four product categories is drawn from a triangular distribution with minimum and maximum values as shown in Table 7 and the median value as the average of these maximum and maximum values.

Table 7. *Receiving time values for all the three product categories.*

Serial #	Product Type	Unit	Minimum time (minutes)	Maximum time (minutes)
1	NON	Number of orders	0.44	1
2	FROZ	Number of customers per producer	0.89	1.18
3	REF	Number of orders	0.2	0.3
4	Plants & Inventory goods	Plants - Number of customers per producer	0.89	1.18
		Inventory goods – Number of orders	0.2	0.3

The number of resources (i.e., food hub personnel) in the DES model is based on the actual number of volunteers available at the food hub over a period of two days for the receiving process. On the day prior to the distribution day (delivery window of eight hours), an average of two volunteers are available; and on the distribution day (delivery window of three hours), six volunteers are available in the entire time window for the receiving process. Given a producer's arrival time, arrival time slot, and quantity and category of products, the DES model outputs the queue time for each producer. The flowchart of the DES model built using *Arena* (14.7) is shown in Figure 19.

Table 8 summarizes the input and output variables used in the DES model. All of the input variables used in the DES model are either informed by the ABM or derived from the food hub's sales database. The parameters used in the DES model related to the receiving process are summarized in Table 9 and have been derived by the food hub manager based on his expert knowledge of the food hub's operations (Huber, 2015).

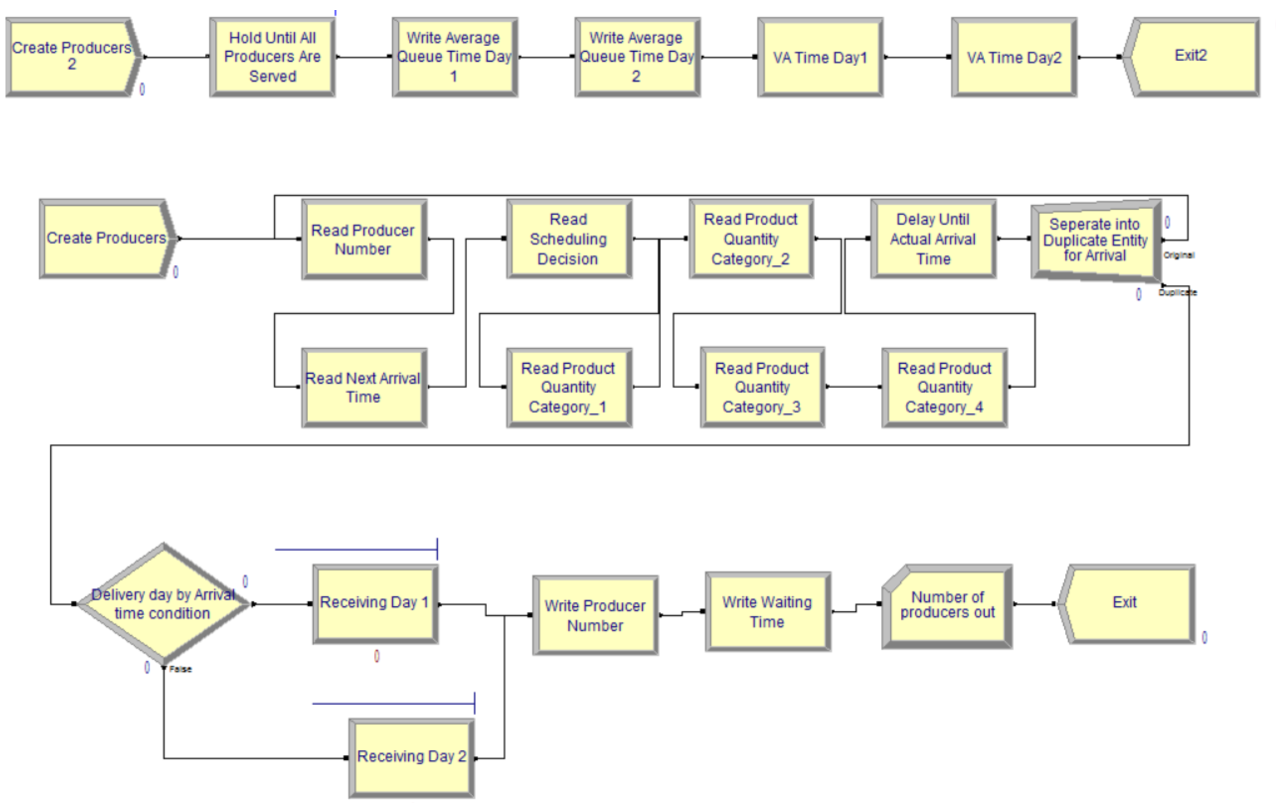

Figure 19. *Flowchart of the Arena simulation model.*

Table 8. *DES variables.*

#	Variable	Description	Source	Possible values
1	producer_arrival_time	Arrival time of the producer at the food hub as per his time slot preferences	ABM	-
2	producer_scheduling_decision	Producer decision if he has scheduled the delivery in advance or not	ABM	0 – not scheduled 1 - scheduled
3	producer_delivery_day	Day of delivery of the producer	ABM	1 – delivery day 1 2 – delivery day 2
4	producer_queue_time	Time spent by the producer in queue waiting for his turn to get checked in	DES	-
5	average_queue_time_day1	Average waiting time of the producers on the day prior to the distribution day	DES	-
6	average_queue_time_day2	Average waiting time of the producers on the day of distribution	DES	-
7	resource_utilization_day1	Man hour utilization rate for the receiving process on the day prior to the distribution day	DES	0 – 100 %
8	resource_utilization_day2	Man hour utilization rate for the receiving process on the distribution day	DES	0 – 100 %

Table 9. *DES parameters.*

#	Parameter	Description	Source	Possible values
1	producer_number	Unique number assigned to each entity in DES corresponding to the agent in the ABM	ABM	1 - 72
2	receiving_time_category1	Time required to check in and store per unit of products sold by the producer in category 1	Time study at the food hub	TRIA(0.2,0.25,0.3)
3	receiving_time_category2	Time required to check in and store per unit of product sold by the producer in category 2	Time study at the food hub	TRIA(0.44,0.72,1)
4	receiving_time_category3	Time required to check in and store products sold by the producer in category 3 for one customer	Time study at the food hub	TRIA(0.89,1.02,1.18)
5	receiving_time_category4	Time required to check in and store per unit of products sold by the producer in category 4	Time study at the food hub	TRIA(0.2,0.25,0.3)
6	number_resource_day_1	Number of volunteers available to check in and store the products on the day prior to the distribution day	Food hub resource data	2
5	number_resource_day_2	Number of volunteers available to check in the products on the distribution day	Food hub resource data	6
6	producer_quantity_category_1	Average quantity of products in category 1 sold by the producer in last year	Food hub historical sales data	-
7	producer_quantity_category_2	Average quantity of products in category 2 sold by the producer in last year	Food hub historical sales data	-
8	producer_quantity_category_3	Average quantity of products in category 3 sold by the producer in last year	Food hub historical sales data	-
9	producer_quantity_category_4	Average quantity of products in category 4 sold by the producer in last year	Food hub historical sales data	-

Hybrid Simulation Model

In this section we have described the four different versions of the hybrid simulation model developed. All the four versions of the model were used to observe the producers' behavior to schedule the delivery under different conditions. Model I i.e. the "Status quo" represents the current condition at the Iowa Food Cooperative, with producers making their scheduling decision based on several factors as described above in the ABM. In rest of the three models, interventions by the food hub have been modeled to encourage producers to schedule the delivery. In Model II, it has been considered that the food hub will provide an option of priority queue to the producers who schedule their delivery. In Model III, it has been considered that the food hub rewards the producers with monetary incentives as well as priority queue for scheduling their delivery. In Model IV, it has been assumed that the food hub will provide feedback to the producers on how their inbound operations get affected due to unscheduled deliveries. The effect of this feedback along with sharing this feedback information among the producers has been modeled to observe the producers' overall scheduling decisions.

Model I – Status Quo

The simulation begins with the ABM. In the first delivery cycle, it is assumed that all of the producers will make their decision to schedule their deliveries based on the two indirect factors (i.e., their decision to combine the delivery with other activities/other deliveries near the food hub location and their harvesting schedule). If any one of these factors affects their decision to schedule the delivery (i.e. not to schedule), it is assumed that the producers will arrive in one of their most preferred (with satisfaction level of 5) time slots. However, if these two factors are not affecting producers' scheduling decision, it is assumed that they will first try to schedule the delivery in one of their most preferred time slot. If all of their most preferred time slots are not available to schedule due to capacity restrictions on the time slots, they will try scheduling in their second most preferred time slot and so on until they are able to successfully schedule the delivery. The actual producer arrival times to the food hub are assumed to be uniformly distributed within the chosen time slots. These arrival times are written to an output file and become inputs to the DES.

At this point, the simulation switches to the DES. Upon arrival to the food hub, the producer (i.e., entity) will either receive service from food hub personnel immediately, or he will wait for service in the queue. The service time is the time required to receive the product into inventory, which includes a quantity check, quality inspection, and product placement in storage which is dependent on the product quantity and category brought by the producer to the food hub. The producer's queue time is written to an output file, which becomes an input file to the ABM. The producer's queue time (Q) is then used to calculate his utility due to convenience (U_C). Also, as per the producer's decision to schedule his delivery in the previous cycle, he will calculate his utility due to autonomy (U_A). The producer's overall utility (U) is then calculated using the weighted utility function.

From the second order cycle, the producer will first determine his scheduling decision due to combining delivery with other activities and harvesting schedule. If these factors don't affect his decision to schedule, then the producer compares his overall utility (U) of the previous cycle with the threshold utility (U_T). If U is greater than U_T, then he will maintain his current strategy to schedule/not schedule; otherwise, he will reverse his decision.

This process of deciding on a scheduling policy, arriving at the food hub, queueing, receiving service, and updating the scheduling policy based on different factors and utility outcomes, occurs for each of the 72 producer agents in every time-step, where one time-step is equivalent to one two-week delivery cycle for the food hub. The overall process is shown in Figure 20.

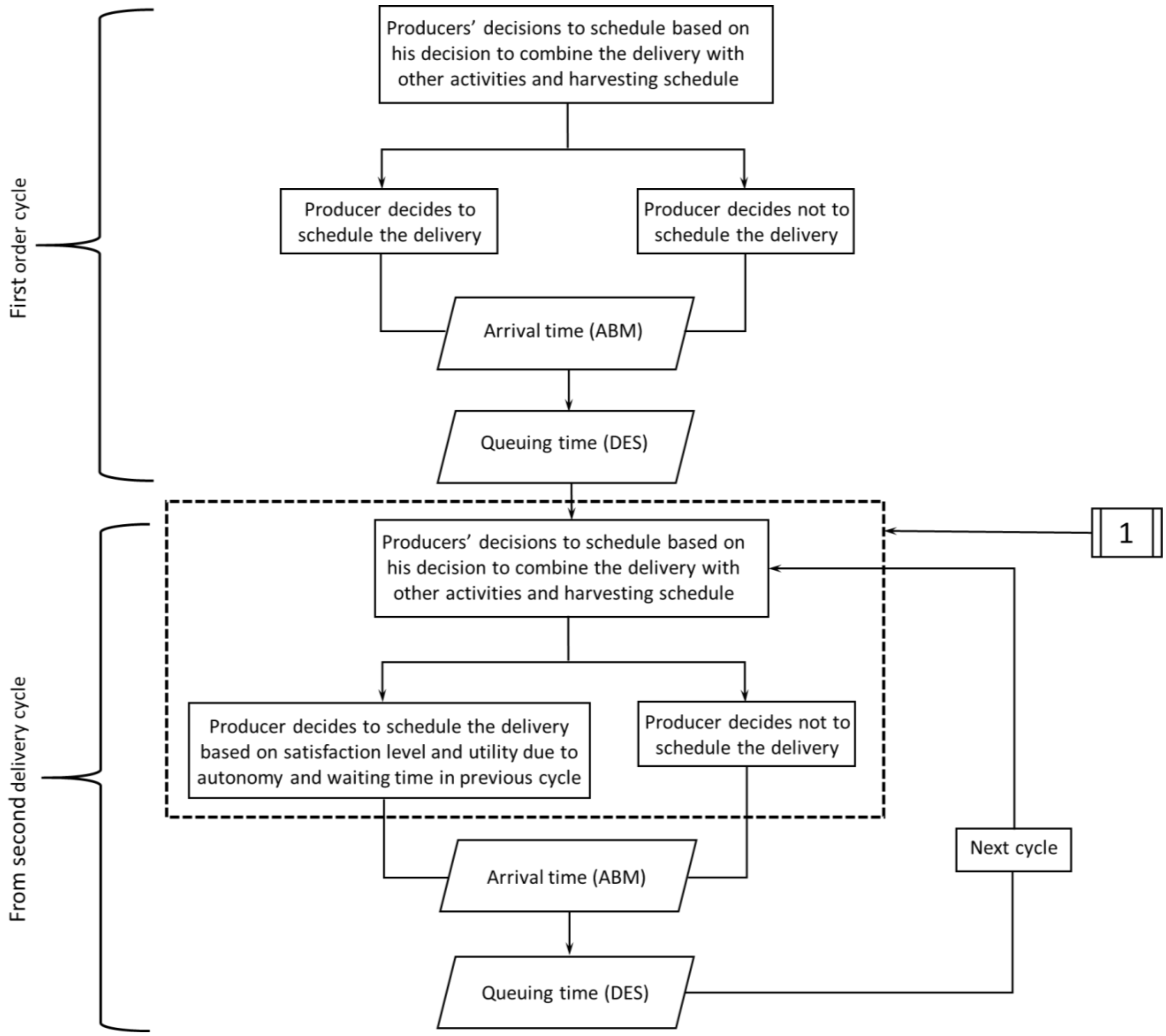

Figure 20. *ABM- DES model overview (Status Quo).*

Food hub interventions

In order to encourage producers to schedule their deliveries, food hub managers should take corrective actions as necessary in order to improve their inbound operation's efficiency and to avoid lost sales due to bad quality or wrong products reaching the customers. In order to reduce these errors, food hubs can consider encouraging producers to schedule their deliveries by providing them with monetary incentives or better performance ratings, providing them alternative delivery options, re-allocate their labor working hours as per the arrival pattern of the producers increasing their number of employees, or by having dedicated and trained labor for quality inspection process.

The implications of two types of measures by the food hub manager are studied in this thesis: providing producers with an option of priority delivery (i.e., they can jump to the front of the queue, if any) or giving producers monetary incentives if they have scheduled their drop-off times in advance.

Model II - Priority delivery incentive

Previous research shows that customers do not like to wait and consumers will go to any extent to reduce their wait time, like jumping the queue or paying a premium to avoid waiting (Pàmies, Ryan, & Valverde, 2015). Conventional companies like airlines and theme parks provide priority entry to customer in return for a cost which becomes a significant source of their revenue (Alexander, MacLaren, O'Gorman, & White, 2012). The author mentions that if the customer pays for not waiting in the long queues then the value directly relates to the difference between their waiting time and that of customers in the main queue. However, priority queue sometimes give a negative impression to the customers in the main queue as treating some customers as VIP (McGuire & Kimes, 2006). In the current operations of the food hub, there is no option for the producers who have scheduled the deliveries in advance to get a priority check in. They have to wait in long queues because of many producers showing up at the same time without scheduling the delivery, even if they have scheduled the delivery in the time slot they have arrived. In order to benefit the producers who have scheduled the delivery in advance we have included a priority delivery option for them at the time of check in. This incentive, illustrated schematically in Figure 21, shows the current and the future conditions of the food hub receiving strategy.

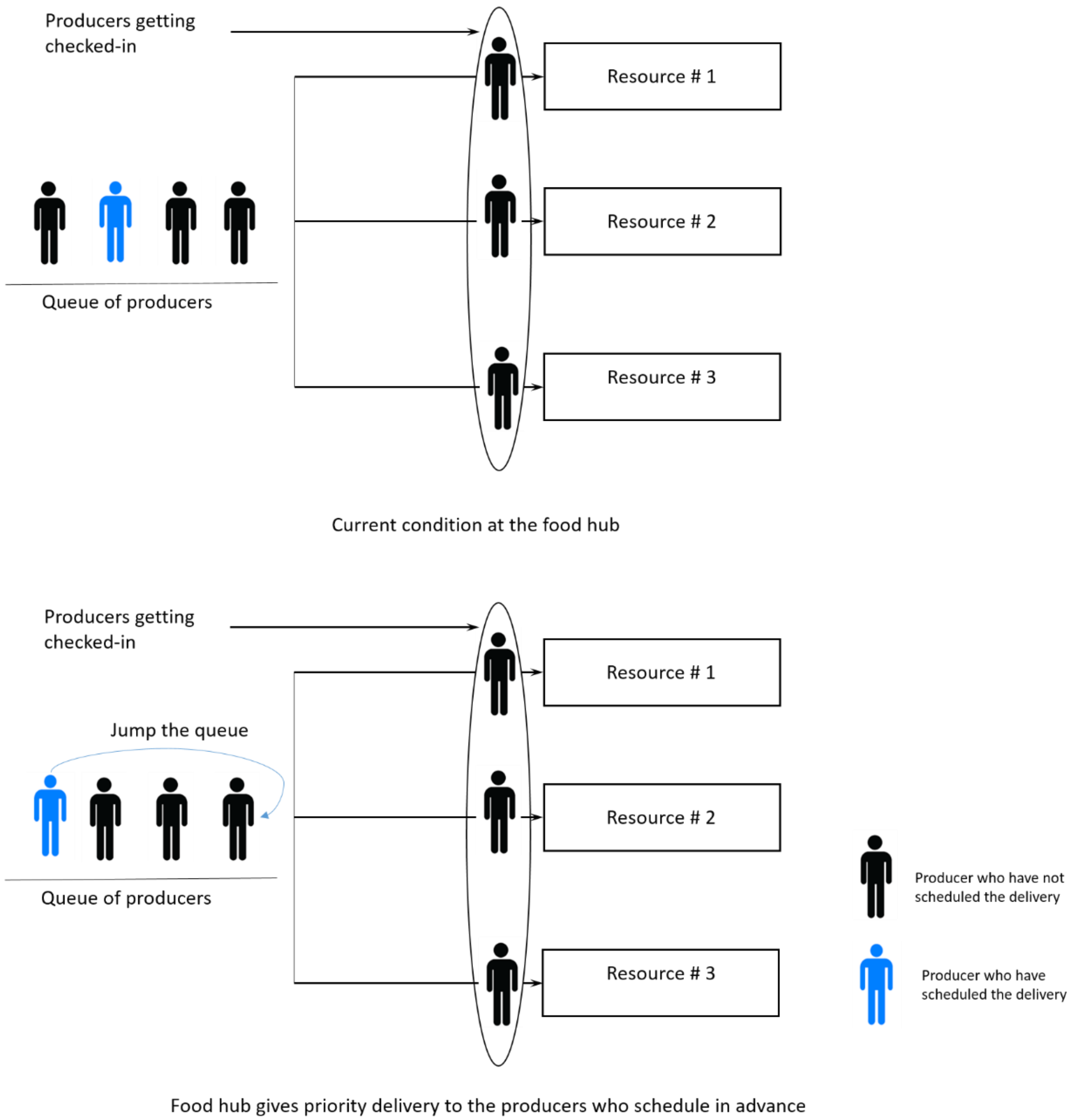

Figure 21. *Priority delivery option to the producers who schedule their delivery times in advance.*

The surveyed producers were asked about how their decision to schedule their deliveries to the food hub would change if the food hub provided them with an option of priority delivery. Figure 22 shows the response of 24 producers in the survey, on how the priority delivery options affects their scheduling decision with 1 as “not likely” and 5 as “highly likely”.

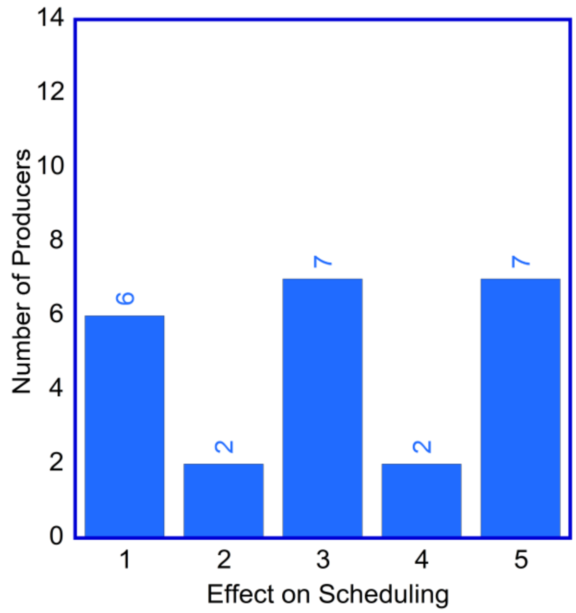

Figure 22. *Survey data showing the effect of priority queue option on the scheduling decision of the producers.*

The decision-making process if the producer is provided with an option of priority delivery is shown in Figure 23. The corresponding snapshot of the flowchart from the DES model is shown in Figure 24. A summary of the hybrid ABM-DES model incorporating the priority delivery option in the producers’ decision-making process is shown in Figure 25.

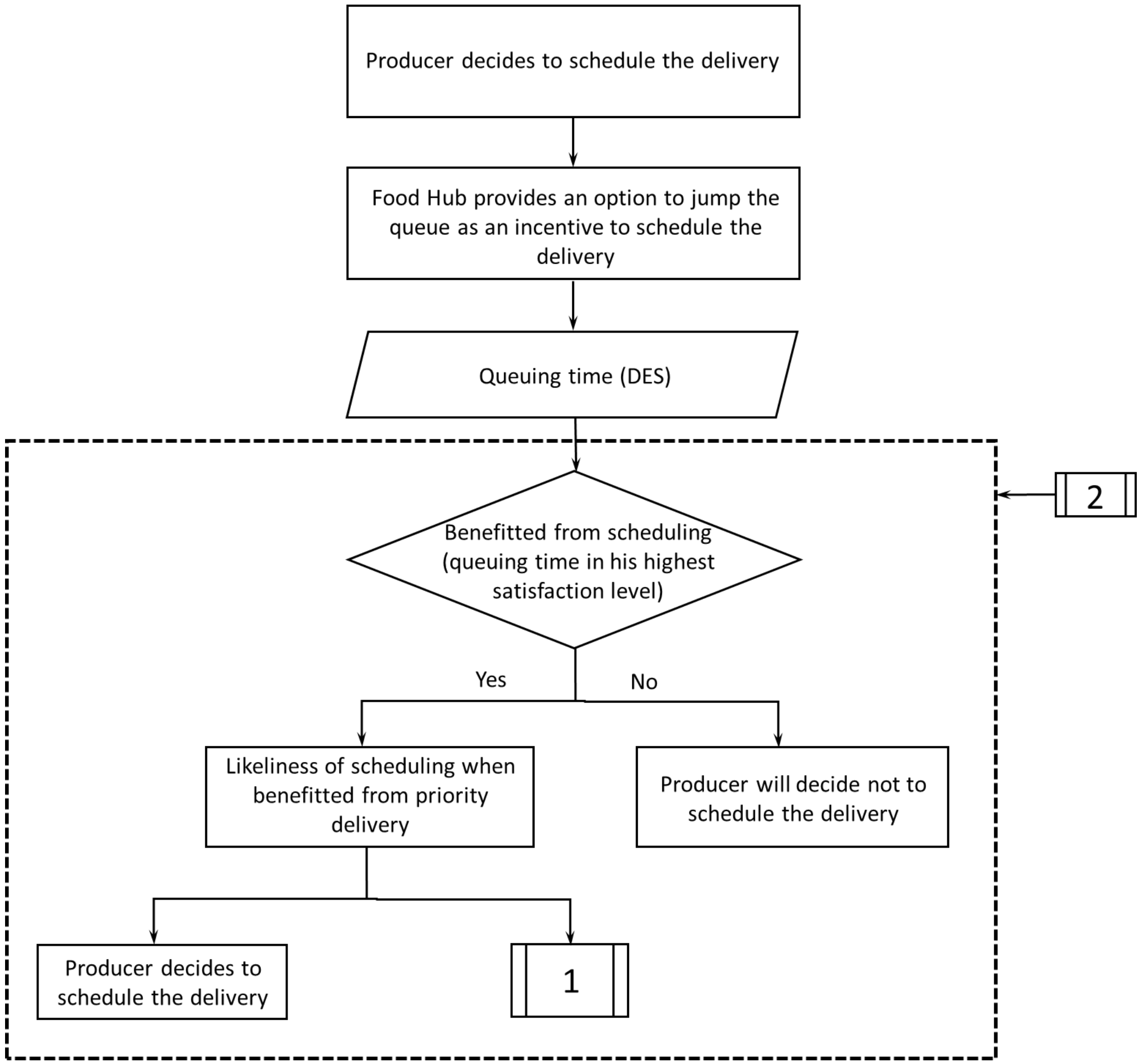

Figure 23. *Producer decision-making process with priority delivery option.*

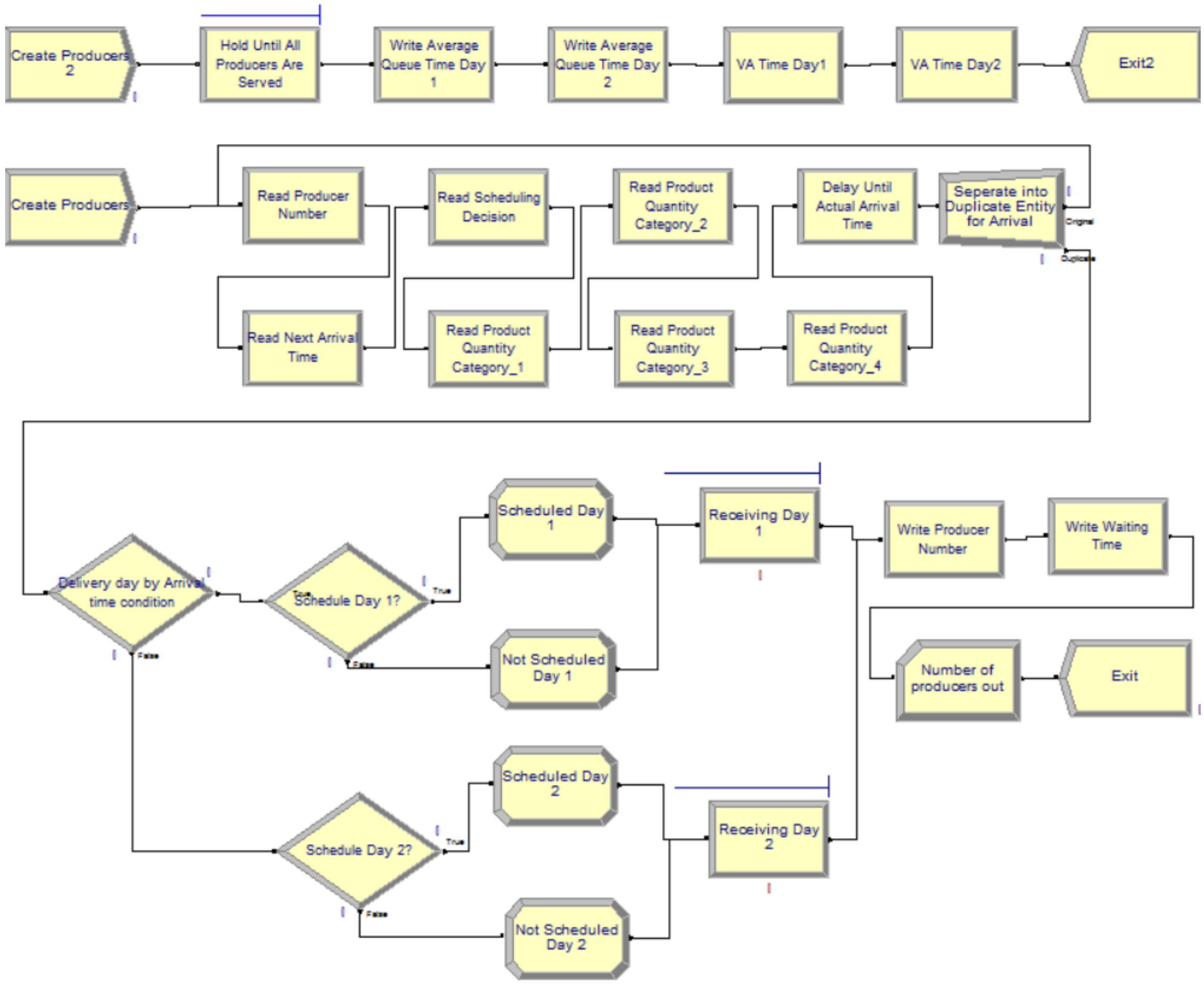

Figure 24. *Snapshot of the Arena simulation model flowchart with priority delivery option.*

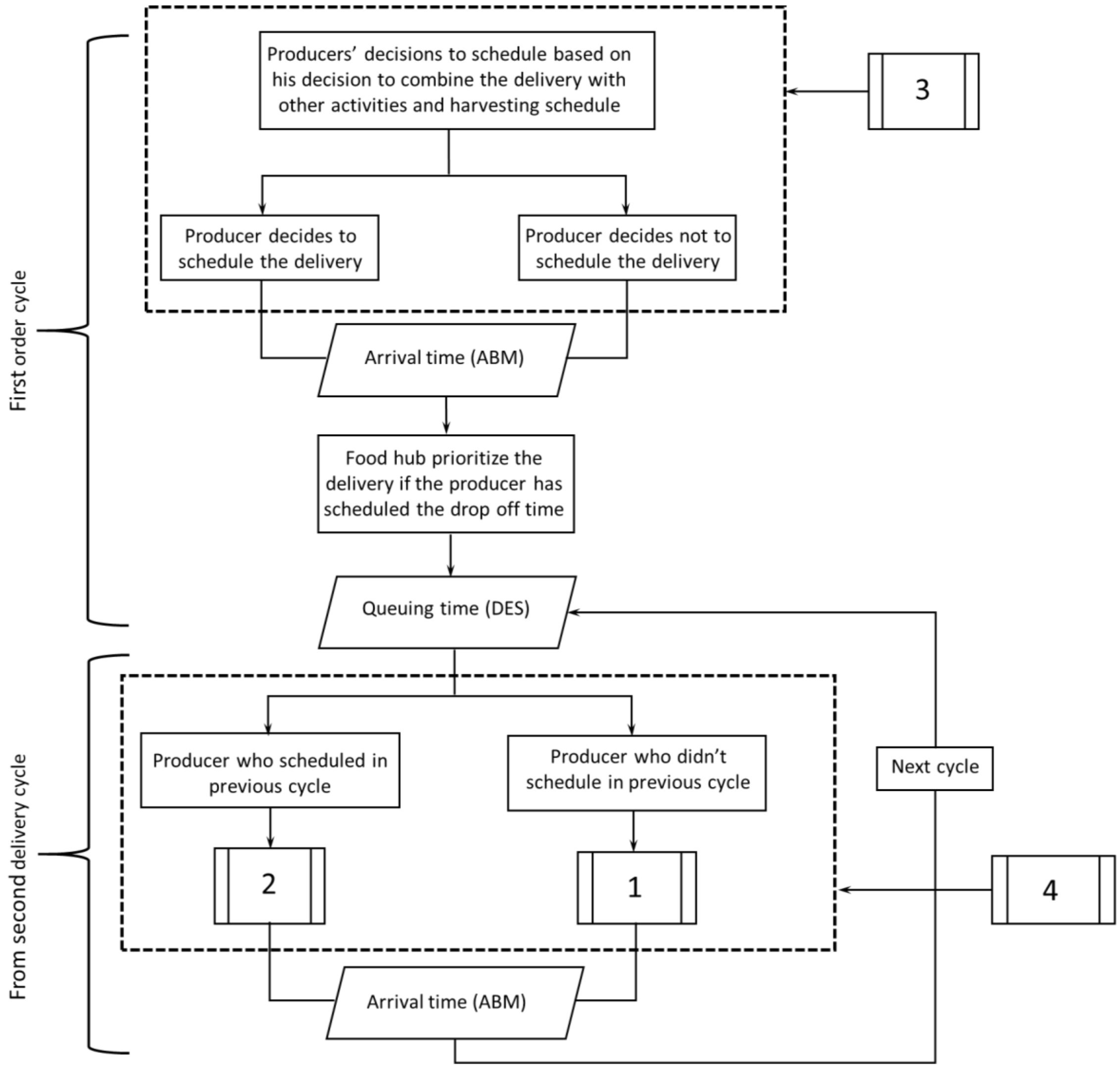

Figure 25. *Hybrid simulation (ABM-DES-ABM) model overview with priority delivery option.*

Model III - Monetary incentives

Suppliers tend to improve quality if an organization provides incentives to the best performing suppliers (Modi & Mabert, 2007). Incentives motivate the supplier to implement the improvements suggested by the buying organization. Firms can motivate suppliers by giving incentives in the form of sharing the achieved cost saving, recognizing suppliers performance through awards or giving them consideration for increased volumes (Giunipero, 1990; Krause, Handfield, & Scannell, 1998; Modi & Mabert, 2007). In order to incorporate the possibility of the food hub's offering monetary incentives producers who schedule their deliveries, a third stage was added to the hybrid simulation model, as shown in Figure 26.

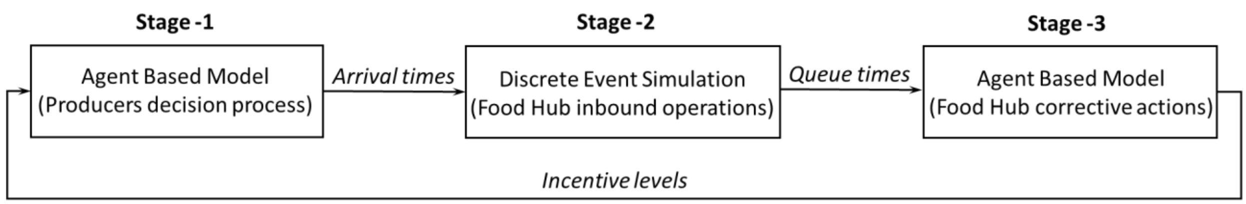

Figure 26. *Hybrid simulation (ABM-DES-ABM) model overview with food hub agent.*

In this version of the hybrid model, a food hub manager agent is included. The food hub manager calculates the food hub's revenue in the last *n* cycles, where *n* is an experimental value in the model. Based on the revenue generated, the food hub manager decides to provide producers a certain percentage of their total sales after the next *n* cycles as a reward if they schedule their delivery in advance before arriving at the food hub. The overall decision-making process of the producer if provided with priority delivery and monetary incentive options is shown in Figure 27. Figure 28 shows the response of 24 producers on how their decision to schedule the delivery will affect for the four different monetary incentives level provided by the food hub with 1 as "not likely" and 5 as "high likely".

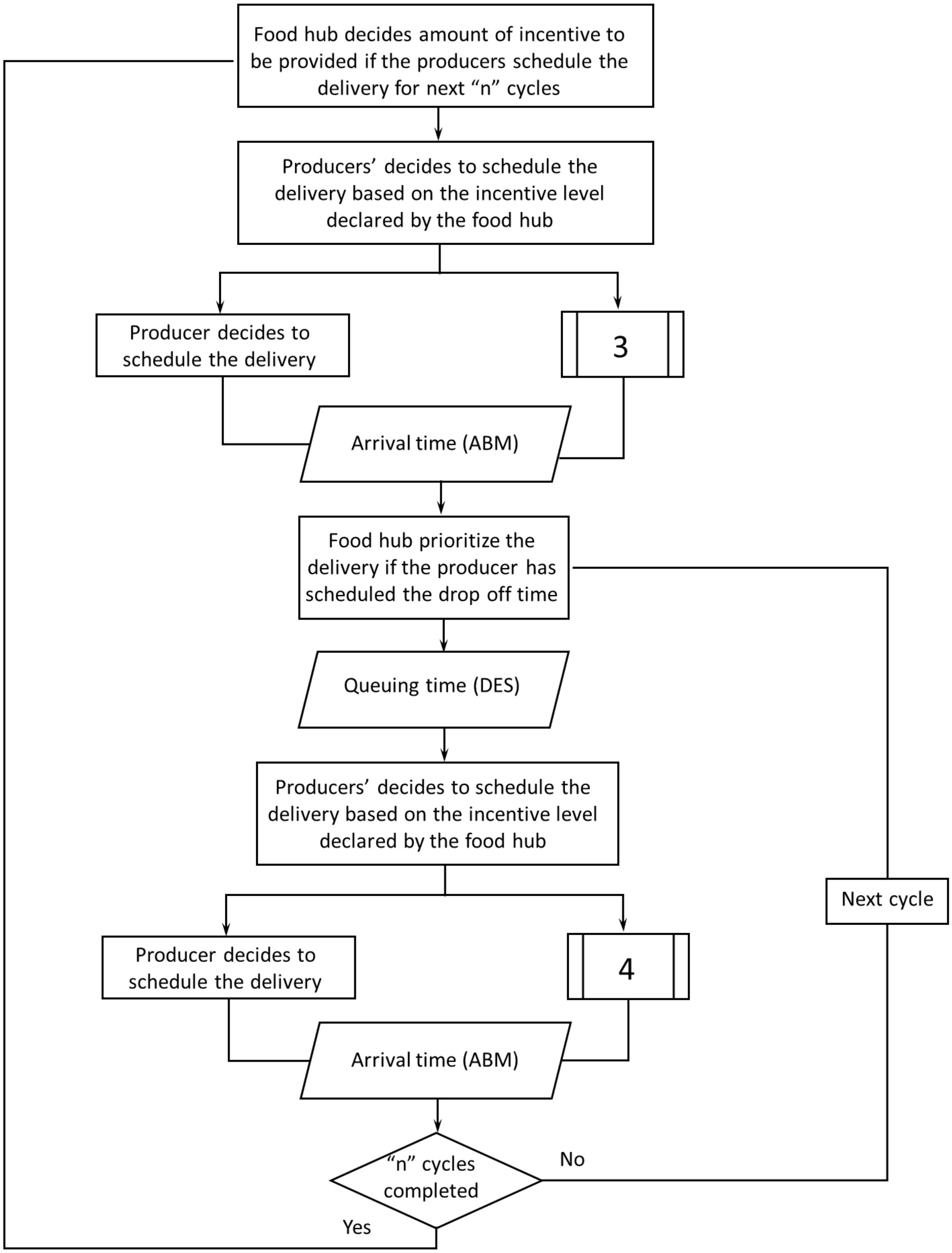

Figure 27. *Hybrid simulation (ABM-DES-ABM) model overview with monetary incentives and priority delivery option.*

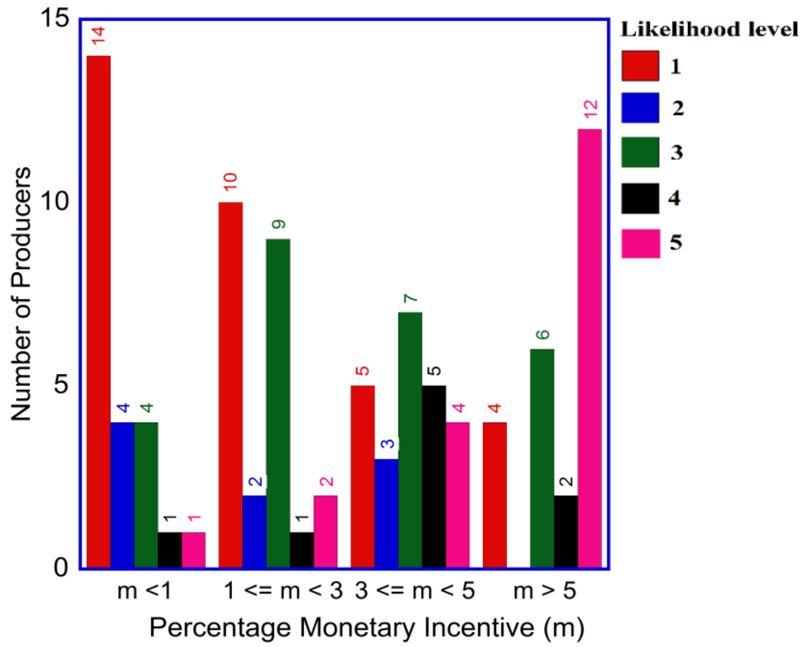

Figure 28. *Survey data showing the effect of monetary incentives on producers scheduling decision.*

Model IV - Food hub – producer and producer - producer interactions

Suppliers feel motivated to improve if the buying firms communicate with the suppliers and provide feedback on their performance (Carr & Pearson, 1999). Communication between a supplier and buying firms can be of two types. First one is the traditional communication e.g. phone, fax or face-to-face. Second type of communication is advanced communication which includes computer-to-computer links, enterprise resource planning (ERP) systems or electronic data interchange (EDI). Since the sophisticated systems required in the advanced communication methods are not yet well implemented in RFSC, regional food hub managers could implement traditional communication techniques to communicate with the suppliers to improve their performance. Also, Leek, Turnbull and Naude (2003) found in their empirical study that traditional communication is perceived to be more useful by the buying firms as compared to the advanced communication techniques.

Supplier performance could increase if the knowledge transfer occurs between the network of suppliers. For example, Toyota rewards the supplier who makes an exceptional knowledge sharing contribution among the network members by giving that supplier additional business or paying it a bonus for its contributions (Nishiguchi, 1994).

To incorporate the above two conditions in the hybrid simulation model developed, we have assumed that the food hub manager will communicate with the producers who didn't schedule their delivery in an order cycle, and inform them about the inconvenience caused in the food hub inbound operations due to unscheduled deliveries. In the survey, respondents have been asked about their satisfaction level while doing business with the food hub. Figure 29 shows the response of 24 producers in their survey for their satisfaction level of doing business with the food hub, with 1 as "least satisfied" and 5 as "most satisfied".

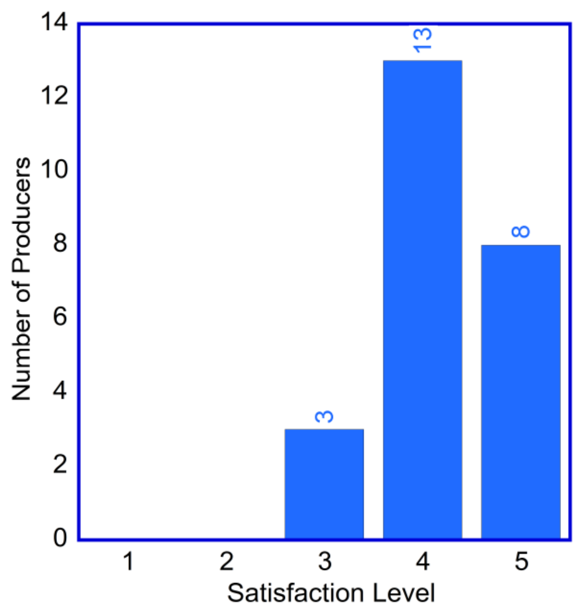

Figure 29. *Survey data showing satisfaction level of the survey respondents with respect to doing business with the food hub.*

We have used this factor as a probability which will affect producers' decision to schedule the delivery in the next cycle if the feedback is given to them by the food hub. It has been assumed in this model that higher the satisfaction level of the producer with respect to doing business with the food hub, higher is the probability that the producer will account food hub feedback in his decision in the next cycle. The probability value has been assigned to 0.8 if the producer satisfaction level is 5, and is assumed to be linearly decreasing to a value of 0, if the satisfaction level decreases to 1. Also the producers who change their decision due to this feedback may convey this information to the other food hub producers thus inspiring them to schedule the delivery.

In the survey, we have asked how often the producers share their experiences amongst them they have with the food hub. This is an important parameter in the ABM, as the producers' decisions can be influenced by information they gain via interactions with other producers between delivery cycles. For example, they may discuss whether or not they are scheduling their deliveries and the degree to which scheduling has benefitted them in reducing the queue time at the food hub. 3 out of 24 producers mention that they don't interact with the other food hub producers when they deliver their products at the food hub. Figure 30 show the response of 21 producers, on how often they share their experience while doing business with the food hub with the other food hub producers. The response was captured on the 5 point Likert scale with 1 as "never share" and 5 as "always share".

We have used this response as a probability of interaction between the two producers. The scale of this probability is defined similarly as described above for the customer satisfaction level. This interaction among the producers could emerge as all the producers in the system start scheduling the delivery as they would realize the benefits of it like less waiting time at the food hub altogether. In this model, we have assumed that this producer-producer interaction happens between a random producer and a producer who gets feedback from the food hub and schedules the delivery in the next cycle.

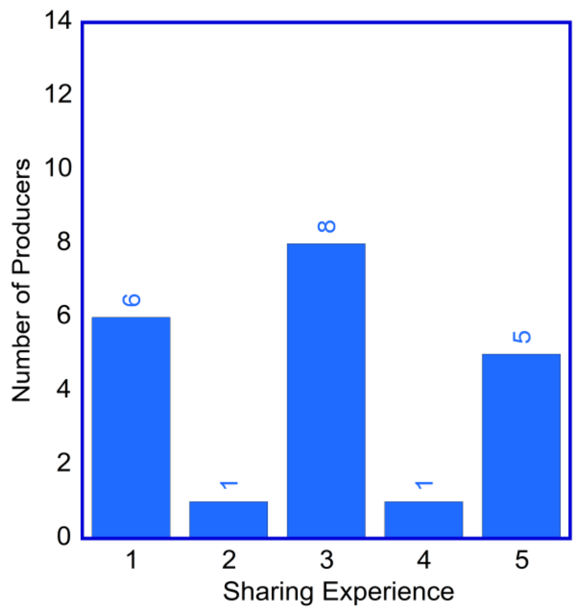

Figure 30. *Survey data showing how often producers share their business experience with food hub with the other food hub producers.*

The snapshot of NetLogo model (Figure 31) shows the different producer agents for one order cycle. The agents in “blue” color represent the producers who got feedback from the producers and decided to schedule the delivery in the next cycle. Agents in “green” color show the producers who decided to schedule the delivery in the next cycle due to information passed to them from the “blue” agents.

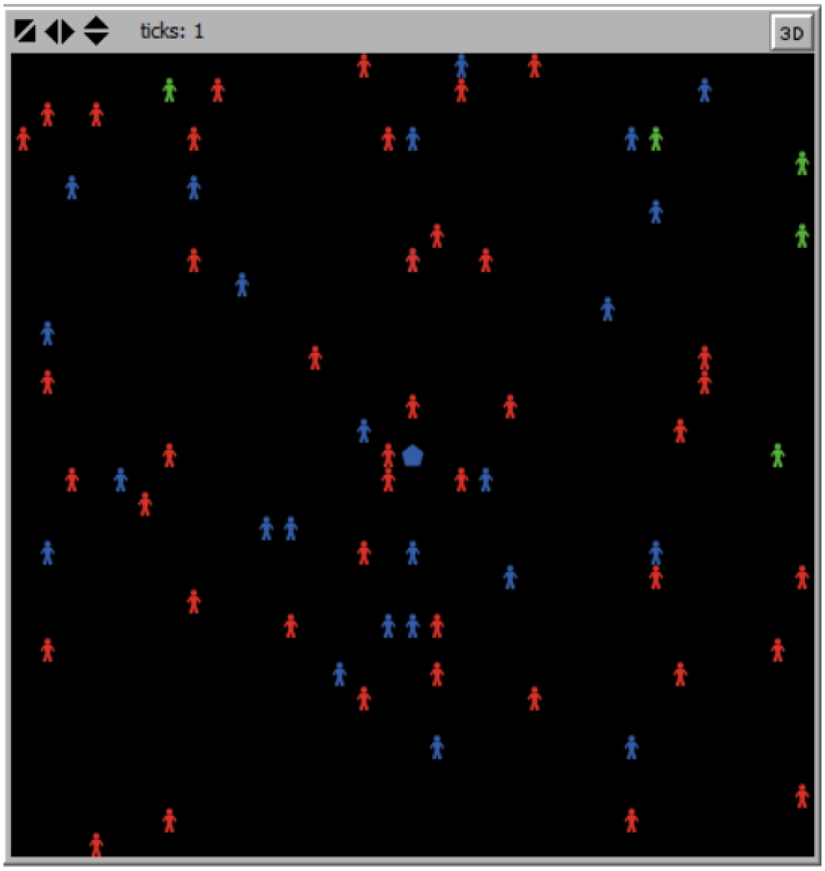

Figure 31. *NetLogo model showing food hub – producer and producer-producer interactions.*

References

Alexander, M., MacLaren, A., O'Gorman, K., & White, C. (2012). Priority queues: Where social justice and equity collide. *Tourism Management, 33(4),* 875-884.

Berger, T., & Schreinemachers, P. (2006). Creating agents and landscapes for multiagent systems from random samples. *Ecology and Society, 11(2),* 19.

Brown, D. G., & Robinson, D. T. (2006). Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl. *Ecology and society, 11(1),* 46.

Carr, A. S., & Pearson, J. N. (1999). Strategically managed buyer–supplier relationships and performance outcomes. *Journal of operations management, 17(5),* 497-519.

Davis, M. M., & Heineke, J. (1998). How disconfirmation, perception and actual waiting times impact customer satisfaction. *International Journal of Service industry Management, 9(1),* 64-73.

Giunipero, L. C. (1990). Motivating and monitoring JIT supplier performance. *Journal of Purchasing & Materials Management, 26(3),* 19.

Grimm, J. (2015, March). Iowa Valley Food Co-op, Cedar Rapids, Iowa. (C. Krejci, Interviewer)

Huber, G. (2015, February). Iowa Food Cooperative, Des Moines, Iowa. (A. Mittal, & C. C. Krejci, Interviewers)

Krause, D. R., Handfield, R. B., & Scannell, T. V. (1998). An empirical investigation of supplier development: reactive and strategic processes. *Journal of Operations Management, 17(1)*, 39-58.

Krejci, C. C., & Beamon, B. (2015). Impacts of Farmer Coordination Decisions on Food Supply Chain Structure. *Journal of Artificial Societies and Social Simulation, 18(2)*, 19.

Krejci, C. C., Stone, R. T., Dorneich, M. C., & Gilbert, S. B. (2015). Analysis of Food Hub Commerce and Participation Using Agent-Based Modeling Integrating Financial and Social Drivers. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 1-22.

Leek, S., Turnbull, P. W., & Naude, P. (2003). How is information technology affecting business relationships? Results from a UK survey. *Industrial marketing management, 32(2)*, 119-126.

McGuire, K. A., & Kimes, S. E. (2006). The perceived fairness of waitlist-management techniques for restaurants. *Cornell Hotel and Restaurant Administration Quarterly, 47(2)*, 121-134.

Modi, S. B., & Mabert, V. A. (2007). Supplier development: Improving supplier performance through knowledge transfer. *Journal of operations management*, *25(1)*, 42-64.

Nishiguchi, T. (1994). *Strategic industrial sourcing: The Japanese advantage*. Oxford University Press.

Pàmies, M. D., Ryan, G., & Valverde, M. (2015). What is going on when nothing is going on? Exploring the role of the consumer in shaping waiting situations. *International Journal of Consumer Studies*.

Punj, G., & Stewart, D. W. (1983). Cluster analysis in marketing research: review and suggestions for application. *Journal of marketing research*, 134-148.

Schreinemachers, P., Berger, T., Sirijinda, A., & Praneetvatakul, S. (2009). The Diffusion of Greenhouse Agriculture in Northern Thailand: Combining Econometrics and Agent-Based Modeling. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie, 57(4)*, 513-536.

Smajgl, A., Brown, D. G., Valbuena, D., & Huigen, M. G. (2011). Empirical characterisation of agent behaviours in socio-ecological systems. *Environmental Modelling & Software, 26(7)*, 837-844.

Sopha, B. M., Klöckner, C. A., & Hertwich, E. G. (2013). Adoption and diffusion of heating systems in Norway: coupling agent-based modeling with empirical research. *Environmental Innovation and Societal Transitions, 8,* 42-61.

Yim, O., & Ramdeena, K. T. (2015). Hierarchical Cluster Analysis: Comparison of Three Linkage Measures and Application to Psychological Data. *The Quantitative Methods for Psychology*, *11(1)*, 8-21.

CHAPTER 4

SIMULATION RESULTS AND DISCUSSION

There are typically a variety of stakeholders involved with the development and outputs of a model, including the model developers, decision makers who will use the information from results of the model to inform their decisions, and individuals affected by these decisions. Therefore, it is highly important that the model and its results are correct (Sargent, 2005). This section describes the process of verification and validation for the proposed hybrid simulation model.

Verification of the hybrid simulation model

Model verification is often defined as “ensuring that the computer program of the computerized model and its implementation are correct” (Sargent, 2005). The hybrid simulation model described in this thesis was verified by running the model under specific experimental conditions and confirming that the input and output variables were consistent with respect to the specified input conditions and assumptions. We have analyzed the outputs under three different conditions:

1) *Condition 1* – It was assumed in the model that all 72 producer agents will deliver in every order cycle and producer will deliver in only one of the 11 time slots assigned by the food hub.

   Output verification – The total number of producers delivering to the food hub and the total number of producers arriving in each of the 11 time slots in every order cycle was always 72.

2) *Condition 2* - A producer's autonomy will be 1 if the producer doesn't schedule the delivery. However, if the producer schedules the delivery, the autonomy decreases linearly from 0.8 to 0 as his satisfaction level for a time slot decreases from 5 to 1.

   Output verification - When there is no capacity limit on the time slots in the model, the autonomy of all the producers was greater than or equal to 0.8 in every order cycle (i.e., each producer was able to schedule in his most-preferred time slot).

3) *Condition 3* - Time slot capacity was fixed to 6 on distribution day 1 and 18 on distribution day 2, and every producer was asked to schedule their deliveries as per their preference level for the time slots

   Output verification – In every order cycle, none of the slots has more producers arriving than the maximum slot capacity

Model I – Status Quo

One strength of empirical simulation models is their ability to be validated with independent external data. Model validation is usually defined as "substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy with the intended application of the model" (Schlesinger, et al., 1979). The initial version of the hybrid simulation model of the food hub (i.e., Model I) was validated using the historical data validation technique (Sargent, 2005). This includes comparing outputs of the developed simulation model with existing historical data of the same system, provided the historical data is completely independent of the simulation input variables and parameters.

The food hub considered in this study has not placed any capacity restrictions on any of the 11 time slots for scheduling the delivery (Huber, 2015). Model I represents the same conditions as that of current food hub operations (i.e., the status quo). This version of the model was run under three different experimental conditions by varying the producers' weights on autonomy (W_A) and convenience (W_C) in the producers' utility function. As per the survey data, 17 out of 19 producers who correctly answered the ranking question considered flexibility in schedule (autonomy) as more important than waiting time in queue (convenience) in their decisions to schedule the delivery. Therefore, in all three experiments, the weight on autonomy was kept higher than the weight on convenience in an effort to validate the model. For each experimental scenario, 10 replications of 120 time-steps each were run (where one time step is equivalent to one "two-week delivery cycle" of the food hub considered in this study). The initial 20 time steps were considered as a warm-up period, to allow the system to stabilize. Therefore, the final 100 of 120 time-steps were considered for analyzing the simulation results.

Simulation results for the three scenarios with different combinations of weights on autonomy and convenience are summarized in Table 10. Figure 32 shows the total number of producers who have decided to schedule their deliveries in each time step over the course of the simulation run for all the three scenarios. The simulation results show that the average number of producers scheduling their deliveries increases as the weight on convenience increases. As the weight on autonomy (W_A) was increased from 0.7 to 0.8, there was a large decrease in the average number of producers scheduling the delivery and reduced variability.

Table 10. *Summary of number of producers scheduling the delivery for Model I.*

Serial #	Different weight combinations of autonomy and convenience	Average number of producers scheduling the delivery	Standard deviation	% of total producers
1	Scenario 1 - (W_A) – *0.6*, (W_C) – *0.4*	15.65	0.78	21.74
2	Scenario 2 - (W_A) – *0.7*, (W_C) – *0.3*	13.48	0.77	18.73
3	Scenario 3 - (W_A) – *0.8*, (W_C) – *0.2*	3.58	0.59	4.97

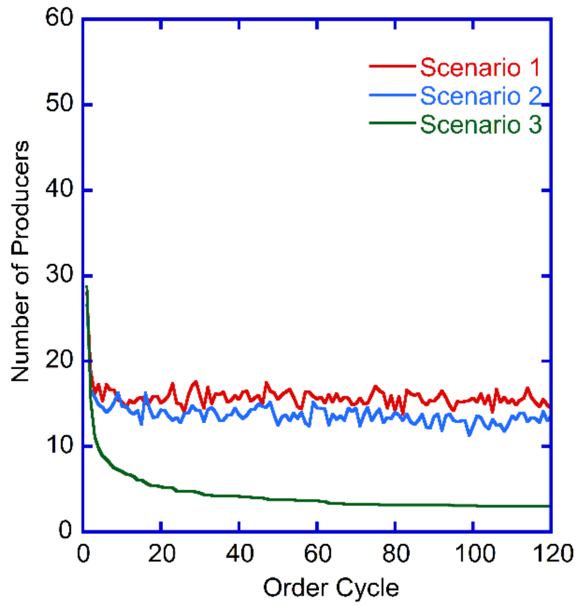

Figure 32. *Number of producers scheduling the delivery in each time step for Scenario 1, 2 and 3 of Model I.*

In order to verify that the change in weights significantly affects producers' behaviors, a student *t*-test was performed. Table 11 provides the *p*-values and the associated conclusions.

Table 11. *Statistical analysis of the outcomes of three tested scenarios in Model I.*

Serial #	Comparison	t statistic	p value	Conclusion
1	Scenario 1 vs Scenario 2	-10.84	< 0.00001	H_0: $\mu_1 = \mu_2$ is rejected, scenario 1 and scenario 2 are significantly different from each other
2	Scenario 1 vs Scenario 3	-38.96	< 0.00001	H_0: $\mu_1 = \mu_2$ is rejected, scenario 1 and scenario 3 are significantly different from each other
3	Scenario 2 vs Scenario 3	-31.56	< 0.00001	H_0: $\mu_1 = \mu_2$ is rejected, scenario 2 and scenario 3 are significantly different from each other

Statistical analysis shows that the three scenarios are significantly different from each other, as the *p*-values were all nearly zero. Current operations of the food hub considered in this study have approximately 25% producers scheduling their deliveries in each order cycle. As the only difference in the input parameters for all the three scenarios is the difference in combination of weights, and since Scenario 1 yields the simulated percentage of participants that is closest to the actual system (21.74%), it was concluded that (W_A) – *0.6,* (W_C) – *0.4* represents the most accurate combination of weights in the producer decision-making process.

Also, in the real food hub system, many producers tend to arrive in the later time slots to deliver their products (Huber, 2015). Figure 33 shows the simulated number of producers arriving in each of the 11 time slots for Scenario 1. The simulation results show a pattern that is similar to the real system, with many producers arriving at the end of the receiving time. Thus the hybrid simulation model has been validated for two different independent metrics, which were not used in the development of the model.

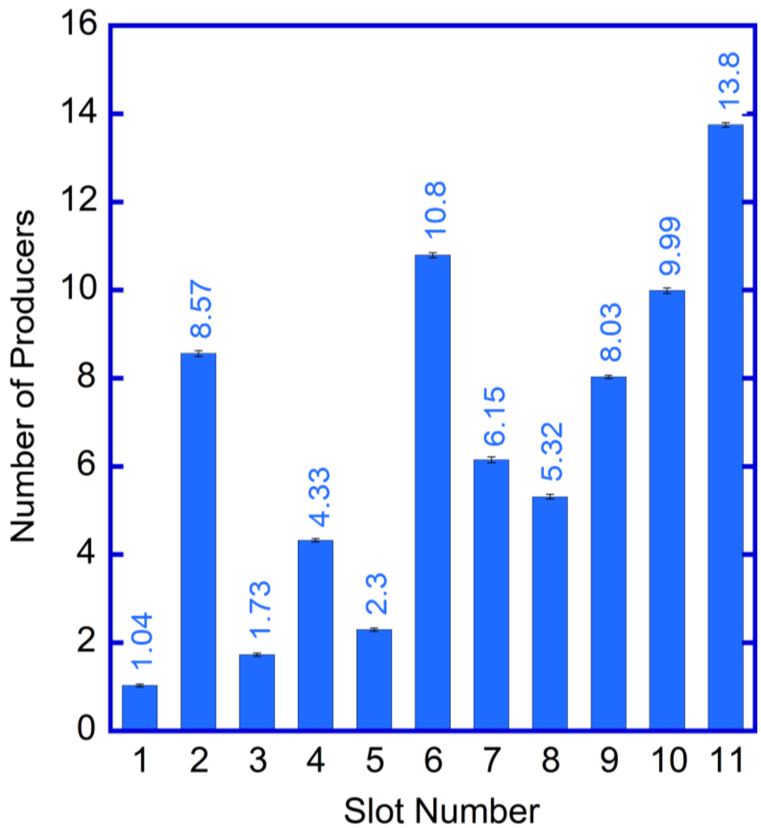

Figure 33. *Number of producers arriving in each time slot for Scenario 1 of Model I.*

Figures 34 through 37 summarize the results of running Model I for the critical measures of system performance: total number of scheduling producers, utilization rate of food hub personnel, and producer queue time at the food hub. Figure 34 shows number of producers arriving on delivery days 1 and 2. On average, 40.2 of 72 producers (55.83%) arrive on day 1 and the remaining 31.8 (44.16%) arrive on day 2. On average, 6.8 of the producers arriving on day 1 (16.9%) are scheduling the delivery and 8.9 of the producers arriving on day 2 (28%) are scheduling the delivery.

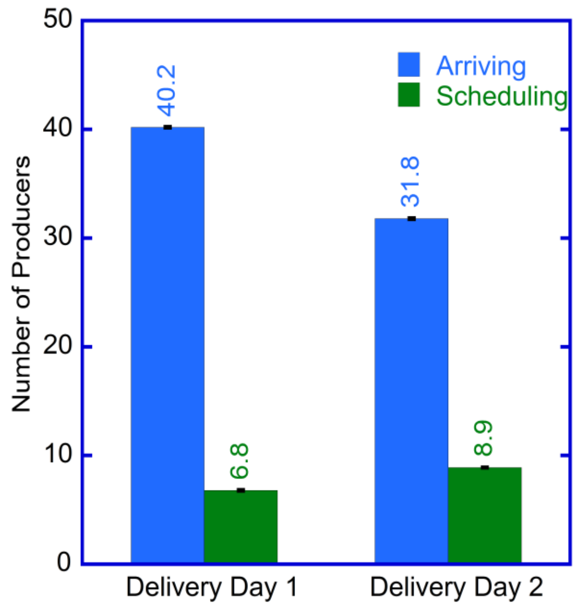

Figure 34. *Comparison of number of producers arriving and scheduling the delivery on day 1 and day 2 for Scenario 1 of Model I.*

Combining multiple deliveries and other activities with the delivery to the food hub was identified as one of the potential reasons that producers fail to schedule their deliveries. Figure 35 compares the average number of producers not scheduling their deliveries per order cycle due to combining multiple deliveries in the area and harvesting schedule. On average, 34.4 of the 72 producers (47.7%) do not schedule their deliveries in an order cycle due to multiple deliveries and other activities in the area and 15.2 (21.1%) due to their harvesting schedule uncertainty.

Figure 36 shows the average man hour utilization rate on day 1 and day 2, calculated using the following expression:

$$Man\ hour\ utilization\ rate = \left(\frac{Total\ man\ hours\ spent\ on\ receiving\ process}{Total\ available\ man\ hours}\right)$$

A total of 2 volunteers are available for 8 hours on receiving day 1 (i.e., 16 man hours) and 6 volunteers are available for 3 hours on day 2 (i.e., 18 man hours). As Figure 34 shows, fewer producers arrive on day 2 (44.16%) and there are more man hours available, resulting in a lower average utilization on day 2 (0.5) than on day 1 (0.7). However, this represents the utilization rates as averages over each day. As Figure 33 shows, very few producers arrive in the 1st, 3rd and 5th slot on day 1; therefore, the utilization rate for these specific time slots will be significantly less than the average. Also, on delivery day 2, the utilization rate in slot 11 on day 2 will be higher than the average rate 0.5.

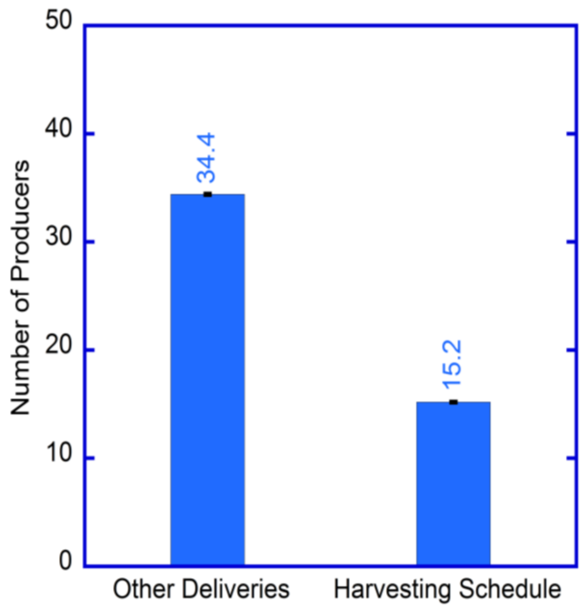

Figure 35. *Average number of producers not scheduling their deliveries due to multiple deliveries and harvesting schedule for Scenario 1 of Model 1.*

Figure 37 shows the average queue times of the producers on day 1 and day 2. The longer average queue time on day 1 is a result of variability in producer arrival times (especially a greater number of producers arriving in the 2nd and 6th slots of day 1), with only 2 volunteers available for the receiving process. This is because the food hub manager has not placed any capacity limits on the time slots. As such, many producers arrive at the same time slot (as per their preferences), whether they scheduled their deliveries or not.

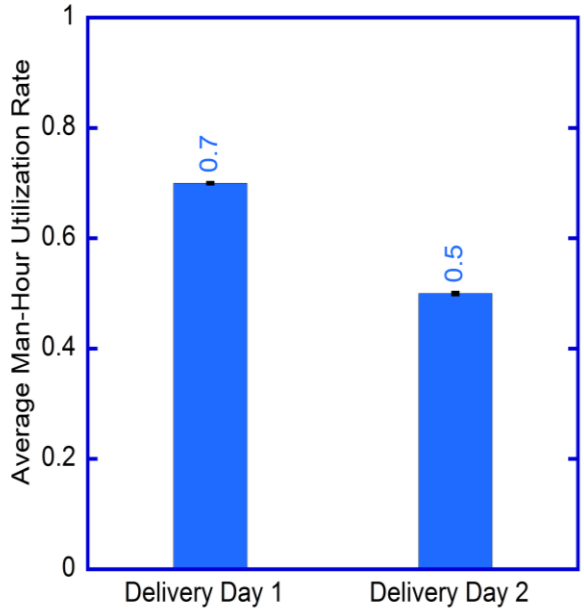

Figure 36. *Average man hour utilization rate on day 1 and day 2 for Scenario 1 of Model I.*

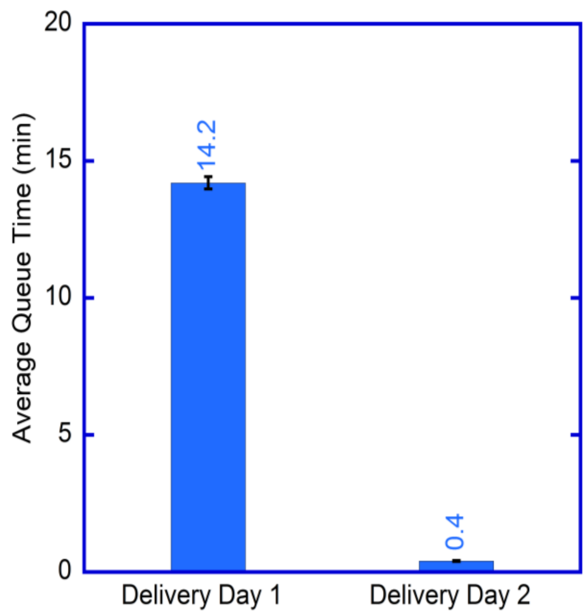

Figure 37. *Average queue time on day 1 and day 2 for Scenario 1 of Model I.*

Originally, it was expected that the average queue time would decrease as more producers decided to schedule their deliveries. In order to test this, the average queue time for the three different scenarios of Model I were compared. The results exhibit variability in the number of producers scheduling their deliveries as the weights on autonomy and convenience (WA and WC, respectively) were changed. Figures 38 and 39 show the average queue times on day 1 and day 2 versus the number of producers scheduling their deliveries on the respective days in the three scenarios. Interestingly, the average queue times on day 1 very slightly increased from Scenario 1 to Scenario 2 and from Scenario 2 to Scenario 3. The average queue time on day 2 increases from Scenario 1 to Scenario 2 and decreases from Scenarios 2 and 3. The statistical analysis shows that the average queue time for day 1 and day 2 is similar for all the three scenarios with $\alpha = 0.05$. This outcome makes intuitive sense - as there is no capacity limit on the time slots, the number of producers arriving in each time slot depends only on their preferences for the time slots, regardless of whether they are scheduling the delivery or not. This is because, if a producer decides not to schedule, he will arrive in one of his most preferred time slot and if a producer decides to schedule the delivery, as there is no capacity restrictions on the time slots, he get to schedule and arrive in his most preferred time slot. This leads to nearly the same number of producers arriving in each time slot for all the three scenarios irrespective of number of producers scheduling the deliveries and hence the average queue time within the scenarios doesn't differ significantly.

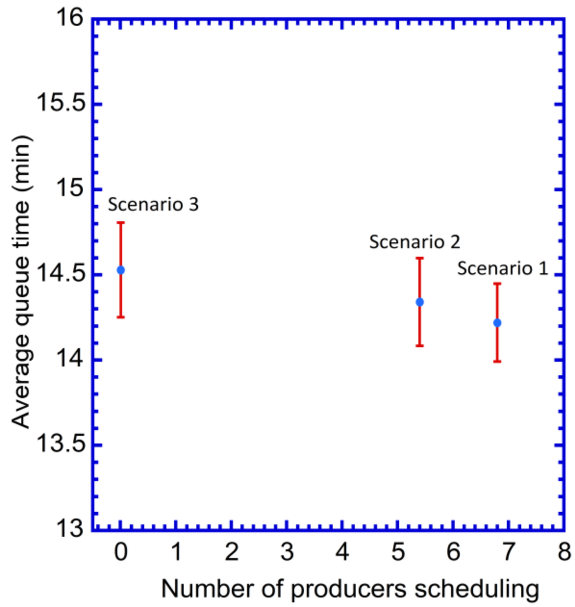

Figure 38. *Average queue time vs number of producers scheduling the delivery on day 1 for Scenarios 1, 2, and 3 of Model I.*

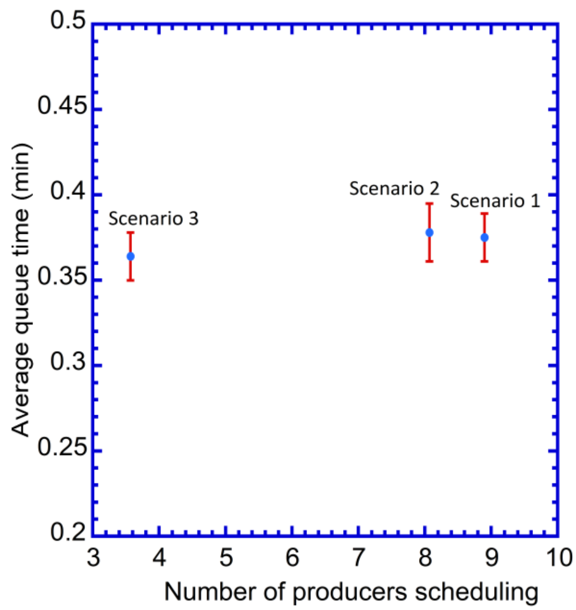

Figure 39. *Average queue time vs number of producers scheduling the delivery on day 2 for Scenarios 1, 2, and 3 of Model I.*

Food Hub Interventions

This section describes the effects of various policies that the food hub can adopt to encourage producers to schedule their deliveries. The Scenario 1 weights ($W_A = 0.6$, $W_C = 0.4$) were used because they are assumed to represent the most accurate combination of weights in the producers' decision-making process.

Model II – Priority delivery option by the food hub

When the food hub provided an incentive of priority delivery to the producers who scheduled their deliveries, an average of only 12.33 producers (17.13%) scheduled the delivery. This outcome shows that the priority delivery option can actually demotivate the producers who were already scheduling. Figure 40 shows the number of producers scheduling the delivery and the ones who are actually benefiting from the priority delivery incentive in each time step. As described in Chapter 3, a producer will be consider benefitted from the priority delivery option, if his waiting time in the queue at the food hub even after getting priority delivery, falls in the time range of his maximum satisfaction level. This satisfaction level for the wait time ranges have been identified from the producers' survey data. In 20% of the order cycles even if a producer schedules the delivery, he is not able to benefit from the priority delivery incentive provided by the food hub (Figure 41). This is because even if the producer is allowed to jump to the front of the queue, he may still have to wait until at least one of the volunteers is available for the receiving process. If this wait time does not yield a satisfactory utility level, the producer will not schedule his delivery in the next cycle, as he did not experience any benefits from scheduling. Figure 42 shows the number of producers in each time step who scheduled the delivery specifically because of the benefit resulting from the priority delivery incentive in the previous cycle. On average, only 2.2 producers (3.3%) were motivated by this incentive to schedule their delivery in the next cycle.

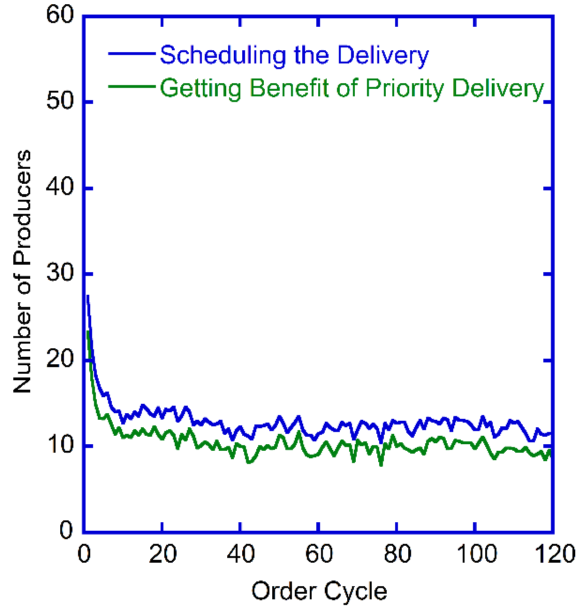

Figure 40. *Number of producers scheduling and benefiting from the priority delivery incentive in each time step of Model II.*

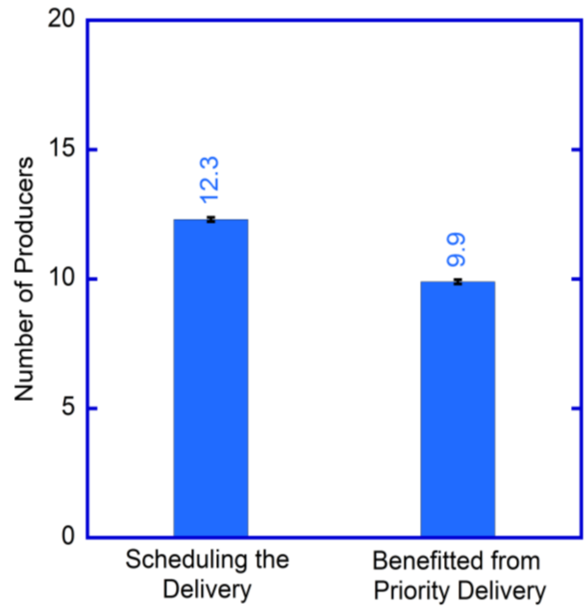

Figure 41. *Average overall number of producers scheduling and benefiting from the priority delivery incentive in Model II.*

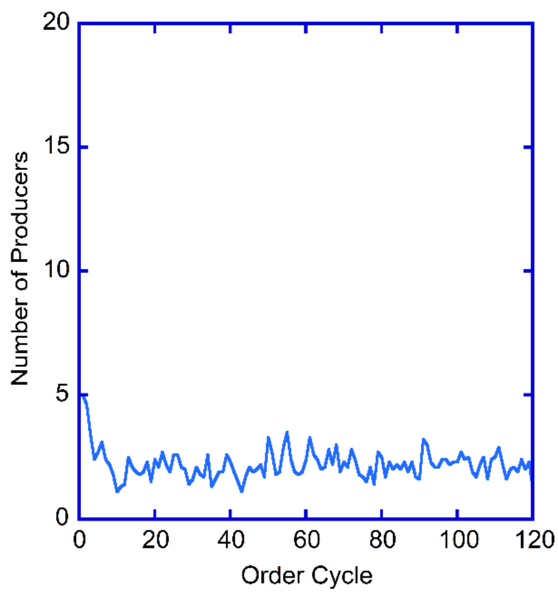

Figure 42. *Number of producers scheduling in each time step in Model II due to benefits of priority delivery in the previous cycle.*

Recommendation to the food hub - The priority delivery option will likely only benefit the food hub under certain conditions:

1) The food hub should place a capacity limit on the number of producers who are allowed to schedule their deliveries in each time slot .Otherwise, having more producers schedule their deliveries will not necessarily lead to a more balanced workload at the food hub, because there are certain time slots which many producers tend to prefer (e.g., the last time slot in day 2). This will cause dissatisfaction and possibly resentment among the producers who, even after scheduling the delivery, must wait in long queues to get their products checked in.
2) To benefit the entire system, enough producers must schedule their deliveries to outweigh the costs of the "freeloaders" who do not schedule. If the food hub merely puts capacity limits on the time slots, there will be many producers who will arrive at the same time slots whether they schedule or not, and it will create disillusionment among the producers

who scheduled their deliveries but had to wait in the queue for a long time anyway. To demonstrate the effects of placing a capacity limit on the time slots when there is a priority queue incentive, the average number of producers who schedule was captured for a modified version of Model II. Given that the average time for a food hub volunteer to check in a producer is 16.8 minutes, to have the shortest possible queue times, each volunteer should check in three producers per hour. Therefore, on day 1, a capacity limit of 6 was assigned to all 8 time slots, and on day 2, a capacity limit of 18 was assigned to all three time slots. Figure 43 shows that the average number of producers scheduling the delivery is almost the same as that of previous case when there were no limits on the time slots, with an average of 12.4 producers (17.2%) scheduling. A *t*-test comparing the two averages gives a *p*-value of 0.55, which clearly shows that the scenarios are not significantly different from one another, indicating that putting limits on the time slot capacities does not affect the producers' decisions.

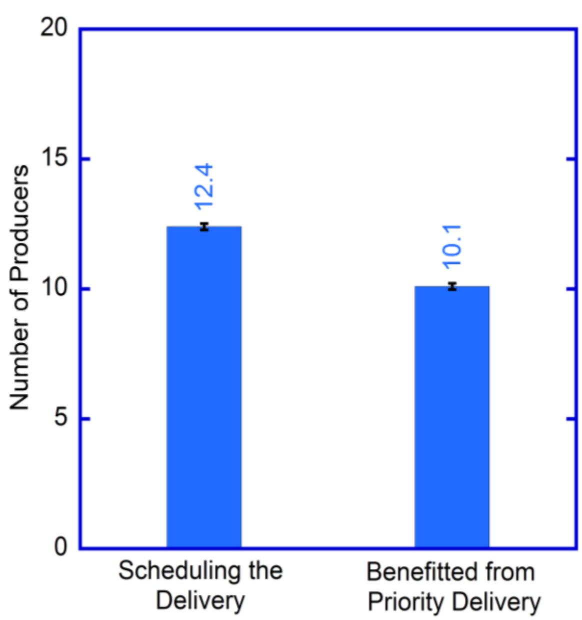

Figure 43. *Average number of producers scheduling and benefiting from the priority delivery incentive if the food hub puts capacity limit on the time slots in Model II.*

Figure 44 shows a comparison of the number of producers arriving in each time slot when the food hub provides a priority delivery incentive to the producers (Model II - with and without capacity limits) with the status quo (Model I). There is no significant difference in the arrival patterns in the different time slots, as very few producers are scheduling the delivery, and every producer is getting his most preferred time slot irrespective of any capacity constraint put on the time slot if they are scheduling the delivery.

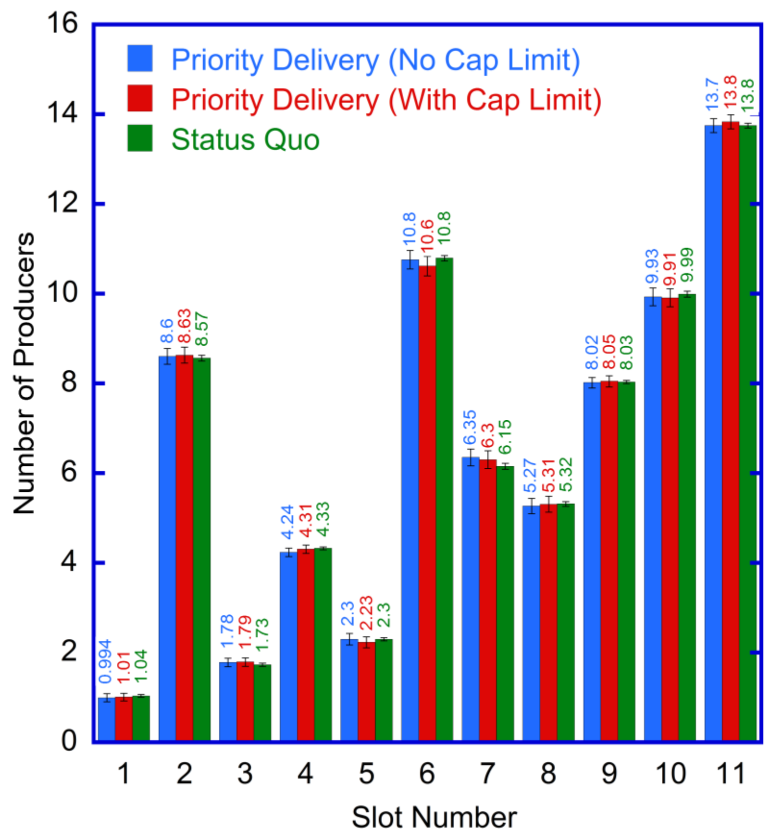

Figure 44. *Number of producers arriving in each time slot when the food hub provides priority delivery benefit to the producers for scheduling (Model II) versus the status quo (Model I).*

Model III – Monetary and priority delivery incentives

When the food hub offers a monetary incentive along with the priority delivery incentive to those producers who schedule their deliveries, on average 42 producers (58.3%) schedule, at an average incentive level of 3.79% of total producer sales. This incentive level is calculated by taking the mean of the monetary incentives range as asked in the survey. For example, if the food hub decides to provide between 1 to 3 % of total sales of a producer as a monetary incentive to the producers for scheduling the delivery, it has been considered that the mean of this incentive range is provided by the food hub in all the iterations of the Model III. Also it has been considered that a maximum of 6% of total sales of a producer is provided by the food hub as a monetary incentive to the producers for scheduling the delivery. However, a food hub would need to carefully assess the tradeoff between the cost of providing the incentive and the operational benefits of having more producers schedule their deliveries.

In this model it has been assumed that the food hub has imposed a capacity limit on the time slots. On day 1, a capacity limit of 6 was assigned to all 8 time slots, and on day 2, a capacity limit of 18 was assigned to all three time slots. Figure 45 shows the number of producers scheduling in each time step and the monetary incentive level provided by the food hub in corresponding time steps. The R-square value when linearly fitting the monetary incentive percentage values versus number of producers scheduling the delivery is 0.75, which indicates a linear relationship between the two. A t test was performed to test the null hypothesis (H_0: $\beta_1 = 0$). The *p*-value of the t test was < 0.0001, confirming this linear relationship. Figure 46 shows the average queue times on day 1 and day 2. There is 21.12 % decrease in average queue time on day 1 from the current conditions at the food hub (i.e., Model I), and on day 2 the average queue time is almost the same.

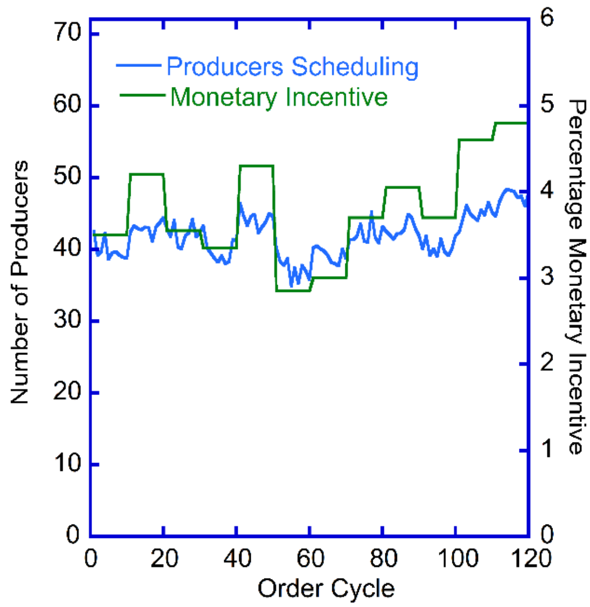

Figure 45. *Number of producers scheduling the delivery and percentage monetary incentive of a producer total sales provided by the food hub in each time step of Model III.*

Figure 46. *Average queue time on day 1 and day 2 if the food hub provides monetary incentive benefits to the scheduling producers in Model III.*

Recommendation to the food hub – Even though the number of producers scheduling the delivery increases by 168.37% as compared to the current food hub operating conditions, the average queue time on day 1 decreases only by 21.12%. The potential reason for this is that many producers prefer particular time slots, while in some slots very few producers show up. Figure 47 compares the number of producers arriving in each time slot for Models I and III. Though more producers schedule their deliveries and the food hub has put capacity limits on the time slots, these limits are often exceeded because of the arrival of unscheduled producers. The 2^{nd} and 6^{th} slots have the maximum number of producers arriving on day 1. The average queue time has not decreased significantly as the number of producers arriving in those two time slots has not decreased significantly. The average queue time on day 1 is high due to around 8.6 producers arriving in the 2^{nd} slot and 10.8 producers in the 6^{th} slot for the status quo conditions. However, when more producers are scheduling due to monetary and priority queue incentives, the number of producers scheduling in this time slot doesn't decrease significantly. This may also lead to fewer producers scheduling their deliveries due to long wait times, despite scheduling in advance. Therefore, in addition to providing monetary incentives, the food hub should also re-allocate its volunteer labor to have more volunteers working during the the most-preferred time slots of the producers.

As mentioned in the results of Model II, the priority delivery incentive will be useful for the food hub to implement if capacity limits are placed on the time slots and if enough producers schedule their deliveries that the overall system benefits. This recommendation is explained with the outcomes of Model III. Figure 48 shows the comparison of number of producers who are unaffected by the monetary incentives but schedule their deliveries due to the benefits of priority delivery in the previous cycle in Model III and the number of producers who are scheduling their delivery due to priority delivery benefits in previous cycle in Model II (without capacity limits on time slots). In Model III capacity limits were placed by the food hub on the time slots and also 58.3% of the producers were scheduling the delivery on average in an order cycle. The average number of producers scheduling the delivery got increased as compared to Model II due to the monetary incentives provided by the food hub. This resulted the system with more uniform arrival time of producers in the 11 time slots, which leads to greater benefits to the producers who are scheduling the delivery due to priority delivery incentive. In Model III an average of 6.8 producers (9.4%) scheduling their deliveries due to only priority delivery benefits, which three times larger than the number of producers who scheduled when there were no capacity limits and only around 12.3% of the producers scheduled their deliveries in Model II.

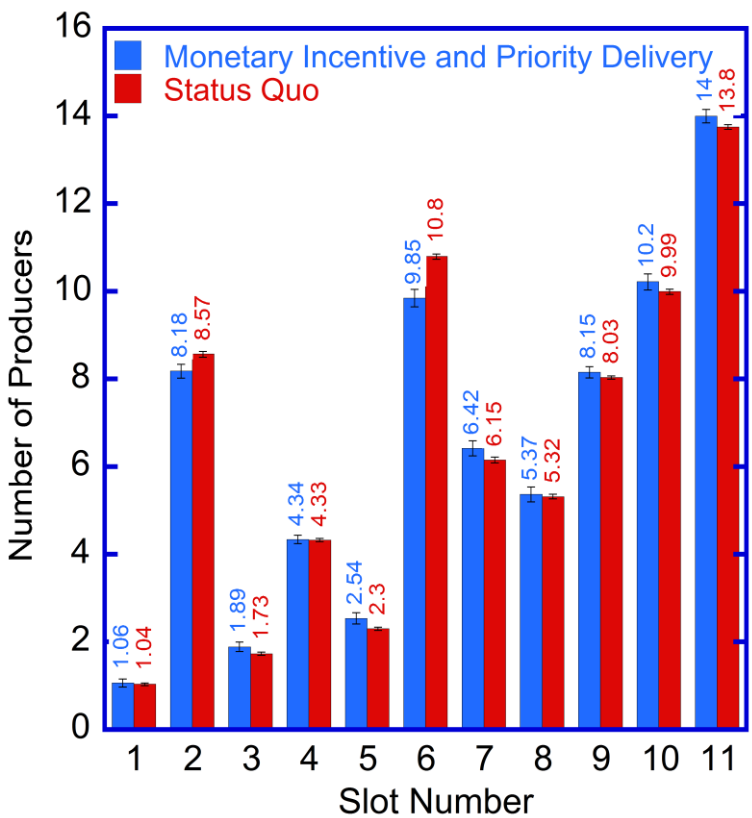

Figure 47. *Number of producers arriving in each time slot when the food hub provides monetary incentives to the producers for scheduling (Model III) versus the status quo (Model I).*

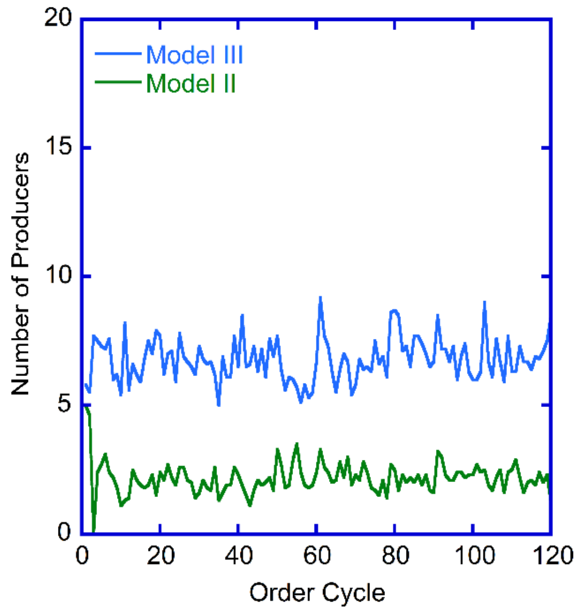

Figure 48. *Comparison of number of producers who are not affected by monetary incentives provided by the food hub but schedule due to benefits of priority delivery in the previous cycle in Model III vs number of producers who schedule the delivery due to priority delivery option in Model II (without capacity limit on time slots).*

Model IV – Agent interactions

Figure 49 shows the number of producers scheduling their deliveries in each time step for Model IV, when the food hub provides feedback to the producers with respect to scheduling their deliveries. On average, 40 producers (55.85%) schedule their deliveries in each cycle. In this model, the probability that an interaction between two producers will lead to scheduling is assumed to be 50%.

Figure 50 shows the number of producers scheduling the delivery due to feedback from the food hub to the producers and due to successful interactions among the food hub producers in each time step for Model IV. Due to food hub–producer interactions, on average 19.8 producers (27.57%) schedule their deliveries in the next cycle (Figure 51). The average percentage of successful interactions between the food hub and a producer is 61.92%, which is the ratio of the number of producers to which the food hub gives the feedback to the number of producers who become motivated to schedule the delivery in next cycle based on the feedback. Also, on average, 2.9 producers (4%) schedule their deliveries upon becoming motivated by other food hub producers. On average, 14.9 % of the time a producer is able to motivate another producer to schedule the delivery in the next cycle.

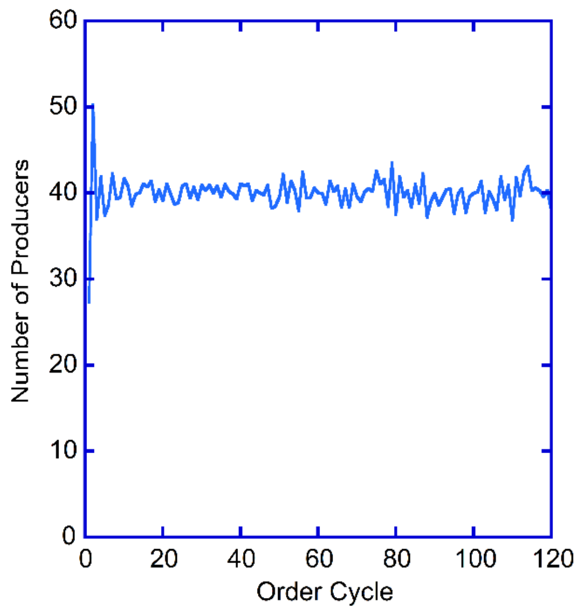

Figure 49. *Number of producers scheduling the delivery in each time step when the food hub provides feedback to the producers and producers interact with each other to share information in Model IV.*

Recommendation to the food hub – It is evident from Figures 47 and 52 that even if more producers schedule their deliveries (58.3% and 55.85%), 2nd and 6th time slots are having more number of producers coming, due to the individual preferences of the producers who schedule or doesn't schedule the delivery. Also in 1st, 3rd and 5th time slot, very few producers show up. Therefore the food hub should consider re-allocation of their volunteer labor in order to reduce producer queue time and efficiently utilize their resources.

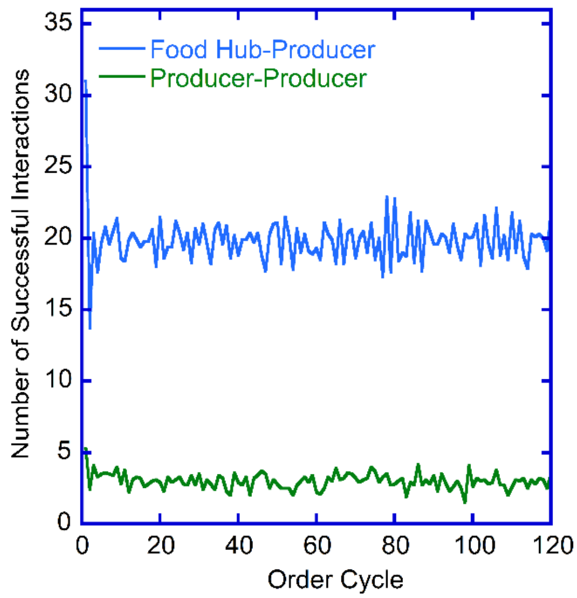

Figure 50. *Number of successful food hub-producer and producer-producer interactions in Model IV.*

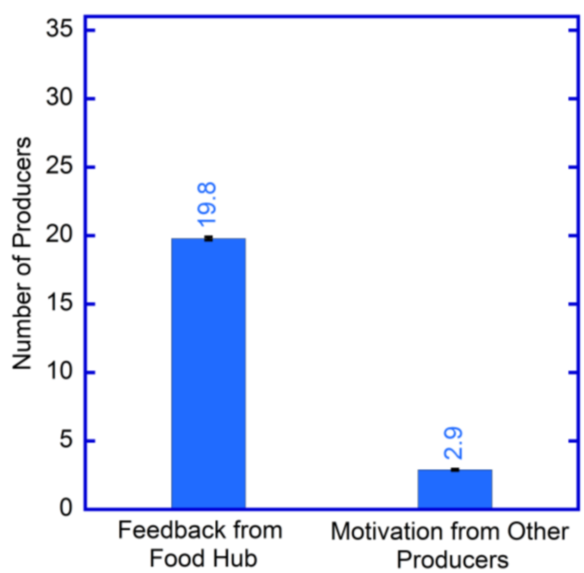

Figure 51. *Number of successful interactions between the food hub and a producer and between two producers in Model IV.*

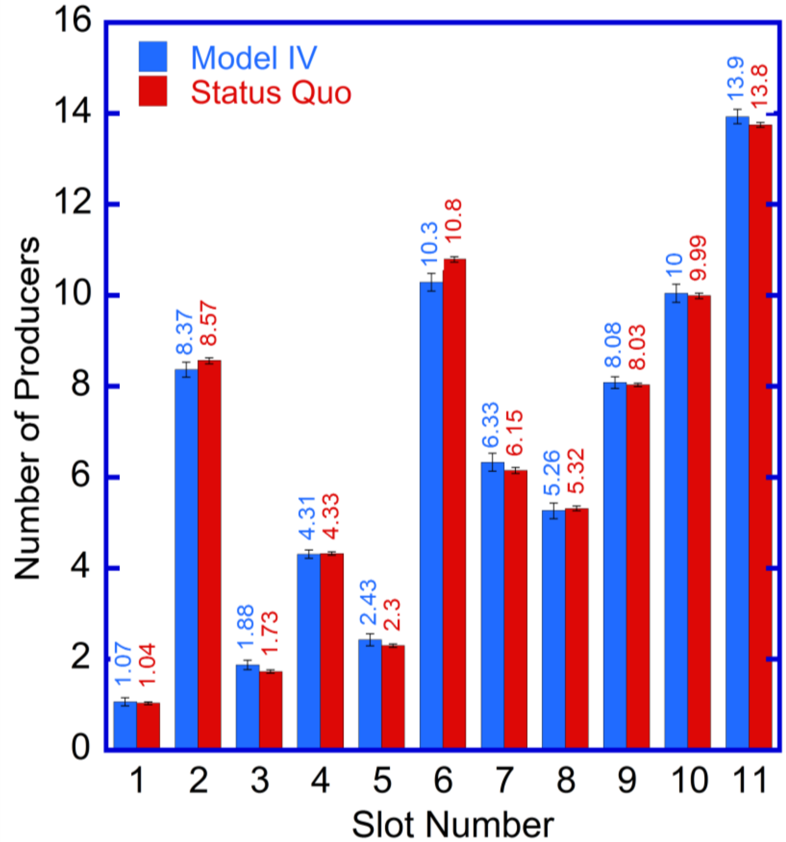

Figure 52. *Number of producers arriving in each time slot when food hub provide provides feedback to the producers for scheduling (Model IV) versus the status quo (Model I).*

References

Huber, G. (2015, February). Iowa Food Cooperative, Des Moines, Iowa. (A. Mittal, & C. Krejci, Interviewers)

Sargent, R. G. (2005). Verification and Validation of Simulation Models. *Proceedings of 2005 Winter Simulation Conference* (pp. 30-143). IEEE.

Schlesinger, S., Crosbie, R. E., Gagné, R. E., Innis, G. S., Lalwani, C. S., Loch, J., . . . Bartos, D. (1979). Terminology for model credibility. *Simulation, 32(3)*, 103-104.

CHAPTER 5

CONCLUSION

General Conclusions

Producer delivery scheduling has the potential to improve a regional food hub's inbound operations by helping it to appropriately allocate its resources and provide better service to its customers through better product quality and fewer order errors. This will likely increase customer loyalty and business for the food hub, thereby improving the economic growth opportunities and quality of life for participating small and mid-sized producers. However, encouraging producers to schedule their deliveries can be very challenging for a food hub manager. Producers greatly value their autonomy, and they tend to resist having constraints placed on their ability to set their own schedules, although some producers may be willing to give up some autonomy in exchange for greater convenience or a financial incentive. Producers' delivery scheduling decisions may also be influenced by social interactions that they have with one another, in which they share information about their experiences with scheduling. As a result, predicting the effects of specific management policies on producer scheduling behavior and subsequent system-wide outcomes is very difficult

To address this problem, an empirical hybrid simulation model of the inbound logistics operations at a regional food hub in Iowa was developed. The model was used to study the impacts of producers' delivery scheduling behavior on food hub warehouse operations and to analyze the feasibility and outcomes of implementing various corrective actions. Discrete event simulation was used to represent the arrivals and queueing behavior of producers at the warehouse, and agent-based modeling was used to represent producer decision making and interactions. This hybrid model was informed by empirically-derived human and system data, which reflected the actual heterogeneous decision-making processes and behaviors of the food hub's participants.

Four versions of the model were described in this thesis. In Model I, the current operating conditions at the food hub were captured. This model was validated using the food hub's historical data, which is independent of the input data that was used to construct the model. Models II, III, and IV were used to observe the effects of different food hub policies on producers' scheduling behavior. Experimental results from Model II suggest that, if implemented inappropriately, incentives can be counterproductive. The results also indicate that increased producer scheduling by itself does not necessarily improve system outcomes. Although advance scheduling provides useful information to the food hub manager, if he does not act on this information (e.g., by scheduling more receiving personnel to work during the producers' most-preferred time slots), neither the food hub nor the producers will benefit.

This thesis demonstrates the need for a hybrid modeling methodology to realistically represent complex sociotechnical behaviors in regional food supply chains. Because agent interactions were not included in Models I and II, it may have been possible to develop these versions of the model using DES alone. However, using DES to model the interactions between the food hub and producers and among the producers in Models III and IV would have impractical. Also, modeling the process-oriented framework (e.g., the priority delivery queuing behavior in Model II) would have been extremely difficult to model and validate using ABM.

Limitations and Future Work

The outcomes of this research can help food hub managers to frame policies that will improve the effectiveness and efficiency of their inbound operations. In future research, it would be interesting to observe how the agents belonging to different behavioral clusters respond to different food hub policy implementations. This will help the food hub manager determine how best to structure incentives to obtain optimal results. For example, producers in Cluster 1 are highly influenced by monetary incentives. However, the results show that even when monetary incentives are offered by the food hub, producers arrival times are concentrated in particular time slots due to the producers who refuse to schedule their deliveries. Therefore, the food hub might consider modifying the monetary incentive by informing the producers that they will receive the benefit only if they arrive in the less desirable time slots. It would be interesting to observe how the behavioral patterns of the producers who were scheduling regularly because of the monetary incentive might change with the implementation of a modified policy.

Additionally, incorporating greater heterogeneity among agents in the system may enable a more realistic representation of the system. In the model presented in this thesis, the utility functions for each producer agent were assumed to be identical. In a future version of the model, heterogeneous utility functions based on individual preferences for autonomy and convenience will be included, based on survey data. Other producer-specific factors could also be incorporated. For example, product type may influence the decision to schedule – requirements for scheduling flexibility can greatly vary for shelf-stable, frozen, and refrigerated goods. The distance that a producer must travel to deliver goods to the food hub warehouse may also impact scheduling decisions.

Another possible future development of the model presented in this thesis is the inclusion of multiple Iowa food hubs, enabling the collection of information from a wider variety of producers and food hub managers. This would improve the generalizability of the model and would allow implications from experimental results to be extended to other food hubs, thereby increasing the model's usefulness as a decision support tool for food hub managers.

Model IV was developed to demonstrate the usefulness of ABM in modeling food hub operations. Future work will include producers' interactions based on their arrival patterns at the food hub. Such interactions could occur between the producers who are waiting in the queue at the food hub, leading to shared knowledge and experiences. The impact of these social interactions on producers' behaviors toward the food hub would be interesting to explore using ABM.

The possibility of using simulation software that has both ABM and DES capabilities (i.e., AnyLogic), or using distributed simulation techniques to automate the integration of two different simulation platforms is currently being explored. This will potentially speed up the execution of the simulation runs, making experimentation more efficient.

Regional food hubs provide a potential solution to the problem of unmet and growing demand for regionally and sustainably-produced food in the United States. However, financial constraints and a strong social mission often prevent them from employing conventional supply chain practices in their operations. Helping food hub managers to address the complex challenge of balancing operational efficiency and social responsibility is critical to food hub success, which has implications for the long-term viability of regional food systems and their participants.

APPENDIX A

PRODUCER SURVEY QUESTIONNAIRE

The purpose of this survey is to gather information on the factors that influence your decision to schedule the delivery at the food hub.

The data collected in this survey will be used to help the food hub managers to take strategic decisions in order to improve their warehouse operations efficiency.

Your answers to the survey questions will be kept confidential.

Please feel free to contact Dr. Caroline C. Krejci at Iowa State University, if you have any questions or concerns at ckrejci@iastate.edu.

Thank you in advance for your contribution in conducting this research study!

Questions for food hub producers.

<u>General information</u>

1) What is your producer ID?

2) How satisfied are you with your business with the food hub?

   a. *Extremely satisfied*
   b. *Very satisfied*
   c. *Moderately satisfied*
   d. *Not very satisfied*
   e. *Not at all satisfied*

3) How far do you live from the food hub?

   a. *< 5 miles*
   b. *>=5 miles and < 15 miles*
   c. *>= 15 miles and < 30 miles*
   d. *>= 30 miles and < 45 miles*
   e. *>= 45 miles*

Scheduling behavior

4) How do you deliver your products to the food hub?

   a. *Ship the products*
   b. *Deliver yourself*
   c. *Someone else deliver on your behalf*
   d. *Other*____

5) Are you aware that the food hub gives an option to schedule your delivery online?

   a. *Yes*
   b. *No*

6) How often do you schedule the delivery online before arriving to the food hub?

   a. *Every cycle*
   b. *Every alternate cycle*
   c. *Once in 2 months*
   d. *Once in 3 months*
   e. *Once in 6 months*
   f. *Never*

7) On the scale of 1 to 5 ("1" as least preferred, "5" as most preferred), what is your preference for delivery in each of the following time slots?

   a. *Day before delivery day (Wednesday)*

I.	*9:00 – 10:00 a.m.*	*Least preferred ---1---2—3—4—5---Most preferred*
II.	*10:00 – 11:00 a.m.*	*Least preferred ---1---2—3—4—5---Most preferred*
III.	*11:00 – 12:00 p.m.*	*Least preferred ---1---2—3—4—5---Most preferred*
IV.	*12:00 – 1:00 p.m.*	*Least preferred ---1---2—3—4—5---Most preferred*
V.	*1:00 – 2:00 p.m.*	*Least preferred ---1---2—3—4—5---Most preferred*
VI.	*2:00 – 3:00 p.m.*	*Least preferred ---1---2—3—4—5---Most preferred*
VII.	*3:00 – 4:00 p.m.*	*Least preferred ---1---2—3—4—5---Most preferred*
VIII.	*4:00 – 5:00 p.m.*	*Least preferred ---1---2—3—4—5---Most preferred*

b. *On delivery day (Thursday)*

IX.	*9:00 – 10:00 a.m.*	*Least preferred ---1---2—3—4—5---Most preferred*
X.	*10:00 – 11:00 a.m.*	*Least preferred ---1---2—3—4—5---Most preferred*
XI.	*11:00 – 12:00 p.m.*	*Least preferred ---1---2—3—4—5---Most preferred*

8) If your most preferred time slot(s) is/are not available, would you still schedule the delivery in a less preferred available slot?

   a. *Yes*
   b. *No*

9) On the scale of 1 to 5 ("1" is least satisfied and "5" as most satisfied) what will be your satisfaction level for the following waiting times to have your products inspected and checked in by the IFC volunteers?

a.	*< 5 minutes*	*Least satisfied---1---2—3—4—5---Most satisfied*
b.	*>=5 and < 10 minutes*	*Least satisfied---1---2—3—4—5---Most satisfied*
c.	*>=10 and <15 minutes*	*Least satisfied---1---2—3—4—5---Most satisfied*
d.	*>=15 minutes and <20 minutes*	*Least satisfied---1---2—3—4—5---Most satisfied*
e.	*>= 20 minutes and <25 minutes*	*Least satisfied---1---2—3—4—5---Most satisfied*
f.	*>= 25 minutes and < 30 minutes*	*Least satisfied---1---2—3—4—5---Most satisfied*
g.	*> 30 minutes*	*Least satisfied---1---2—3—4—5---Most satisfied*

10) Are you the producer of the items that you are delivering?

   a. *Yes*
   b. *No*

11) Do you typically incorporate your delivery with other activities in the area?

   a. *Yes*
   b. *No*

11.a. If **YES**, what activities?

a. *For full time employment*
b. *For other deliveries*
c. *For personal activities*
d. *Other: ____*

11.b. If **YES**, how likely is it that this affects your decision to schedule the delivery?

Not likely---1---2—3—4—5---Highly likely

12) How good is the internet connectivity at your residence/ workplace?

Low---1---2—3—4—5---High

13) How often do you combine/ coordinate the deliveries to the food hub with other producers?

a. *Every cycle*
b. *Every alternate cycle*
c. *Once in 2 months*
d. *Once in 3 months*
e. *Once in 6 months*
f. *Never*

13.a. If the food hub offers you monetary incentives to coordinate/share the delivery, how likely would you be to coordinate your delivery with other producers?

Not likely---1---2—3—4—5---Highly likely

14) How will your decision to schedule the delivery change for each of the following monetary incentive levels provided by the food hub?

a. *<1% of your total sales (in one cycle)*	*No effect---1---2—3—4—5---Always schedule*
b. *>=1 and < 3% of your total sales*	*No effect---1---2—3—4—5---Always schedule*
c. *>=3 and <5% of your total sales*	*No effect---1---2—3—4—5---Always schedule*
d. *>=5 % of your total sales*	*No effect---1---2—3—4—5---Always schedule*

15) If the food hub offers you priority delivery (i.e. go to the front of the line for receiving) as an incentive to schedule, how likely would you be to schedule your delivery?

Not likely---1---2—3—4—5---Highly likely

16) Do you interact with other food hub producers?

a. Yes

b. No

16. a. If **YES**, how many producers on average do you interact within an order cycle?

c. 1

d. 2

e. 3

f. 4

g. 5 or more

16.b. If you interact with other producers, how often do you share the experiences you have with the food hub?

Never---1---2—3—4—5---Always

17) Do you harvest, pack and label the products on the day of delivery?

a. Yes

b. No

17.a. If **YES**, how likely is it that this affects your decision to schedule the delivery?

Not likely---1---2—3—4—5---Highly likely

18) With “1” as most influential and “8” as least influential, rank the following factors according to how strongly they affect your decision to schedule the delivery:

a. Convenience of internet access ___

b. Flexibility in delivery ___

c. Wait time for product inspection/check in by volunteers ___

d. Combine/coordinating delivery with other producers ___

e. *Combining your delivery with other activities near the food hub* ___

f. *Monetary incentives from the food hub* ___

g. *Priority delivery incentive from the food hub* ___

h. *Harvesting and packing schedule* ___

19) Are there any other factors that influence your decision to schedule your delivery at the food hub?

Factor 1: ____

Factor 2: ____

Factor 3: ____

Factor 4: ____

19.a. If there are any other factors, where within the 8 factors mentioned above (question #20) would you rank these factors?

Factor 1 between _____ and _____ (mention the ranks associated with the factors)

Factor 2 between _____ and _____

Factor 3 between _____ and _____

Factor 4 between _____ and _____

APPENDIX B

AGGLOMERATIVE SCHEDULE

Agglomeration Schedule

Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	8	21	3.000	0	0	14
2	1	6	7.500	0	0	12
3	9	24	13.500	0	0	12
4	4	10	19.500	0	0	14
5	11	16	26.000	0	0	15
6	15	22	34.500	0	0	10
7	12	19	43.500	0	0	13
8	3	23	53.000	0	0	18
9	2	5	63.500	0	0	16
10	15	20	75.000	6	0	20
11	7	17	88.000	0	0	15
12	1	9	102.750	2	3	18
13	12	18	119.750	7	0	19
14	4	8	137.250	4	1	17
15	7	11	157.000	11	5	16
16	2	7	178.917	9	15	19
17	4	13	205.617	14	0	21
18	1	3	233.533	12	8	21
19	2	12	271.200	16	13	22
20	14	15	310.700	0	10	23
21	1	4	374.106	18	17	22
22	1	2	447.450	21	19	23
23	1	14	560.708	22	20	0