

A HYBRID SIMULATION MODEL OF INBOUND LOGISTICS OPERATIONS IN REGIONAL FOOD SUPPLY SYSTEMS

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ABSTRACT

Regional food hubs aggregate, distribute, and market local food, with a goal of promoting environmental and social sustainability. They provide an alternative distribution channel through which small-scale producers can access wholesale markets. However, food hubs face many barriers to growth and success. In particular, they are often unable to achieve the logistical and operational efficiencies that characterize conventional large-scale food distribution. One possible method of improving food hub efficiency targets inbound logistics operations – specifically, the scheduling of producer deliveries to the food hub. In this paper, we describe a hybrid simulation model of the inbound logistics operations of a food hub. Using this model, we observe the scheduling behavior of the producers under different conditions and explore the effectiveness of implementing incentives to encourage producers to schedule their deliveries in advance.

1 INTRODUCTION

The demand for locally-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 locally using sustainable methods over food from the conventional food supply system. According to the USDA, direct-to-consumer sales of local food increased by 215% from 1992 to 2007, and in 2008, local food sales via both direct-to-consumer and intermediated channels were estimated to be \$4.8 billion (Low and Vogel 2011). According to the National Grocery Association, 87.2% of consumers regard the availability of locally-grown produce and other locally-produced food as important in their grocery shopping decisions (Tropp 2014). Their reasons vary widely, including: ensuring the nutrition, quality, freshness, and safety of their food, saving money, 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 2002; Brown 2003; Wolf et al. 2005).

Traditionally, the most common market channel for local food produced by small- and medium-scale producers has been direct-to-consumer, via farmers' markets and community supported agriculture (CSA) schemes. 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 et al. 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, 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 et al. 2011; Diamond and Barham 2012).

To address these challenges, alternative wholesale market channels for local food, such as regional food hubs, have begun to emerge throughout the U.S. The USDA defines a regional 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 their 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. They can play an instrumental role in increasing small producers' operations. However, despite the benefits that they can provide, a 2013 national food hub survey indicated that food hubs are not profitable on an average. This suggests that there is a need for a better understanding of the practices of local food chains in order to increase their overall operational efficiency (Fischer et al. 2013).

The literature suggests that food hubs should adopt conventional business practices for their long-term growth and sustainability (Rogoff 2014). However, conventional food supply chains 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 and Pirog 2013). By contrast, local and regional food supply chains focus on both financial performance and the well-being of all stakeholders. Therefore, 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 et al. 2014). 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.

One example of such a method involves the inbound operations of a warehouse, which include receiving goods, performing quality inspections, and storing goods at desired inventory storage locations. In a conventional supply chain, suppliers are generally assigned to specific time slots on particular days in which they are supposed to deliver their goods (Gopakumar et al. 2008). 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 and Gebresenbet 2004). This helps them to plan their receiving operations in advance, enabling better man-hour utilization and allowing more time for quality inspections of received material, thereby benefiting customers. Regional food hubs, which have comparatively smaller operations, typically do not assign a fixed delivery time to their suppliers. A fixed delivery time is perceived as burden on food producers, who are known to highly value their autonomy and schedule flexibility (Krejci and Beamon 2015) and prefer to deliver goods at their convenience. For small producers, fixing arrival times could also affect their transportation costs if they are unable to schedule at a preferred time, as they might be combining the delivery 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. One of the major challenges faced by food hubs in Iowa is that many of their producers arrive for delivery at the same time, 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 queue length increases, service time tends to decrease, thereby negatively affecting the quality of service (Anand et al. 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. These errors result in customer dissatisfaction, due to poor quality of products or wrong delivery.

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 in advance online by selecting preferred 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 actually delivered in the time window that they indicated on the schedule (Huber 2015). Similar observations have been made by the Iowa Valley Food Cooperative (Grimm 2015). Even though this causes operational problems for the food hub, the managers have not implemented any corrective action or provided incentives for improved scheduling behavior.

It would be valuable for food hub managers to have a better understanding of the conditions that would encourage producers to decide to schedule their deliveries to the food hub, as well as the impacts of scheduling on food hub performance. To investigate this problem, we have developed a hybrid agent-based/discrete-event simulation model of the inbound logistics operations of a food hub. This hybrid model integrates the benefits and capabilities of both modeling methodologies, allowing us to capture the fundamental elements and behavior of the system.

2 RESEARCH METHODS

Many studies using discrete-event simulation (DES) have been conducted in the domain of supply chain management (Terzi and Cavalieri 2004), and specifically for food supply chains. For example, DES has been used to evaluate the performance of a supply chain for chilled food products (Van der Vorst et al. 2000), as well as comparing different transport modes in terms of logistics cost, energy use, CO₂ emissions, and product quality decay (Van der Vorst et al. 2009). DES has also been used to study the terminal operations of a warehouse, which involves loading, unloading, and other warehouse-specific activities (Liong and Loo 2009; Deshpande et al. 2007). Liong and Loo (2009) used DES to develop a strategy to optimize the residence time of delivery trucks 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.

However, real-time decision making by an individual supply chain actor is difficult to incorporate in a DES model, because very strict assumptions pertaining to human choices need to be made in order to accommodate human behavior in DES (Dubiel and Tsimhoni 2005). By contrast, agent-based modeling (ABM) is well-suited to modeling complex systems involving human decision making (North and Macal 2007). 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 et al. 2013). Such emergent system behavior can be difficult to predict without the use of an ABM. ABM has been used in the field of logistics and transportation management, including proposing new strategies in courier services (Knaak et al. 2006) and in the areas of air and road traffic management (Davidsson et al. 2005).

In order to integrate human decision making with the capabilities of DES, researchers have combined DES with ABM to form hybrid simulations (Huanhuan et al. 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 and Mustafee 2014; Zulkepli et al. 2012). Hybrid simulation has been used to simulate transportation evacuation and disaster response systems (Zhang, Chan, and Ukkusuri 2011; Wu et al. 2008). 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 and Tsimhoni 2005). A hybrid DES-ABM simulation of patients in a clinic in the United Kingdom incorporated patient interactions into the clinic's fundamental queuing problem (Viana et al. 2012; Brailsford et al. 2013). The literature suggests that hybrid simulation modeling is a growing trend, but the concept is still in early stages of development (Eldabi et al. 2008).

A number of simulation modeling techniques have been used in the area of supply chain management and logistics, but most of these techniques have been used in isolation (Mustafee et al. 2015). In this paper we have developed a hybrid DES-ABM model that employs an ABM to capture food hub producers' delivery scheduling decisions and behaviors and uses DES to incorporate the food hub queuing system, with the DES model providing feedback to the ABM. It is possible that the specific model we describe in this paper could be developed using DES alone. However, in the future we intend to extend this model to capture more complex and realistic agent behaviors (e.g., the effects of interactions among the agents on their scheduling decisions), and doing so would be rather cumbersome, if not impossible, using DES. Therefore, we present the framework for a hybrid simulation model upon which we can build more complex models in future.

The ABM was developed using NetLogo (5.1.0), and the DES model was developed using Arena (14.7). The two models are run in sequence over multiple iterations, with outputs from the ABM (i.e., agent scheduling decisions) informing the arrival times of the entities in the DES model, and outputs of the DES model (i.e., queue times) influencing agent utility in the ABM, as shown in Figure 1. The data exchange between these two separate models was performed manually using the read/write functions of both software platforms. The decision to use these two different modeling platforms was based on the authors' previous experience and detailed knowledge of the software (Krejci and Beamon 2015). We are currently exploring 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, to develop the future version of this model (Brailsford et al. 2013; Mustafee et al. 2015). This will speed up the execution of the simulation runs.

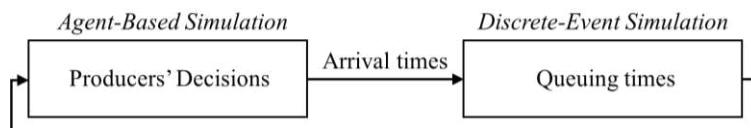


Figure 1: Hybrid simulation framework.

3 HYBRID SIMULATION MODEL DESCRIPTION

In this section we describe a hybrid simulation model of inbound logistics operations for a regional food hub. This theoretical model is loosely based on the operations of the Iowa Food Cooperative (www.iowafood.coop).

3.1 Agent-Based Model

A single type of agent inhabits this model: the producer agent. The model contains 100 producer agents, which is representative of the size of the Iowa Food Cooperative supplier base. A producer agent's decision regarding whether or not to schedule his delivery time with the food hub manager depends upon

his current level of satisfaction (i.e., his utility), which is based on two conflicting factors: autonomy and convenience. This representation reflects the characteristics of food hub producers in real life. Producers (i.e., farmers) are known to highly value their autonomy, and they are often willing to make significant sacrifices to maintain it (Krejci and 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. Thus, producers' decisions with respect to the food hub involve a tradeoff between convenience and autonomy. 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 must spend waiting in a queue to receive service from personnel at the food hub during a delivery, where less queue time corresponds to greater convenience. The producer's utility is a weighted sum of autonomy and convenience.

Each producer has a time preference for delivering goods to the food hub. We have assumed that all 100 producer agents in the system must deliver their products within this five-hour time window, which represents the Iowa Food Cooperative's afternoon receiving operation. Every producer is assigned a preference order of five one-hour time slots. For example, a producer preference [4 3 5 2 1] signifies that the producer's first preference is to deliver in the fourth time slot, while the first time slot is least preferred. It is assumed that preference order does not change over the course of a simulation run. 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 component of a producer's utility due to autonomy (U_A) is defined on a scale from 0 to 1 and is assigned a value of 1 if the producer doesn't schedule his delivery, a value of 0.75 if the producer decides to schedule the delivery and is able to get his most-preferred time slot, or a value of 0 if the producer attempts to schedule but is unable to get his most-preferred time due to capacity constraints in each time slot. These values are currently theoretical. However, in a future version of this model, the utility scale of autonomy will be empirically developed using survey data from Iowa Food Cooperative producers.

Utility due to convenience (U_C) is a function of producer queue time at the food hub (Q), where increase in queue time reduces the producer's utility. Previous research has shown that an inversely proportional relationship exists between customer waiting time in queue and a customer satisfaction (Davis and Heineke 2007). Therefore, we have assumed U_C to be a linear function of Q , with a maximum value of 1 when $Q = 0$ and a minimum value of 0 when $Q \geq 1$ (where Q is measured in hours). This linear function is defined as: $U_C = 1 - Q$.

The overall utility (U) of a producers' decision is a weighted combination of U_A and U_C , given by: $U = W_A U_A + W_C U_C$, where W_A and W_C are measures of the producer's relative preference for autonomy and convenience, respectively. Every producer has a minimum satisfaction level, and if he makes a decision and is not satisfied with it, he will update his decision-making strategy in an attempt to achieve that satisfaction level. To define this satisfaction in terms of utility, every producer has been assigned a constant threshold utility value (U_T) of 0.75, below which a producer will be dissatisfied.

3.2 Discrete-Event Simulation Model

The DES model captures the processes of producers arriving at the food hub, queueing for service, receiving service from food hub personnel, and exiting the food hub. The entities in this model represent the producer agents of the ABM, with arrival times that are determined by their scheduling decisions. The DES model outputs the queue time for each producer, which depends upon their respective arrival and service times. In this model we have assumed that a single resource is responsible for the receiving process at the food hub.

3.3 Hybrid Model Overview

The simulation begins with the ABM. In the first delivery cycle, it is assumed that all 100 producer agents decide to schedule their deliveries according to their preference and time slot availability. 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. 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 20-producer 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. The producer's utility due to autonomy (U_A) depends upon whether or not he gets his most-preferred time-slot. 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. Service time is assumed to follow a triangular distribution. 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) using the linear function of Q . The producer's overall utility (U) is then calculated using the weighted utility function as defined above. If U is greater than the producer's threshold utility (U_T), he will decide to schedule his delivery again in the next cycle. Otherwise, he will decide not to schedule. It is assumed that if a producer decides not to schedule the delivery, he will deliver in his most-preferred time slot, and the arrival time of the producer at the food hub is assumed to be a uniformly-distributed random value in that time slot.

This process of deciding on a scheduling policy, arriving at the food hub, queueing, receiving service, and updating the scheduling policy based on utility outcomes, occurs for each of the 100 producer agents in every time-step, where one time-step is equivalent to one two-week delivery cycle for the Iowa Food Cooperative. The overall process is shown in Figure 2. Multiple conversations with the food hub manager helped to verify that this process correctly represents actual system behavior.

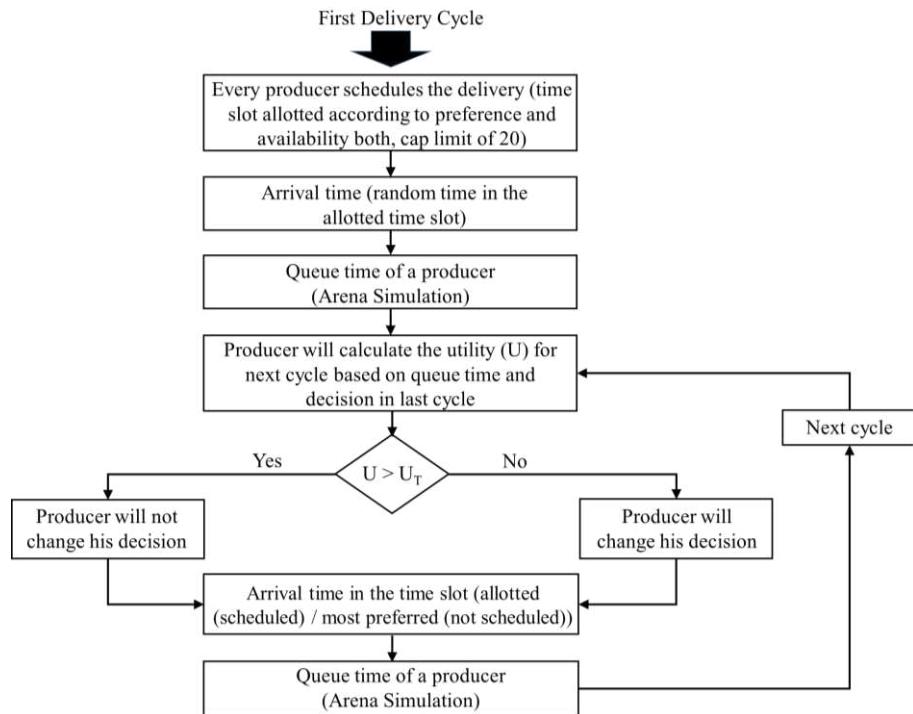


Figure 2: Model overview.

4 EXPERIMENTAL DESIGN

The hybrid model was used to perform experiments to test the impact of different factors on the producers' scheduling behavior over time. These factors and their experimental levels are summarized in Table 1. Three different combinations of weights on autonomy and convenience utilities have been considered, where all 100 producer agents are assigned the same utility weights in each experiment. Additionally, two possible producer preference orders have been assessed: random - every producer is assigned a random preference order for the five time slots and ordered: every producer is assigned the same preference order, i.e. [5 4 3 2 1]. Two different sets of parameters for the triangular service time distribution were also used: a low-variability distribution with minimum, mode, and maximum set to 1, 3, and 5 minutes, respectively, and a high-variability distribution with parameters set to 0.5, 3, and 7 minutes.

Table 1: Experimental input parameters and values.

Description	# of Levels	Experimental Values
Weight combinations of autonomy and convenience (W_a, W_c)	3	(0.8, 0.2), (0.5, 0.5), (0.2, 0.8)
Producer preference order of time slots	2	Random, Ordered
Receiving time distribution	2	TRIA(1,3,5), TRIA(0.5,3,7)

The twelve experiments were categorized into four different experimental scenarios according to receiving time distribution and preference order (as summarized in Table 2). The output metrics that were captured in each time-step (i.e., delivery cycle) include the total number of producers who decide to schedule their deliveries and the average producer queue time. For each experiment, the average output metric values over five replications of 100 time-steps each were captured. Five replications was considered adequate for this pilot study, due to the relatively low variability observed across runs for the mean number of producers scheduling and queue time in most of the experimental scenarios.

Table 2: Description of different experimental scenarios.

Scenario	Receiving Time Distribution	Preference Order
Scenario 1 (S1)	TRIA(1,3,5)	Random
Scenario 2 (S2)	TRIA(0.5,3,7)	Random
Scenario 3 (S3)	TRIA(1,3,5)	Ordered
Scenario 4 (S4)	TRIA(0.5,3,7)	Ordered

5 RESULTS AND DISCUSSION

Figures 3, 4, 5, and 6 show the total number of producers that have decided to schedule their deliveries in each time-step over the course of the simulation run. Comparing the results of Scenario 1 with Scenario 2 and the results of Scenario 3 with Scenario 4 indicates that greater variability in receiving times results in greater producer decision variability from one time-step to the next. Figure 7 compares the average number of producers who decide to schedule in the final time-step for each experimental scenario. The results show that the average number of producers scheduling their deliveries increases in all four scenarios as the weight on convenience increases.

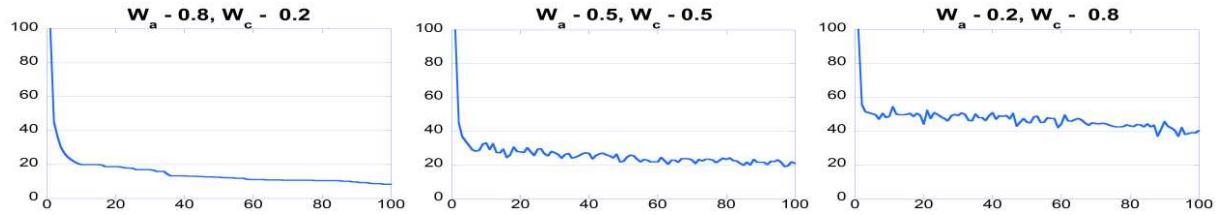


Figure 3: Number of producers scheduling in each delivery cycle (S1).

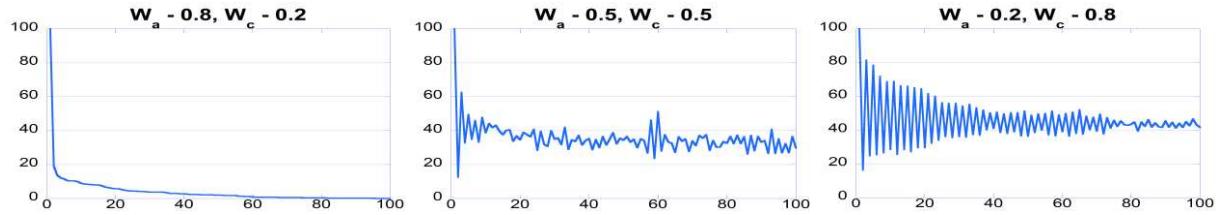


Figure 4: Number of producers scheduling in each delivery cycle (S2).

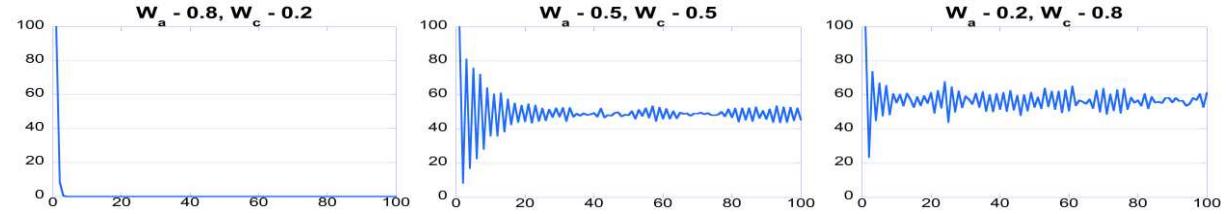


Figure 5: Number of producers scheduling in each delivery cycle (S3).

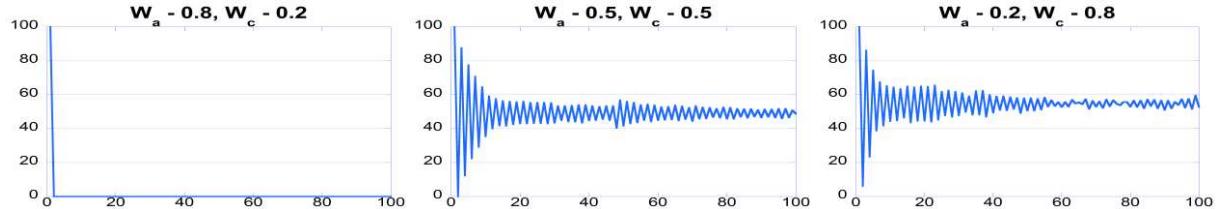


Figure 6: Number of producers scheduling in each delivery cycle (S4).

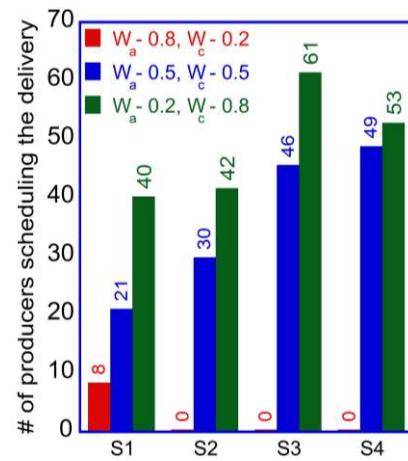


Figure 7: Average number of producers scheduling in each experimental scenario.

We originally expected that the average queue time would decrease as more producers decided to schedule their deliveries, but interestingly, when producer time slot preference orders were randomly assigned, this was not the case – average queue times remained almost the same, regardless of the number of producers scheduling. However, when all producers were assigned the same preference order, as more producers scheduled their deliveries, the average queue time was reduced. Figure 8 shows the average queue time vs number of producers scheduling for all four scenarios. This outcome makes intuitive sense – if the producers have the same preferences for time slots and do not schedule their deliveries, all of them will end up delivering in the same time slot, and this will increase the average queue time. In the case of random preference order, arrival times will tend to be uniformly distributed among all five time-slots, irrespective of the producers' scheduling decisions.

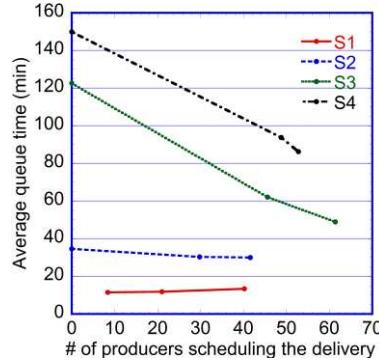


Figure 8: Average queue time vs number of producers scheduling for all four scenarios.

Food hubs can implement policies to encourage producers to adopt scheduling behavior. To capture this, a new component (U_I) was added to the producer utility function to represent the utility gained from receiving a scheduling incentive from the food hub. U_I takes a value of 1 if the producer schedules his delivery and 0 otherwise. The weight on U_I is denoted by W_I . The overall utility function for a producer becomes: $U = W_A U_A + W_C U_C + W_I U_I$.

Figure 9 compares the average number of producers scheduling in the final time-step of the simulation with and without the incentive. For the case without the incentive, equal weight is given to autonomy and convenience (0.5). For the case in which the incentive is included, the weights on autonomy, convenience, and the incentive are 0.5, 0.4 and 0.1, respectively. As Figure 9 shows, the average number of producers that choose to schedule increased from 21 to 53, indicating that it could be worthwhile to the food hub to provide this incentive. 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.

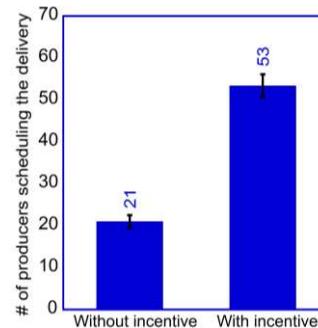


Figure 9: Comparison of average number of producers scheduling with or without an incentive.

6 CONCLUSION AND FUTURE WORK

This paper describes a hybrid DES-ABM simulation model of the inbound logistics operations at a regional food hub. The model was used to observe the delivery scheduling behavior of the producers, given different producer preferences and different levels of service time variability at the food hub. The impact of scheduling behavior on average queue time at the food hub was also captured. The experimental results indicate that if a food hub incentivizes producers to schedule their deliveries in advance, more producers will schedule, thereby reducing negative impacts on the inbound operations of the food hub.

Future work will allow us to explore the influence of the interactions and information sharing among the producers' on their scheduling behaviors. Additionally, case study data from Iowa food hubs will be gathered and incorporated into the model, allowing us to more accurately capture the impact of long queues on service quality at the food hubs. The outcomes of this research will help to inform food hubs' strategic decision making to make their inbound logistics operations more effective and efficient.

ACKNOWLEDGMENTS

The authors would like to thank Gary Huber of the Iowa Food Cooperative and Jason Grimm of the Iowa Valley Food Co-op for their valuable inputs and assistance in conducting the research summarized here.

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