Evaluating disintermediation in regional food systems using agent-based modeling

by

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NOMENCLATURE

OEM	Original Equipment Manufacturer
ABM	Agent-based Model
GIS	Geographic Information Systems
RL	Reinforcement Learning
ODD	Overview, Design concepts and Details
IRB	Institutional Review Board

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ABSTRACT

Consumers are increasingly seeking fresh and healthy food that has been sustainably produced by regional food producers. However, most consumers also value convenience and efficiency and prefer to purchase food from retailers and restaurants, rather than from producers directly or farmers' markets. Regional food hubs provide aggregation, warehousing, transportation, and marketing services for these regional food producers, allowing them to focus on food production rather than logistics and marketing. Additionally, food hubs give small and mid-sized producers the ability to reach larger markets and customers than they could reach on their own. These services can help producers tremendously in their efforts to grow their businesses.

However, once food hub managers have helped to establish connections between producers and new customers, they often find themselves cut out of the regional food supply chain when the producers decide to sell their products directly to the customers, thereby avoiding the food hub's service fees. While this can have short-term financial benefits for the producers, widespread disintermediation can eventually lead to food hub failure, which can disrupt the entire regional food system. To avoid this, food hub managers must develop and implement policies that will support long-term and mutually beneficial relationships with their producers and customers.

This thesis describes an agent-based modeling methodology to study disintermediation in an intermediated regional food supply network in Iowa. The model is designed to serve as a decision support tool for food hub managers, allowing them to simulate the effects of various supply chain management strategies on producer decision making and long-term organizational and system success. The methodology is tested by conducting three experiments. Further, this thesis develops an empirical study to validate the computational model and conducts a pilot test of the study. Based on the results of the experiments and pilot study, the computational model proves useful for studying the problem of disintermediation.

CHAPTER I

INTRODUCTION

Many consumers have concerns about the environmental sustainability and production practices of conventionally-produced food. Some of these consumers perceive regionally-produced food, where food is produced and consumed in the same geographic region, to be more sustainable, of higher quality, and healthier than conventionally-produced food, and they are therefore increasingly demanding this food (Jones, Comfort, & Hillier, 2004). In fact, many consumers value these perceived benefits enough to pay higher prices for regionally-produced food than they would pay for the same conventionally-produced items (Adams & Adams, 2011). Despite this preference for regional food, a lack of convenient access, such as inconvenience of farmers' markets, can be a significant barrier for consumers.

In an effort to make regionally-produced food more accessible to consumers, facilities known as regional food hubs have been developed over the past decade throughout the U.S. A regional food hub acts as an intermediary in a regional food supply chain by aggregating, marketing, and distributing food from small-scale and midsized producers to customers that are located in the same region, facilitating a connection between them (Barham, Tropp, Enterline, Farbman, Fisk, & Kiraly, 2012). Some regional food hubs sell directly to consumers, while others sell to wholesale customers (e.g., retailers, restaurants, institutions), where consumers can access local food more conveniently. Wholesale customers can be particularly challenging for small and midsized food producers to retain on their own, because they lack sufficient volumes and adequate processing, storage, and transportation infrastructure. Additionally, not all wholesale buyers are willing to manage many accounts, which is required if they are filling their demand for food directly from small-scale producers.

Producers can greatly benefit from a food hub's ability to provide aggregation, warehousing, and transportation services, which allow the producer to focus on their core business competencies. In addition to logistics services, food hubs often provide producers with marketing services, which can help producers to grow their sales to current as well as new customers. In contrast with conventional food distributors, regional food hubs view their producers as strategic supply chain partners, rather than interchangeable suppliers (Stevenson & Pirog, 2013). A core part of the food hub mission is to ensure that suppliers are treated fairly and any business decisions are made with the welfare of all participants in mind.

However, after facilitating a connection between regional food producers and customers, food hubs tend to be susceptible to having their producers cut them out of transactions and sell directly to food hub customers. This phenomenon, known as disintermediation, is not unique to regional food supply chains. Disintermediation is the removal of an intermediary in a supply chain in return for lower costs for the customers and suppliers (Mills & Camek, 2004). In a regional food system, widespread disintermediation can make a food hub no longer financially viable.

Food hub managers across the U.S. have reported experiencing producer disintermediation and recognize that it threatens their business (McCann & Crum, 2015). Although circumventing the food hub may have short-term benefits for certain producers (e.g., avoiding service fees), if the food hub fails, the producers who rely on the food hub's services to deliver all their products may struggle to succeed on their own. All producers previously using the food hub will find their business growth limited to a smaller geographical area and may be unable to deliver all their products. The loss of this key intermediary in a regional food supply chain could threaten the survival of the entire system.

The manager of a food hub in western Iowa that provides transportation and warehousing for small-scale regional producers has reported experiencing disintermediation. This manager is in charge of all operations at the food hub, with help from several part-time employees. Her responsibilities include long-term strategic planning, managing relationships with producers and customers, and providing logistics support on a weekly basis. The food hub manager has observed that several of her producers use the food hub services for some products, while selling other products around the hub directly to the food hub's customers, thereby avoiding the food hub service fee. The producers selling directly to food hub customers originally gained those customers through the food hub – they did not sell to those customers prior to working with the food hub.

The problem, however, is potentially more widespread than the manager reported, since the producers who have been caught perform the disintermediation openly (i.e., they readily admit this behavior to the manager). As the food hub takes on new producers and tries to grow, the manager is concerned that this problem will persist and eventually become so widespread that her business will fail. Not only does disintermediation threaten the viability of the food hub in Iowa, but also other food hubs across the country that are experiencing the same problem.

In an effort to gain a better understanding of the underlying causes of disintermediation in a regional food supply chain and to provide managers with possible solutions, a new modeling method that combines agent-based modeling and reinforcement learning was developed to study the problem for the Iowa food hub manager. The conceptual model described in this thesis enables a realistic representation of human decision-making, and it has the ability to generate system-level behaviors that emerge over time as a result of these decisions. A pilot empirical study was performed in an effort to begin gathering data to inform and validate the computational model. The purpose of the research described in this thesis is to answer the following questions:

- Is combining reinforcement learning with agent-based modeling effective in modeling the food hub system?
- When agents use reinforcement learning to make decisions individually, how does it affect system behavior?
- Are the initial assumptions regarding the Iowa food hub disintermediation problem correct?
- What are the most effective strategies for the Iowa food hub to curb sales around the hub?
- Can the food hub experience long-term organizational success in an intermediated regional food supply chain?

Thesis Organization

Chapter 2 of this thesis provides a background on the previous research in the regional food, disintermediation, agent-based modeling, and reinforcement learning fields. In Chapter 3, the new modeling method, which combines agent-based modeling and reinforcement learning to study disintermediation, is described. Next, the abilities of the conceptual model described in Chapter 3 are demonstrated in Chapter 4 through three sets of experiments and their results. Chapter 5 describes the empirical study that was designed to provide the conceptual model with actual data points from the Iowa food hub system. Finally, Chapter 6 provides a conclusion and recommends directions for future research.

CHAPTER II

LITERATURE REVIEW

Regional Food Systems

Regional food systems emerged as an environmentally and socially sustainable alternative to conventional food systems, and regionally-produced food is increasing in popularity with consumers. There is no universally accepted definition of regional food; however, several definitions do exist (Jones, Comfort, & Hillier, 2004). One set of definitions is based on the producer's geographic proximity to the consumer. However, a different set of definitions is instead grounded in whether the food is produced according to environmental and socially sustainable criteria. The regional food movement primarily serves small and midsize food producers, who make up 94% of farms participating in regional food supply chains (USDA, 2013). These producers have operations that are incompatible with conventional food supply chains, because of low volumes, inflexible labor, and inexperience in distribution (Day-Farnsworth & Miller, 2014).

Some consumers perceive regionally-produced food to be of better quality and healthier than conventionally-produced food. Many of these consumers are even willing to pay higher prices for regional food to reap the perceived benefits (Adams & Adams, 2011). Despite their willingness to pay, a lack of convenient access can prevent consumers from enjoying regional food products. There are two main market channels through which consumers can access regionally-produced food items: direct-to-consumer channels and intermediated channels. Direct-to-consumer channels include roadside stands and farmer's markets. In intermediated channels, producers sell products through a distributor or intermediary before they are sold to both individual consumers and wholesale accounts. Typical wholesale customers in regional food systems are grocery stores, restaurants, and farm-to-school programs. However, small and midsize producers often struggle to sell directly to wholesale customers without assistance from an intermediary. Food hubs, in particular, can help a small or midsize food producer reach larger markets.

Regional food hubs

Regional food hubs act as aggregators, distributors and marketers for the food produced by small and mid-sized producers (Barham, Tropp, Enterline, Farbman, Fisk, & Kiraly, 2012). Regional food hubs may sell products directly to consumers, wholesale to retailers and restaurants, or to both consumers and wholesale accounts. A food hub can exist as a non-profit, a cooperative, or a for-profit business (Fischer M. , Hamm, Pirog, Fisk, Farbman, & Kiraly, 2013). Social and environmental responsibility is a core aspect of a food hub's operation. As part of their mission, many food hubs aim to bring regionally-produced food to communities lacking fresh and healthy food (Barham, Tropp, Enterline, Farbman, Fisk, & Kiraly, 2012). Food hubs also encourage producers to engage in environmentally sustainable farming practices and reduce the amount of energy needed in the distribution process. Food hubs view producers as strategic partners, rather than interchangeable entities, as they might be viewed in a conventional supply chain (Stevenson & Pirog, 2013). Food hubs strive to make mutually beneficially decisions with producers and ensure they are treated fairly. In doing so, food hubs provide many benefits to producers. Small and midsize producers find growing their distribution scale challenging, so regional food hubs provide them with increased market reach (Barham, Tropp, Enterline, Farbman, Fisk, & Kiraly, 2012). This increased market reach is a result of increasing the geographic reach of a producer's products via distribution services, as well as enabling producers to sell to larger customers like grocery stores, schools and hospitals. Beyond aggregation and transportation, many food hubs provide valuable marketing services for producers. However, producers are not the only supply chain member that benefits from the presence of a food hub as an intermediary - customers benefit, as well. Food hubs provide a single point of purchase for large customers, rather than requiring a buyer to communicate with many smaller producers. Similarly, food hubs can meet the volume demands of larger buyers by combining products from multiple producers.

Challenges in regional food systems

While food hubs offer improvements to regional food supply chains, they have not been entirely successful. In particular, regional food supply chains struggle to achieve economies of scale, making transportation inefficient and costly. Because regional food producers are small and midsized, they often use personal vehicles to transport products (Bosona, 2011). Due to the use of personal vehicles by producers, many small vehicles are transporting small amounts of regional food. For example, a study on a regional food supply chain in Sweden discovered that the average load rate of vehicles was less than 50% (Gebresenbet, 1999). Regional food transportation, which moves small amounts of food short distances, is usually less efficient than full truckloads of conventional food moving long distances (Day-Farnsworth & Miller, 2014). These inefficiencies tend to occur at the very beginning or very end of the supply chain. Balancing supply and demand is another common challenge for regional food supply chains. Many food hubs report that consumer demand exceeds what they are able to provide (Barham, Tropp, Enterline, Farbman, Fisk, & Kiraly, 2012). There are several reasons for this gap in supply and demand, including poor demand planning between aggregators and producers (Woods, Velandia, Holcomb, Dunning, & Bendfeldt, 2013). Another issue is the inherent seasonality of producing regional food, which typically results in low supply during the winter months (Schattman & Cannella, 2008). Exacerbating the difficulty in meeting demand is an inadequate labor force. Food hubs report that labor unavailability prevents them from growing their business (Fischer M. , Hamm, Pirog, Fisk, Farbman, & Kiraly, 2013). Additionally, some regional food supply chains are dependent on volunteer labor to operate, which creates further operational inefficiencies and inconsistencies.

A major challenge for regional food hubs is avoiding being cut out of the supply chain. This occurs when a producer sells products directly to a customer that was introduced to them by the food hub. If this disintermediation becomes common practice for many producers, the hub may fail, and as a result, the regional food supply chain may be disrupted.

Disintermediation

Removing an established intermediary from a supply chain to reduce costs for suppliers and/or customers is known as disintermediation (Mills & Camek, 2004). An intermediary acts as the middleman between a supplier and end customers. Examples of intermediaries are distributors, brokers, and wholesalers. Intermediaries arrange market access for suppliers, provide routine for business transactions and create economically efficient exchanges by using economies of scale (King, Sen, D'aubeterre, & Sethi, 2010). Although there are benefits to having intermediaries in a supply chain, if an intermediary provides less value or is perceived to provide less value than the costs they incur suppliers and customers, they risk disintermediation (Shunk, Carter, Hovis, & Talwar, 2007). For example, aerospace original equipment manufacturers (OEMs) have found themselves competing with opportunistic suppliers in aftermarket sales (Rossetti & Choi, 2008). Traditionally, these suppliers produce and sell aftermarket parts to the OEM, who then sells them to customers. However, some suppliers are circumventing the OEM and selling directly to customers to receive higher margins. The advent of the Internet and e-commerce resulted in a new business environment where traditional brick and mortar intermediaries have become increasingly irrelevant and are therefore susceptible to disintermediation (King, Sen, D'aubeterre, & Sethi, 2010). For example, music retailers and optometrists in the contact lenses industry have been affected by the growth of e-commerce (Atkinson, 2001). As the primary product for each intermediary evolved and became more conducive to e-commerce, consumers stopped using the intermediary. For the contact lenses industry, the creation and subsequent popularity of disposable lenses meant contact wearers needed fewer eye examinations than previously. Without the need for frequent eye exams, many contact wearers prefer to avoid the price markup associated with purchasing contact lenses through an optometrist. In the music industry, most consumers now prefer digital versions of music, which do not require a music store and can be easily downloaded from a computer or smartphone. Since the early 2000s, one industry that has been particularly plagued by disintermediation due to e-commerce is the travel industry (Tse, 2003). Traditionally, consumers paid travel agents a fee to help them arrange their travel plans, including providing recommendations and making reservations. However, the growth of the Internet has enabled consumers to perform research independently and make reservations with travel companies directly. This allows consumers to bypass traditional travel agents and avoid paying their commissions. Another industry that experienced massive disintermediation with the growth of e-commerce is the book industry. Online book retailers have lower operational costs and are able to sell books globally, which creates a challenging competitive environment for traditional book retailers (Miles, 2011). Book publishers have also been cut out of the supply chain because of e-commerce, which has facilitated the development of digital books. This new form of book consumption has given authors the ability to bypass traditional publishing companies and self-publish digital versions of their work, for which they receive higher margins (Waldfogel & Reimers, 2015).

Potential solutions to disintermediation

Intermediaries that provide value but still experience disintermediation from opportunistic suppliers should shift their focus from short-term profits to building mutually beneficial long-term relationships with their suppliers (Rossetti and Choi 2005). By treating suppliers as business partners, rather than interchangeable entities, OEMs can expect suppliers to forgo short-term gains in order to receive the long-term benefits from the supplier-OEM relationship (Liker & Choi, 2004). To do this, OEMs should avoid frequent supplier switching, high-pressure tactics, and inflexible contracts requiring annual price decreases with suppliers (Rossetti & Choi, 2008).

By contrast, traditional intermediaries that have experienced disintermediation due to e-commerce often must completely transform their services in order to continue to provide value (King, Sen, D'aubeterre, & Sethi, 2010). For example, intermediaries have begun to return to the travel industry in the form of online travel agents, who offer services (e.g., hotel and airline reservations) to consumers (Law, Leung, Lo, Leung, & Hoc Nang Fong, 2015).. This new type of intermediary provides value to both consumers and travel companies (hoteliers, airlines etc.) - consumers can conveniently compare travel options, and companies obtain an additional market channel. Some travel intermediaries have successfully leveraged e-commerce to provide services that were previously unavailable. For example, they have developed websites that are dedicated to distributing hotels' last-minute excess inventory to consumers at a reduced price to the consumer (Buhalis & Licata, 2002). The most well known low cost travel intermediary is Priceline, who, like other low cost travel intermediaries, operates using a reverse auction form on their website and mobile app (Anderson, 2009). Consumers enter information regarding the hotel services they require and the price they want to pay on Priceline's website, and Priceline matches them with a specific hotel. Previously, people in need of a last minute hotel would have to call individual hotels to find a room, but these intermediaries make it simple for a customer to book a room and for hotels to fill excess demand.

Intermediaries can still be successful in the book publishing and retail industry, but this will require a shift in the intermediary's business model to ensure that it is providing value to both authors and consumers (Waldfogel & Reimers, 2015). Rather than providing traditional publishing services, intermediaries should now consider facilitating self-publishing services for authors. They should also consider providing new retailing services, such as selling digital books that consumers can purchase directly from their electronic reading devices. For example, Amazon has transitioned from being a physical book retailer to offering publishing and retailing services for digital books.

Another solution for traditional intermediaries that are unable to shift to an e-commerce business model is to leverage expert knowledge that cannot be replicated by another supply chain member (Shunk, Carter, Hovis, & Talwar, 2007). For example, travel agents can focus on making travel arrangements that most customers would find difficult to arrange independently, such as group travel or travel to destinations requiring visas. In the book industry, McGraw Hill is working with professors to customize existing textbooks to meet the specific needs of their courses and reduce costs for students (Shunk, Carter, Hovis, & Talwar, 2007).

Disintermediation in regional food systems

As with distributors in other industries, regional food distributors report that they often experience disintermediation. Local Food Marketplace, a software vendor for regional food hubs (localfoodmarketplace.com), notes that disintermediation by producers is a common challenge experienced by food hub managers (McCann & Crum, 2015). Food hubs experience disintermediation when producers sell directly to food hub customers after the hub forged the relationship. In talking to both producers and food hubs, McCann and Crum (2015) found three frequently-cited reasons for food hub disintermediation: 1) the food hub is not meeting the producer’s expectations, 2) the producer is undervaluing the services provided by the hub, or 3) the food hub is not working with producers who are a good fit for their hub. Although producers avoid paying the food hub’s service fees by selling directly to customers, if enough producers sell around the hub, the food hub is at risk of financial failure. Without a food hub, producers may struggle to market and distribute their products independently. In fact, food hub disintermediation potentially threatens the survival of the entire regional food system.

To help food hub managers address this problem, Local Food Marketplace has provided both formal and informal recommendations for preventing producers from selling around the food hub (McCann & Crum, 2015). Formally, they advise food hubs to create producer contracts that consider the risks incurred by both producers and the food hub. Some issues the contact might include are: quality issues, market based price fluctuations, volume and supply issues, and contract breaches. The food hub should review the contract with producers prior to signing. The contract should be crafted specifically for the hub and be written in language that can be understood by a layperson. Additionally, the contract should specify how any contract breaches by either party are to be handled. The food hub should update the contract annually, as the hub grows and changes. Informally, Local Food Marketplace suggests that food hubs make strategic decisions regarding which producers to work with. After carefully selecting producers, food hubs should engage in conversations with the producers about their expectations, and they should strive to exceed, these expectations and establish value. If producers undervalue food hub services, food hubs can use info graphics, such as pie charts, in conversations with producers to break down the hub's pricing structure and demonstrate financial benefits (Crum, 2015). If a producer does not see value in the hub and sells around the hub purposefully, Local Food Marketplace recommends ending the business relationship with the producer and finding new sources for their product.

Agent-Based Modeling

Agent-based models (ABMs) are computer simulation models that are composed of autonomous agents that are situated in an environment and interact with one another (e.g., by sharing information or performing commercial transactions) while following simple rules and adapting (Macy & Willer, 2002). Agents are defined by four criteria: attributes, goals, decision-making rules, and an ability to learn. These agents can represent animals, people, or businesses (Macal & North, 2008). Their attributes can be simple or complex. Simple attributes include demographic information, such as age, income, and gender for agents representing people, or annual revenue, number of employees, or number of customers for business entity agents. More complex attributes could include purchasing history, purchasing preferences, or lists of customers.

Each agent has one or more goals that it strives to achieve (Macal & North, 2008). Agent goals must be measurable, but need not be the same for each individual agent or agent class. Common agent goals include maximizing sales earnings and minimizing effort in completing a task. A performance measure (e.g., sales earnings, required effort) is assigned to each goal to help an agent assess how well it is meeting its goals.

In an effort to achieve its goals, each agent will use a set of decision-making rules. Decision-making rules for an agent need not be complex, but rather rules like social conventions and heuristics (Macy & Willer, 2002). These simple rules at an individual level can bring about complex behavior at a system level, which is an advantage of using ABM. During the simulation, the agent will assess the current state of its performance measures and other aspects of its current state and execute the appropriate decision-making rule to continue working towards its goal.

Additionally, an agent's decision-making rules may change throughout a simulation run. This adaption reflects the agent's ability to use its memory to learn from experience and modify its behavior accordingly to better meet its goals (Macal & North, 2008). Adaption can occur at either the individual or population level. At an individual level, an agent may learn through Bayesian updating or reinforcement, but at the population the learning may be through evolutionary processes of selection or imitation (Macy & Willer, 2002). Once all agents are defined properly, they are placed in an environment together. The system is simulated over time, and outputs of interest are measured to ascertain the overall system behavior.

ABM is particularly advantageous for providing insight into complex adaptive systems. In complex adaptive systems, no one individual exerts controls over the system (Choi, Dooley, & Rungtusanatham, 2001). The overall observable system behavior results from the entirety of multiple autonomous individuals making individual decisions. Since the system behavior emerges from many individual decisions and actions over time, it can be difficult to predict and control. ABM captures the emergent system-level outcomes in systems composed of heterogeneous, autonomous, and interacting agents acting without centralized control (Bonabeau, 2002). The emergent outcomes are more than simply the sum of each individual's behavior, as the relationship between individuals is nonlinear and dynamic (Pathak, Day, Nair, Sawaya, & Kristal, 2007).

For a system dependent upon human behavior, ABM is the natural choice since it provides a simulation that is close to reality (Bonabeau, 2002). Additionally, ABMs provide flexibility to the modeler and can be altered in multiple ways for experimental purposes

(Bonabeau, 2002). Alterations could be adding or removing agents, changing the decision-making rules for some agents or all agents, or changing the adaptability of the agents.

One advantage of ABM is normative understanding, where modeling is used to ascertain results from certain policies and designs (Axelrod & Tesfatsion, 2005). It enables the modeler to test different strategic policies and system scenarios in a model. This helps the modeler gain a better understanding of the impacts of their decisions and allows them to change their policies to obtain the system outputs and outcomes that best match their objectives (North & Macal, 2007).

ABM applications

ABM can be used in a variety of application areas, including biology, social sciences and economics, and business and technology. Biological applications include studying ecosystems and disease transmission. Invasive species, such as the crucifer flea beetle, have been simulated in ABM (Ameden, Boxall, Cash, & Vickers, 2009). The authors created a model consisting of U.S./Mexico ports of entry, broccoli shipments, and crucifer flea beetle. The model provided insight to the economic impact of various border enforcement policies. Perez and Dragicevic (2009) studied the spread of measles by integrating geographic information systems (GIS) in an agent-based model of a human population located in Burnaby, BC, Canada. The agents in the model performed daily activities like working or going to a shopping mall, and through these activities are potentially exposed to measles. The simulation proved useful to better understanding disease outbreaks and how to prevent them.

Social scientists also use ABM in their research. Epstein (2002) used ABM to study the dynamics of civil violence. Epstein created two types of models: one in which a central authority attempts to suppress a rebellion, and another in which the central authority attempts to suppress violence between two groups. The models provided a better understanding of the complex behavior involved in decentralized rebellion and can be used to test the effectiveness of different policies to prevent violence. One specific area of the social sciences utilizing ABM is economics. For example, the stock market has been simulated using an ABM. NASDAQ utilizes ABMs to understand the effects of changing trading policies before they are implemented (Bonabeau, 2002).

ABM has been utilized in the business field, and it is well-suited to supply chain management due to its ability to model complex adaptive systems. Supply networks are complex adaptive systems, where each individual member of the network attempts to maximize its own profit by selling and purchasing products with other individuals (Choi, Dooley, & Rungtusanatham, 2001). Akanle and Zhang (2008) studied how ABM could be used to help manufacturers optimize supply chain configurations. Agents in their model are tasked with choosing the best resource allocation combination to meet customer orders over a period of time. Jiao, You, and Kumar (2006) proposed using ABM to model negotiation between members of a global manufacturing supply chain. The model will help an organization make negotiation decisions when contracts with multiple autonomous suppliers are being negotiated concurrently.

Reinforcement Learning

Humans do not behave or make decisions perfectly rationally (Gigerenzer & Selten, 2002). When modeling human agents, using heuristic decision-making rules can reflect real human decision-making. One heuristic learning method is reinforcement learning, which is a machine learning technique in which an agent attempts to maximize the rewards it receives over time from the decisions it makes (Sutton & Barto, 1998). Agents receive higher rewards for good behavior, and smaller rewards for bad behavior. The agent aims to maximize its total long-run reward, which is a sum of the individual rewards it receives from each action it chooses to take in a sequential decision process, also known as a Markov decision process.

Markov decision processes

A Markov decision process involves sequential decisions in which the outcome involves randomness (Puterman, 2014). The decision maker works towards developing a decision-making policy that generates the most rewarding outcome for the decision maker. A Markov decision process includes five components: decision stage, actions, states, transition probabilities, and rewards. In discrete time Markov decision processes, decisions are made between time periods and the decision triggers the next time period. The point at which a decision is made is the decision stage of the process. At each point a decision is made, the decision maker exists in a unique state. When a decision is made, the decision maker either remains in the same state or moves to another unique state. The next stage of the decision maker depends on the action they choose while making a decision. Similarly, the actions available to the decision maker depend on the current state they occupy. Once an action is chosen, the resulting state is determined by the transition probability. An action may have a stochastic or deterministic outcome. Finally, once a decision maker moves to a state, they receive a reward value associated with the given state.

There exist two categories of methods that solve Markov decision processes and develop optimal decision-making policies (van Otterlo & Wiering, 2012). The first category is model-based algorithms, known as dynamic programming. These algorithms require that a model of the process be known and used to compute policies. The second category of algorithms is model-free, also known as reinforcement learning. In reinforcement learning, the decision-maker has no model or knowledge of the system and instead uses interactions with the environment to develop optimal policies.

Q-Learning

Since a decision maker using reinforcement learning has no knowledge of the system, the agent must use a trial and error search to find the most rewarding actions in the long term (Sutton & Barto, 1998). Agents will begin to be able to differentiate good actions from poor actions by interacting with the environment and observing state transitions and the rewards associated with them. In order to develop a good policy, the agent must both exploit the current knowledge it has from interacting with the system and explore other actions to make better decisions in the future. By exploiting its current knowledge of the system, the agent can ensure that its immediate action yields a relatively high reward, but in order to improve its understanding of the potential rewards for each action, exploration is needed. Upon convergence, the agent has developed a policy to guide its decision making in the system.

One popular reinforcement-learning algorithm is the Q-learning algorithm. The Q-learning algorithm iteratively updates Q values, which store the values for each state s and action a as Q(s,a). The Q values are used to estimate the value of each action for an agent in a given state, where an agent prefers to select actions that yield the highest possible Q(s,a) (Watkins, 1989).

In order for the agent to explore, it must not solely exploit its knowledge of the system. To balance the exploration and exploitation, an ε-greedy method can be used (Tokic, 2010). In this method, ε is a probability between 0 and 1 chosen by the modeler, which dictates how often the agent will select a random action rather than the action with the highest value. The ε-greedy method is shown in Equation (1), where π(s) represents the action selected. If the uniform random number between 0 and 1, x, is less than ε, a random action from the set of actions A(s) is chosen. If the random number, x, is larger than ε, the greedy action is chosen. The greedy action is the action with the largest value in A(s).

$$\pi(s) = \begin{cases} random\ action\ from\ A(s) & if\ x < \varepsilon \\ argmax_{a \in A(s)}\ Q(s,a) & otherwise \end{cases} \tag{1}$$

In order to choose the greedy action, the agent must have Q-values that update as it moves through the Markov decision process. Q values are updated using the Q-learning algorithm, which corrects the Q value to reflect new information gained throughout a simulation. The algorithm is shown in Equation (2) (Sutton & Barto, 1998):

$$\mathrm{Q}(\mathrm{s_t}, \mathrm{a_t}) \leftarrow \mathrm{Q}(\mathrm{s_t}, \mathrm{a_t}) + \alpha(\mathrm{r_t} + \gamma \mathrm{max_a} \mathrm{Q}(\mathrm{s_{t+1}}, \mathrm{a_t}) - \mathrm{Q}(\mathrm{s_t}, \mathrm{a_t})) \tag{2}$$

This algorithm updates the Q values by first adding the immediate reward (r_t) received by the agent upon arriving in a state to the discounted goal Q value. The discount rate, γ, is a number between 0 and 1. The discount rate reflects how long the agent is willing to wait for a long-term reward. A small value for γ indicates that an agent will choose actions that yield high immediate rewards. Next, the current Q value (i.e., the value of Q at time t) is subtracted. This quantity is then multiplied by the learning rate α, which determines how much weight the agent places on information recently gained. The learning rate is a number between 0 and 1. A learning rate of 0 means the agent will never learn and a learning rate of 1 means the agent will only consider the most recent information. Finally, this entire quantity is added to the current Q value, which creates an updated Q value. This updated Q value replaces the current Q value in the next time-step. The process is then repeated each time an agent receives a reward/punishment for taking an action.

Reinforcement learning in ABM

Reinforcement learning (RL) has previously been utilized in agent-based models to inform agent decision-making. RL's use in ABM has not been limited to a specific discipline. In an effort to improve decision-making for shipyard crane operators, Fotuhi, Huynh, Vidal, and Xie (2013) integrated reinforcement learning into an ABM of a shipyard. The authors aimed to improve decision making such that the operators choose to service trucks in a sequence that minimizes the waiting time for the trucks. The model was created in NetLogo, an ABM platform, and each crane operator agent was modeled to use Q-learning as its decision making rule. The model results show the Q-learning model is effective in improving the decision making of the crane operators. The authors envision that the model could be used as a tool for the crane operators in the real system to automate decision-making and improve yard operations.

Reinforcement learning has also been used to model systems in which agents have conflicting objectives. Bone and Dragicevic (2010) used reinforcement learning in their ABM to improve the ability of the model to determine optimal forest harvesting strategies among agents with conflicting goals. Their study consists of two stakeholders with differing objectives who attempt to achieve a single management strategy for the system. Each stakeholder is modeled as an agent and through reinforcement learning learns which strategies lead to cooperation between agents. The model and its outputs are useful for the stakeholders in forest management to understand the impact of possible management strategies and can lead to better forest management decision-making.

Reinforcement learning has also been integrating into agent-based models of supply chains. Q-learning has been used to represent supplier decision making in a manufacturing supply chain model (Valluri & Croson, 2005). In this model, the authors seek to determine how to select suppliers who consistently produce high quality goods. To do this, a single buyer agent places orders for products from multiple supplier agents. Suppliers who provide high-quality products receive rewards. Next, each supplier uses Q-learning to determine the quality level of its next batch of products for the manufacturer. The supplier can choose quality levels ranging from their individual maximum quality to low quality levels. As the simulation runs, the suppliers that are capable of producing high-quality products and have learned to do so consistently distinguish themselves from other suppliers. Using this model, the authors develop an optimal supplier selection policy for the buyer agent.

CHAPTER III

AGENT-BASED MODEL

A regional food hub in Iowa ("Western Iowa Food Hub") provides transportation and marketing services for regional food producers across Iowa and eastern Nebraska. These producers list their products on the hub's website, where customers select which products they want to purchase through the hub. Customers purchase products on a weekly basis, which represents one order cycle for the food hub. At the end of an order cycle, the food hub picks up customer orders from the producers and delivers them to customers. Western Iowa Food Hub primarily sells to wholesale customers (e.g., restaurants and grocery stores) that are concentrated in the metropolitan areas that encompass Omaha and Des Moines. The food hub strives to help small and midsize producers reach new markets, as well as helping customers meet their demand for regionally-produced food. The food hub's services allow some producers to sell products to customers that are distant from their farms.

Despite its mission to be a key supply chain partner to small and mid-sized farmers, Western Iowa Food Hub is experiencing disintermediation. The food hub manager has noticed that after having fulfilled orders between certain producers and customers, the producers have begun selling products directly to those customers, thereby cutting out the hub. These same producers have continued to use the food hub's services to sell products to other customers. The food hub manager believes the producers are initiating transactions around the hub to the food hub customers. The manager is extremely concerned that if more producers choose to sell products around the hub, the hub will no longer be financially viable. If the food hub fails, all of the hub's producers will be forced to either deliver their products via their own transportation, make separate transportation arrangements, or lose customers. The manager has attempting to curb this behavior by asking new producers to sign an agreement in which they promise not to sell around the hub. However, she is unsure it of its effectiveness and does not know how to prevent this behavior.

This section describes a conceptual agent-based model based on a case study regional food system. The model was developed in NetLogo (version 5.3). A standard protocol is useful when describing agent based model, which can be a lengthy process. This section uses the Overview, Design concepts and Details (ODD) protocol proposed by Grimm et al. (2006).

Purpose

Ideally for the food hub, all producers would sell all products intended for food hub customers using the food hub's services, rather than selling directly to those customers. The purpose of model is to demonstrate how an ABM can be used as a tool for the Western Iowa Food Hub manager and other food hub managers to evaluate the effectiveness of various management strategies in preventing producers from selling around the hub. Using an ABM allows the manager to understand the impact of a management policy without assuming any of the risks of actual implementation. In addition to studying the effects of management strategies, modeling the case study supply chain in an ABM also allows the modeler to examine whether the food hub is necessary for small and mid-sized producers to be successful. If the food hub is not necessary for those producers to be successful, then it might not be a viable business entity in its current form.

Entities and Variables

The regional food supply chain where the case study hub is a participant has three main actors: producers, customers, and the food hub. In the ABM, the producers and customers are modeled as agents. The food hub also represented by an agent, implements management strategies for the system. This model is based on the assumption that the decision to sell products around the hub is initiated by a producer (rather than a customer), in an attempt to increase their profits. In each time-step, the producer agents choose what they believe will be the most profitable market channel for their products: through the hub, directly to customer agents, or some combination. By contrast, the customer agents have a passive role. They will not initiate a transaction around the hub, but if they are prompted by a producer agent, they will evaluate whether they want to accept the producer agent's offer to purchase products directly.

The model environment consists of two metropolitan areas that are equal in size, each being 9 units in width and 9 units in length. Figure 1 shows the model environment, where the metropolitan areas are shaded gray. Each geographical unit represents approximately 5 minutes of driving distance. The metropolitan areas are Omaha and Des Moines and are located on the far left and far right of the model space, with 23 units located between the centers of each metropolitan area. Connecting the cities is an interstate, which runs directly between the two areas.

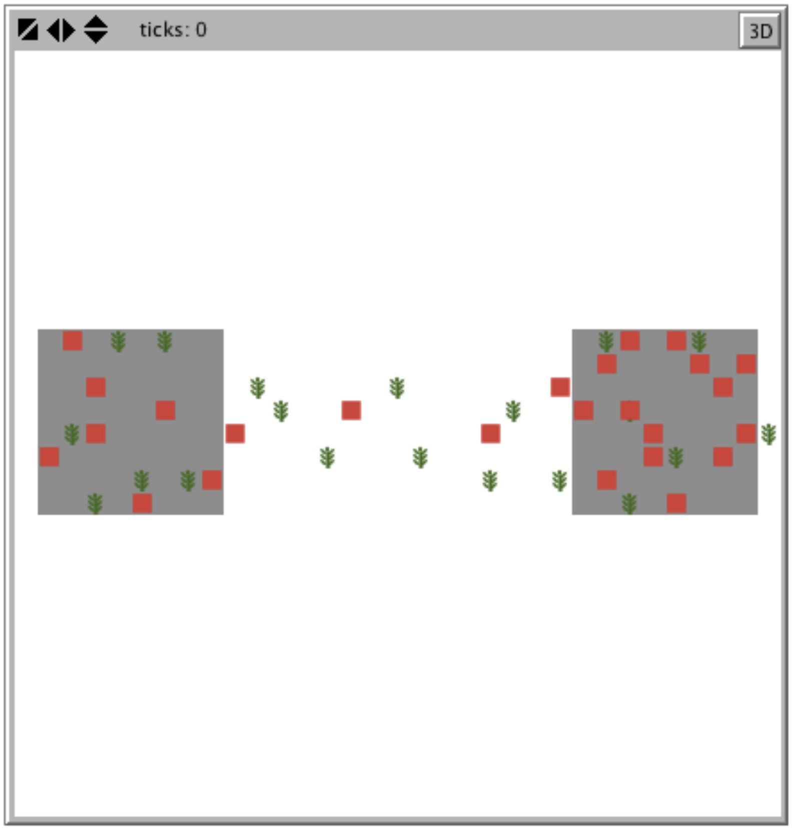


Figure 1. *Agent based model space*

Food hub agent

There is one food hub agent in the model, representing the case study food hub. The food hub agent aggregates and delivers products to customer agents on a weekly basis, corresponding to one order cycle. The food hub agent will always purchase products from the food hub producer agents if they have supply available at the end of the order cycle. The food hub will also always fulfill any demand for the customer agents at the end of an order cycle using the supply they purchased from producer agents. The food hub has the ability to detect when producer agents sell products around the hub to food hub customer agents, and respond to the behavior by employing a management strategy.

Producer agents

There are 20 producer agents in the model, which is roughly the number of regularly active producers in the case study system. The producer agents in the model are represented by green plants in Figure 1. These producer agents have previously sold products through the food hub agent, and all relationships they have with customer agents were created through using the food hub. Currently, the food hub agent will accommodate entirety of supply each producer produces each order cycle, so producer agents do not experience competition when selling through the hub. In this theoretical model, there is only one type of food item sold by the producers and demanded by customer agents, and each item is priced the same. In order to keep food hub transportation costs low, the case study food hub manager requires her producers to be located in or around one of the two metropolitan areas or along the interstate. If a producer is not located in one of those areas and wants to do business with the food hub, that producer must be willing to meet the food hub's truck near the interstate. Due to these food hub restrictions, the producer agents in the model are arbitrarily located in the metropolitan areas or close to the interstate (within two units). Six producer agents are located in Omaha, an additional six are located in Des Moines, and eight producer agents are located along the highway shown in Figure 1.

The producer agents are categorized into three sizes, based on the number of products the producer agent has available for purchase through the food hub for one order cycle. Each order cycle in the model is one week long; the same length as the case study order cycle. The breakdown of producer agents belonging to each size is shown in Table 1. Producers are encouraged by food hubs to reduce their business risk and utilize other market channels (e.g., farmer's markets) in addition to using the food hub. The case study food hub is also unconcerned with any sales the producer makes to food hub customers with whom they have a relationship that existed prior to their working with the food hub. Therefore, the items available to the food hub agent and food hub agent's customers do not represent the entirety of the producer agent's yield. It is assumed that each small, medium, and large producer agent can supply a maximum of 100, 200, or 300 units, respectively to the food hub agent in each order cycle.

Table 1. *Producer agent size summary*

Producer Agent Size	Items Available Per Cycle	Number of Producer Agents
Small	100	4
Medium	200	6
Large	300	10

It is assumed that the producer agents are unable to communicate with one another directly, and do not know what actions other producer agents are taking.

Customer agents

There are 25 customer agents in the model, which are represented in Figure 1 by red squares. These customer agents purchase local food items through the food hub agent to sell to their own customers. Each customer agent allocates 100, 200 or 300 units of local food in their operation each cycle and the size distribution is shown in Table 2. These agents are primarily located randomly within Omaha and Des Moines. A few customer agents are located along the interstate, as the case study food hub manager will do business with customers located near the highway. The Omaha area includes 12 customer agents, the Des Moines area includes 14 customer agents, and four customer agents are located within two units of the highway.

Table 2. *Customer agent size summary*

Customer Agent Size	Items Demanded Per Cycle	Number of Customer Agents
Small	100	11
Medium	200	7
Large	300	7

Some real life food hub customers choose to use a food hub to purchase local food items so they can avoid working with individual producers. It is assumed that these customers will be unwilling to buy products directly from producers. Therefore, each customer agent is assigned a value that represents its willingness to work with producer agents. The values for customer agent buying preference fall between 0 and 9, where values less than 5 mean the customer agent is unwilling to order items directly from producer agents and values 5 and greater mean the customer agent is willing to order directly from producer agents. These values are randomly assigned to customer agents and summarized in Table 3.

Table 3. *Customer agent buying preferences summary*

Customer Agent Buying Preference	Values	Number of Customer Agents
Unwilling to work directly with producer agents	0-4	14
Willing to work directly with producer agents	5-9	16

Model Overview

This section provides an overview of the model for one time step, where one time step is equivalent to one order cycle. Producer agents use reinforcement learning to decide how much of their product to attempt to sell around the food hub to the customer agents in each time-step. After the producer agent makes its decision, it will either begin to offer customer agents direct sales offers or proceed to sell all products to the food hub agent. When a producer agent makes its first sales offer, it will always offer the entirety of products it allocated to sell around the hub. Subsequent sales offers will be the entire amount the producer agent allocated leftover after the products sold through earlier offers are subtracted. Producer agents will only make sales offers to customer agents belonging to its customer list. This customer list is a list of customer agents within a specified radius of the producer agent, representing how far the producer agent is willing to travel to make a direct sale.

When a customer agent is approached by a producer agent with a sales offer, the customer agent will determine if it wants to purchase items directly from the producer agent and if so, how much of the product they will buy. The customer agent may choose to purchase all that was offered to them, a partial amount of the offer that meets their demand, or reject the producer agent's offer outright depending on if they have unfulfilled demand and if they are willing to work directly with producer agents as described by their buying preferences.

If a producer agent's offer was rejected or was only partially accepted, it will approach the next customer agent in its customer list with an offer to purchase the remaining product. This customer agent will follow the same decision making procedure as the first customer agent. The producer agent will continue to make offers to customer agents in its customer list until no product remains to be sold around or they have approached all customer agents once.

As the order cycle concludes, each producer agent that sold around the hub may have its behavior detected by the food hub agent based upon the amount the producer agent attempted to sell around. Next, the food hub agent will extend punishments or rewards to each producer agent based upon the producer agent's action and whether or not it was caught selling around the hub. The rewards/punishments resulting from the food hub agent response, combined with producer agent revenue create an overall reward for the producer agent in a given cycle. This overall reward is used within the reinforcement learning algorithm, which informs producer agent decision-making. The flowchart in Figure 2 summarizes one time step of the model.

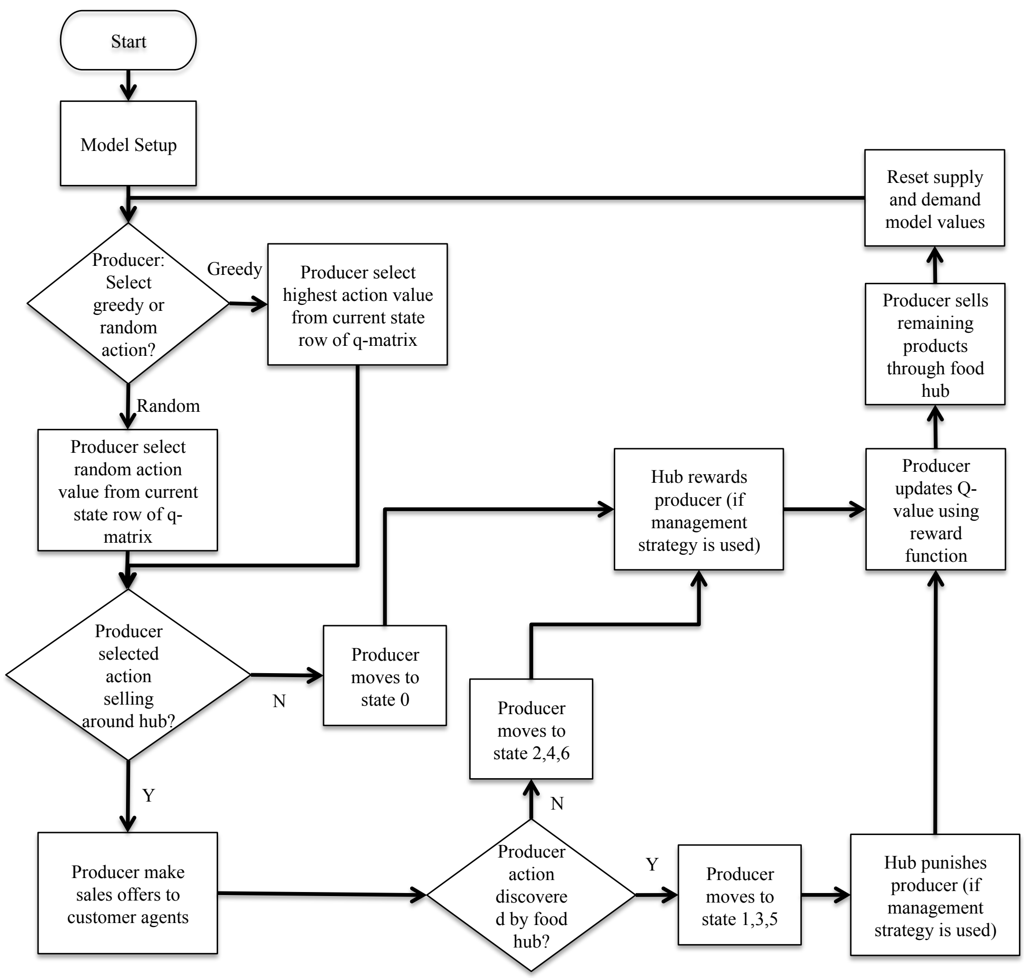


Figure 2. *Flowchart summarizing one model time step*

Tables 4 and 5 summarize all parameters and variables used in the model.

Table 4. *Model Parameters*

#	Parameter	Description	Possible Values	Source of Values
1	producer_number	Unique identification number for producer agents	0-19	-
2	initial-supply	Quantity of products each producer agent allocates for the food hub or food hub customers each cycle	100, 200, 300	Assumption
3	initial-demand	Quantity of local food products each customer agent purchases each cycle	100, 200, 300	Assumption
4	customer_number	Unique identification number for customer agents	0-24	-
5	direct-value	Willingness of customer agents to work with individual producer agents	0-9	Assumption
6	tcost	Transportation cost rate for producer agents selling directly to customer agents	9	Assumption
7	fhrate	Rate for food hub agent services	20%	Case Study
8	alpha	Learning rate (Q-Learning algorithm)	0-1	Experimentation
9	y	Discount factor (Q-Learning algorithm)	0-1	Experimentation

Table 5. *Model Variables*

#	Variable	Description	Possible Values
1	supply	The current number of items a producer agent has to sell through the hub	0-300
2	none-list	Q-value list for none state	0-1000
3	Attempt25-Caught-list	Q-value list for Attempt25-Caught state	0-1000
4	Attempt25-Success-list	Q-value list for Attempt25-Success state	0-1000
5	Attempt50-Caught-list	Q-value list for Attempt50-Caughtstate	0-1000
6	Attempt50-Success-list	Q-value list for Attempt50-Success state	0-1000
7	Attempt75-Caught-list	Q-value list for Attempt75-Caughtstate	0-1000

***Table 5.** (continued)*

8	Attempt75-Success-list	Q-value list for Attempt75-Success state	0-1000
9	sold-produce	Number of items a producer agent sold directly to customer agents	0-300
10	final-travel-distance	Sum of distances from a producer agent to the producer agent's direct sales customer agents	0-250 units
11	current-state	The current state of the producer agent in the model (None, Attempt25-Caught etc)	0,1,2,3,4,5, or 6
12	next-action	The action selected by the producer agent while in the current-state (ex: Attempt to sell 25% items around hub)	0,1,2, or 3
13	next-state	The subsequent state of the producer agent in the model based upon the next action and food hub agent detection (None, Attempt25-Caught etc)	0,1,2,3,4,5, or 6
14	around?	Customer agent variable indicating if they purchased items around the hub in a given cycle	0 or 1
15	demand	The current number of local food items a customer agent wants to purchase	0-300
16	hub-supply	Number of products the hub agent receives from producer agents to sell to customer agents each cycle	1150-4600
17	time	Number of time steps in model	0-∞

Sub-Models

The model is comprised of several sub-models. The first sub-model, Initialization and Set-up, will run only once at the start of each simulation. The other sub-models, Reinforcement Learning, Sell Remaining Products Through Hub, and Reset Values, are run each time step.

Initialization and set-up

First, the two metropolitan areas are created in the model environment shown in Figure 1. Next, the producer and customer agents are created and placed in the model environment. When the producer agents are created, they are placed in their assigned locations and have their supply set to the assigned value shown in Table 1. Since producer agents use Q-learning to make decisions, they each have a matrix of q-values represented by seven lists with four values in each list. All values in the q-value lists are set to 1000 initially, which provides the producer agent time to explore actions during the simulation runs. Setting the q-values to 1000, which is significantly higher than where the q-values will end, prevents the producer agent from getting caught in a local maximum early in the simulation. The customer agents are also created and placed in their assigned locations and have their demand set to the assigned value, based on their size shown in Table 2. Each customer agent is also given their assigned buying preference value described in Table 3, which indicates whether the customer is willing to work directly with producer agents Once the model environment, producer agents, and customer agents are created, the model is ready for the food hub selling cycles to begin.

Reinforcement learning

Producer agents use Q-learning, described in the previous chapter and shown in Equation (3) to decide how they will sell their products in a given cycle. Producer agents use the equation to update their q-value matrix, which represents the expected value of choosing a specific selling action. Each time step, the producer agents receive a reward, r_t and add it to a discounted optimal future reward estimate. They then subtract the previous q-value from this “learned value” and multiply it by a learning rate, α. This value is then added to the previous q-value and replaces the previous q-value in the matrix. Producer agents use a greedy rule to choose their action as the q-values update. The specific greedy rule is described in detail in the next section.

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_t + \gamma \max_a Q(s_{t+1}, a_t) - Q(s_t, a_t)) \tag{3}$$

First, the producer agents use a greedy rule to choose an action to take. Next, they execute the action, which results in the producer agent moving to the next state. After reaching the next state, the producer agent receives the associated reward with the next state and updates its q-value. To update the q-value, the producer agent uses the q-value list of their previous state and selects the value in the list that corresponds with the selected action. The q-value updated is the using Equation (3). This process repeats for every selling cycle. The following sections break down the reinforcement learning process for producer agents.

Make selling decision

Producer agents have four possible actions to choose from each order cycle: selling no products around the hub, offering 25% of their products directly to customer agents (i.e., around the hub), offering 50% of their products directly to customer agents, or offering 75% of products directly to customer agents. These possible actions are shown in Table 6.

Table 6. *Producer agent action number key*

#	Producer Agent Action
0	Sell all items through hub
1	Attempt to sell 25% items around hub
2	Attempt to sell 50% items around hub
3	Attempt to sell 75% items around hub

Producer agents will choose their next action greedily 90% of the time, and the other 10% they will randomly choose between the four possible actions. If the producer agent is choosing the greedy action, it will find the highest q-value in the list corresponding to its current state and proceed with that action. For each producer agent, a random number between 0 and 99 is generated. If the number is larger than 9, the producer agent proceeds with the greedy action; otherwise, it chooses a random action. During the first selling cycle, if the producer agent chooses the greedy action, it will select the first action in its q-value list. The first action in each list is selling all products through the hub.

Producer agents execute actions

Producer agents that chose to sell a portion of their products around the hub agent will next begin offering to sell products directly to customer agents. Producer agents that choose not to sell any products around the hub will not make any sales offers to customer agents and move directly to the next sub-model: determining their next state.

It is assumed that the producer agents prefer to sell directly to customer agents located closest to them. By selling to customer agents near their facility, producer agents can reduce the labor, time, and costs needed to transport products directly to customer agents. Due to this preference, when producer agents make the decision to sell around the hub, they will begin making sales offers to customer agents closest to them. The producer agents will offer the entire amount they intend to sell around the hub to the customer agent.

The customer agent then has three options: accept the entire amount, accept a partial amount, or reject the offer outright. The customer agent will accept the offer if it is willing to work directly with producer agents and has remaining demand to be filled. If the customer agent is going to accept and has enough demand to accept the entire order, it will do so. Otherwise the customer agent will accept an amount that will fill its remaining demand. If a customer agent has no remaining demand or is unwilling to work directly with producer agents, it will reject any offer outright. When a customer agent purchases products directly from a producer agent it will update its demand value to reflect the number of products it purchased.

If the producer agent's closest customer agent rejects its offer, it will make an offer to the next closest customer agent, and so on, until it has no supply remaining or it has exhausted all selling options. Whenever a producer agent makes a direct sale to a customer agent, it will reduce its supply value by the number of products they sold and increase its sold-produce by the same number. The producer agent will also calculate the distance to customer agent to whom it sold products and add it to its final-travel-distance value. The largest producer agents have the first opportunity to make sales offers to customer agents, followed by the smaller producer agents. Larger producer agents have more employees and resources, giving them the ability to make and execute their selling decisions quickly. If producer agents are of the same size, the tie is broken randomly. The producer agents are all attempting to sell their products to the same set of customer agents, so it is possible that a producer agent that attempts to sell products around the hub will end up being unsuccessful. Any products the producer agent is unable to sell around the hub will be sold through the hub. For each successful sale around the hub, the producer agent sums the distance to all the customer agents to whom they sell directly in a selling cycle. This sum (final-travel-distance) is used in assessing the rewards for the producer agents.

Determine next state

Once every producer agent has selected and executed its preferred action, that action will result in one of seven possible states, as shown in Table 7. For example, if a producer agent chooses the action “Attempt to sell 50% of items around hub” and their behavior was detected by the food hub agent, they would move to state Attempt50-Caught, also known as state 3. After an action to sell items around the hub is executed, the producer agent will either be discovered or go undiscovered by the hub agent. If the producer agent sells all products through the hub, the producer agent will move directly to the state associated with no sales around the hub (i.e., State 0).

Table 7. *Producer agent resulting state summary*

Action	Discovered by hub?	Resulting State	State #
Sell all items through hub	N/A	None	0
Attempt to sell 25% items around hub	No	Attempt25-Caught	1
	Yes	Attempt25-Success	2
Attempt to sell 50% items around hub	No	Attempt50-Caught	3
	Yes	Attempt50-Success	4
Attempt to sell 75% items around hub	No	Attempt75-Caught	5
	Yes	Attempt75-Success	6

Producer agents that sell around the food hub agent are more likely to be discovered when they offer a larger percentage of their items to customer agents. The amount offered and the likelihood of getting discovered are correlated because the hub agent is more likely to notice when a producer agent sells a greater number of products around the hub agent. The food hub agent knows how many products a producer agent has allocated to sell through the hub, so a producer agent selling a relatively small amount will be perceived to be acting suspiciously to the food hub agent. Additionally, even if the offers to customer agents were unsuccessful, there is a relatively higher number of customer agents who may share the producer agent's action with the hub agent. The likelihood of getting caught is assumed to have a linear relationship with the amount the producer agent attempts to sell around the hub agent. When producer agents offer 25%, 50% and 75% of their products around the hub, they have a 25%, 50% and 75% chance, respectively, to be discovered by the hub agent.

Assess rewards

The producer agent will receive a reward based on the state that results from its action and how the food hub agent responds to if it detects a producer agent selling around the hub. The reward is also dependent upon the customer agents' response to the producer agent's action. The food hub agent may choose to employ a management strategy to respond to disintermediation. Management strategies can either financially reward loyal producer agents or financially punish producer agents who sell around the hub. In this model, the food hub agent can use one of three strategies. Each management strategy will use a different reward equation to calculate the reward for producer agents.

Baseline Strategy- The baseline strategy is the management strategy currently employed by the case study food hub. Under the baseline management strategy, the producer agents are not punished in any way for selling products around the hub. The reward structure is that producer agents earn 80% of the profit on items sold through the food hub, since the food hub charges a rate of 20%. For products successfully sold direct to customer agents, the producer agents receive 100% of the profit. For one item sold, 100% profit would earn the producer agent one point. Therefore, an item sold through the hub earns the producer agent 0.8 points and an item sold directly to a customer agent earns a producer agent one point. Producer agents are penalized for transportation and labor costs associated with selling directly to customer agents. They receive -9 points (tcost) for each distance unit to each customer agents to whom they sold directly. To calculate the reward under the baseline strategy, the producer agent first multiplies the final distance they traveled to deliver products directly to customers due to sales around the hub, finaltraveldistance, by the transportation penalty, tcost. Next, the producer agent multiplies the number of products they sold directly to customer agents, soldproduce, by one, meaning they received the full revenue from those sales. This around the hub revenue is added to the transportation penalty value. Finally, the producer agent multiplies the number of products they sold through the hub, supply, by (1-fhrate) to calculate the revenue they received after the food hub charges the service fee. This last part of the reward equation is added to the rest of the equation to calculate the final reward value shown in Equation (4).

$$
\begin{aligned}
r_t = (tcost \times finaltraveldistance) + (1 \times soldproduce) \\
+((1 - fhrate) \times supply)
\end{aligned}
\tag{4}
$$

Profit Sharing Strategy-Under the profit sharing management strategy, producer agents who did not or were not detected to sell any products around the hub will incur a reduced food hub service fee. Each order cycle, eligible producer agents will receive a reduction of 5% of their service fee. For example, if the regular service fee is 20%, the reduced fee would be 15% Producer agents who were detected to sell any amount of products around the hub are not eligible to receive the reduced service fee. Calculating the reward under the profit sharing strategy depends on if the producer agent attempt at sales around the hub was detected by the food hub agent. In situations where the behavior was not detected by the food hub agent, the producer agent first multiplies the final distance they traveled to deliver products directly to customers due to sales around the hub, finaltraveldistance, by the transportation penalty, tcost. Next, the producer agent multiplies the number of products they sold directly to customer agents, soldproduce, by one, meaning they received the full revenue from those sales. This around the hub revenue is added to the transportation penalty value. Finally, the producer agent multiplies the number of products they sold through the hub, supply, by ((1-fhrate) + 0.05) to calculate the revenue they received after the food hub charges the service fee reduced by 5%. This last part of the reward equation is added to the rest of the equation to calculate the final reward value shown in Equation (5).

$$r_t = (tcost \times finaltraveldistance) + (1 \times soldproduce) \\ +(((1 - fhrate) + \ .05) \times supply) \tag{5}$$

In situations where the producer agent was detected to have sold or attempted to sell products around the hub, the producer agent first multiplies the final distance they traveled to deliver products directly to customers due to sales around the hub, finaltraveldistance, by the transportation penalty, tcost. Next, the producer agent multiplies the number of products they sold directly to customer agents, soldproduce, by one, meaning they received the full revenue from those sales. This around the hub revenue is added to the transportation penalty value. Finally, the producer agent multiplies the number of products they sold through the hub, supply, by (1-fhrate) to calculate the revenue they received after the food hub charges the non-discounted service fee. This last part of the reward equation is added to the rest of the equation to calculate the final reward value shown in Equation (6).

$$r_t = (tcost \times finaltraveldistance) + (1 \times soldproduce) + \big((1 - fhrate) \times supply\big) \tag{6}$$

Producer Removal Strategy- The final management strategy is that the food hub agent will eventually stop working with producer agents that sell any amount of products around the hub. To simulate the effects of a producer agent losing the food hub agent as a supply chain partner, a producer agent that is caught selling any amount of items around the hub will lose the opportunity to use the hub to sell products that cycle. Any remaining items a producer agent has left after being discovered selling around the hub will remain unsold for the selling cycle. Calculating the reward under the producer removal strategy depends on if the producer agent attempt at sales around the hub was detected by the food hub agent. In situations where the behavior was not detected by the food hub agent, the producer agent first multiplies the final distance they traveled to deliver products directly to customers due to sales around the hub, finaltraveldistance, by the transportation penalty, tcost. Next, the producer agent multiplies the number of products they sold directly to customer agents, soldproduce, by one, meaning they received the full revenue from those sales. This around the hub revenue is added to the transportation penalty value. Finally, the producer agent multiplies the number of products they sold through the hub, supply, by (1-fhrate) to calculate the revenue they received after the food hub charges the service fee. This last part of the reward equation is added to the rest of the equation to calculate the final reward value shown in Equation (7). This reward function is identical to the baseline reward function.

$$r_t = (tcost \times finaltraveldistance) + (1 \times soldproduce) + \big((1 - fhrate) \times supply\big) \tag{7}$$

When the producer agent was detected to have sold or attempted to sell products around the hub, the producer agent first multiplies the final distance they traveled to deliver products directly to customers due to sales around the hub, finaltraveldistance, by the transportation penalty, tcost. Next, the producer agent multiplies the number of products they sold directly to customer agents, soldproduce, by one, meaning they received the full revenue from those sales. This around the hub revenue is added to the transportation penalty value and used as the final reward function shown in Equation (8). In this reward function the producer agent does not receive any revenue through the food hub because the food hub agent did not do business with producer agent in the cycle.

$$r_t = (tcost \times finaltraveldistance) + (1 \times soldproduce) \tag{8}$$

Optimal future value estimate

The reinforcement learning equation requires each action to have an associated optimal future value estimate. That is, an estimate of the value of taking that action given the optimal outcome occurs. This part of the Q-learning equation helps producer agents know which actions can, but not necessarily will, lead to big rewards. Each action has one associated optimal value estimate, and will vary producer to producer depending on producer agent size. In general, the optimal outcome for a producer agent attempting to sell products around the hub is to sell all those products to a single customer agent located one unit away without the behavior being detected by the food hub agent. This outcome optimizes the number of products successfully sold around the hub and minimizes the associated transportation costs for doing so. For example, consider the optimal outcome for a producer agent with initial-supply of 100 selecting action "attempt to sell 50% of products around the hub". The optimal outcome this specific scenario is that the producer agent sells 50 items to a customer agent one unit away and the producer agent ends up in state Attempt50-Success (State 4). The reward associated with this optimal outcome is the optimal future estimate used in the Q-learning equation.

Update q-values

Once the producer agent receives the reward corresponding to its action and resulting state, the producer agent will update a q-value to reflect the reward. The producer agent updates the list assigned to the state in which the producer agent began the time step. Each list contains four values, and the producer agent updates the one corresponding to the action they chose during the time step. The value is updated using the Q-learning algorithm and the specific reward earned by the outcome of the action. For example, a producer agent currently in state 0 (not selling any products around hub), chooses action 3 (attempt to sell 75% of products around hub), and will move to next state 5 (caught selling 75% around hub). This producer agent will update the fourth value (action 3) of none-list (list 0) with the reward associated with being caught selling a high amount of product around the hub. Once the producer agent updates the q-value, it moves to the next state by setting the next state as its current state.

Sell remaining products through hub

After all the direct sales are made, the food hub agent collects the rest of the supply from producer agents and fulfills the remaining demand from customer agents. The food hub agent keeps track of how many customer agents purchase products through the hub each selling cycle, and the total number of items sold to those customer agents each selling cycle.

Reset values

After one selling cycle is completed and the producer agents have received rewards and updated their q-value lists, certain model variables are reset to prepare for the next selling cycle. For the entire model, the variables monitoring the items going through the food hub agent (hub-supply, hub-demand, hub-producer-number, hub-customer-number) are all set to zero. Additionally, all producer agents have their supply levels reset to their assigned values, and all customer agents have their demand levels reset to the assigned values. Producer agents also have sold-produce and final-travel-distance reset to zero. Customer agents have around? reset to zero. Once the variables have been reset, the model is ready to move the next time step and repeat.

CHAPTER IV

EXPERIMENTATION AND RESULTS AND DISCUSSION

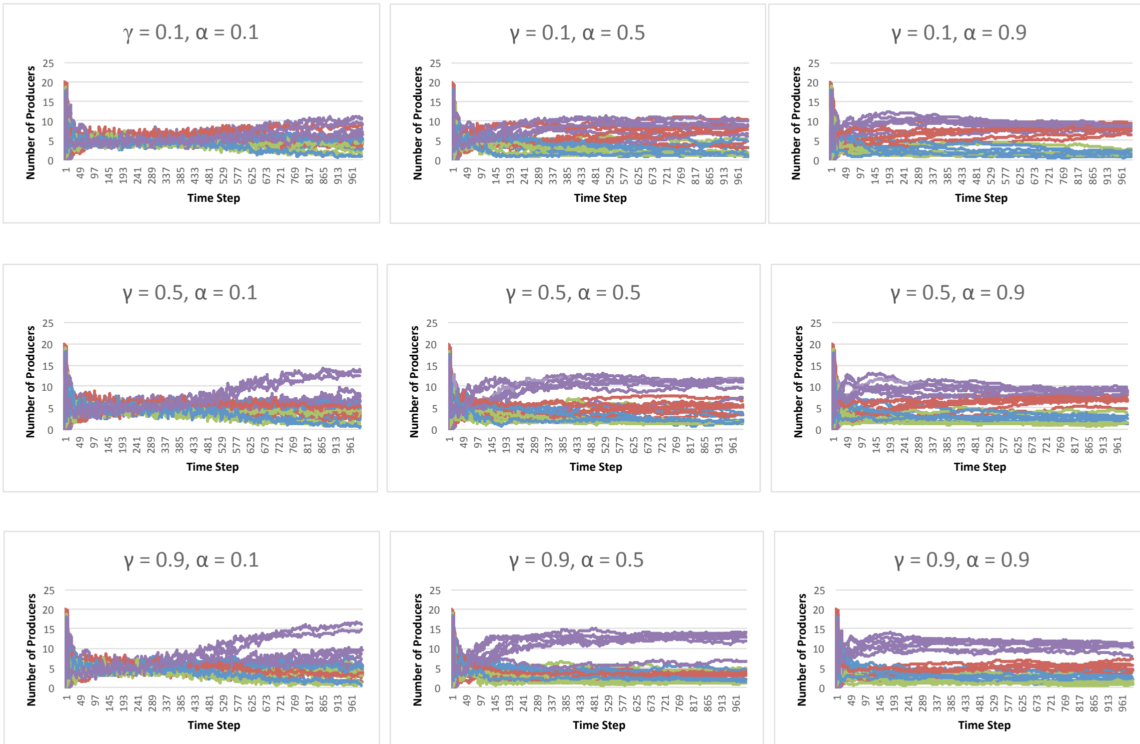
Multiple experiments were performed using the conceptual model previously described. First, model parameters were tuned to ensure that the producer agents decide on a selling policy in a reasonable amount of time. Next, the model was used to test the effects of several different food hub management strategies on producer disintermediation, and to demonstrate the ability of the model to be used by the food hub manager to test "what if" scenarios.

Tuning the Learning Rate and Discount Factor (α and γ)

To determine appropriate values for the learning rate (α) and discount factor (γ) of the q-learning algorithm in this particular model, a full factorial experimental design was used. The values must allow the producer agents to develop their selling policies in a reasonable time frame. High, medium, and low values were selected and assigned to α and γ a. The values chosen were 0.9, 0.5, and 0.1. For the purposes of tuning the q-learning parameter values, no management strategy was implemented, the food hub's rate was fixed at 20%, and producer agents were parameterized such that they were only willing to sell directly to customers located within 30 minutes driving distance (6 units). Each experiment was run for 1000 times steps, which corresponds to 20 years (assuming 50 order cycles per year). All experiments were replicated 10 times, results are averages over the replications.

Learning rate and discount factor (α and γ) results and discussion

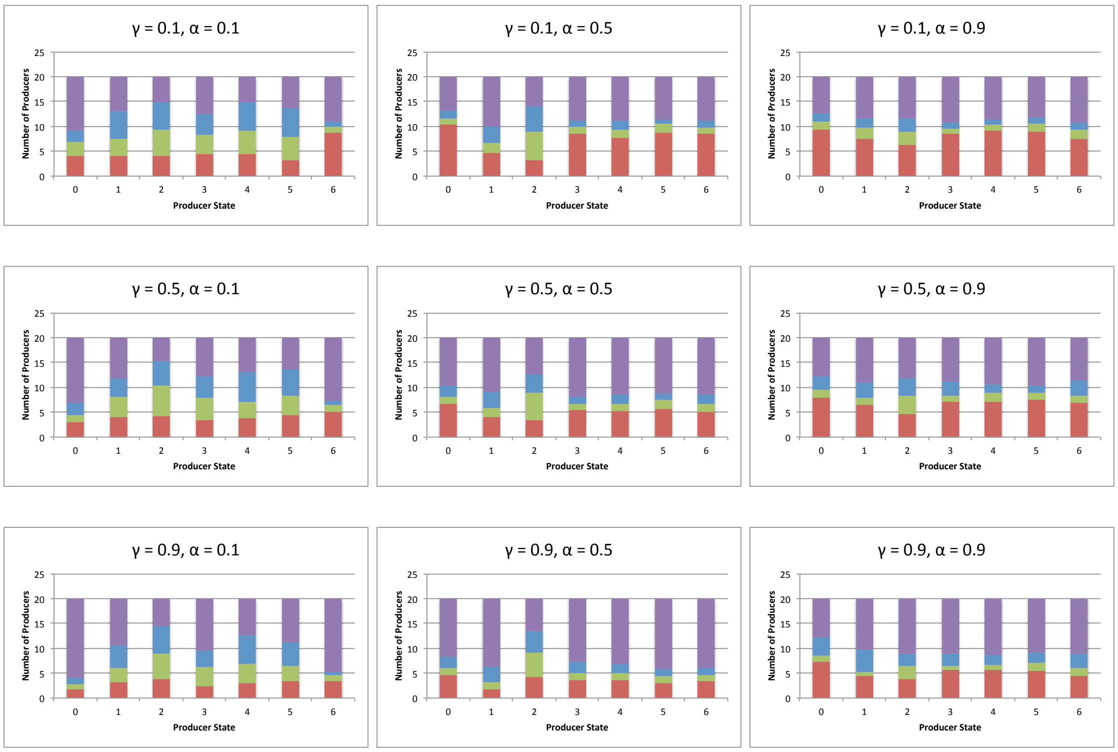
The results of the experiment throughout the entire run are shown in Figure 3. Each line represents the number of producer agents that find a certain action to be the best policy to follow, given the state that they are currently in. The best policy is the set of actions that yield the highest value for the producer agent when they are in each state. The four different line colors in the figure represent the four possible actions that can be taken by a producer agent in each time-step. For each color (i.e., action), there are seven lines, each of which represents a possible producer state, such that there are 28 lines total in each plot. Since a producer may only have one best action to follow in every state, the sum of the y-values for all lines is the same at every time step (i.e., it is equal to the total number of producers multiplied by seven, for the seven states). Throughout the experiments, if one strategy is clearly the best, the lines corresponding to that strategy emerge to the top of the graph, while other strategies fall to the bottom. In some cases, a best policy for a producer agent may be comprised of two or more strategies, meaning a producer agent may prefer action 1 while in state 1, but prefer action 2 in state 2. Prior to a best policy emerging, the producer agents are learning and the graphs exhibit noise where the best policy changes rapidly.



Color Key for Graphs		
Color	#	Best Action
	0	Sell all items through hub
	1	Attempt to sell 25% items around hub
	2	Attempt to sell 50% items around hub
	3	Attempt to sell 75% items around hub

Figure 3. *Results of tuning learning rate and discount factor over simulation run*

Figure 4 summarizes the policy selection by producers in the final time step (i.e., time step 1000). The plots use the same color key as Figure 3, where red represents selling all items through the hub. Each bar shows the distributions of the best action for all 20 producers, given they are the state corresponding to the value on the x-axis. For example, in the first graph where $\gamma = 0.1$ and $\alpha = 0.1$, the bar labeled 0 represents the distribution of best actions of all producers when they are currently in state 0 (i.e., the state in which they sold all items through the hub in the preceding time step). While in this state, 11 of the producers preferred to attempt to sell 75% of their products around the hub, two preferred to attempt to sell 50% of their items around, three preferred to attempt to sell 25% of their items around, and four preferred to sell all items through the hub.



Producer State Key	
State #	State Name
0	None
1	Attempt25-Caught
2	Attempt25-Success
3	Attempt50-Caught
4	Attempt50-Success
5	Attempt75-Caught
6	Attempt75-Success

Color Key for Graphs		
Color	#	Best Action
	0	Sell all items through hub
	1	Attempt to sell 25% items around hub
	2	Attempt to sell 50% items around hub
	3	Attempt to sell 75% items around hub

Figure 4. *Results of tuning learning rate and discount factor at time step 1000*

In all nine experiments, the action to sell 75% of products around the hub emerged as the most popular strategy. At time step 1000, average number of producers who would select to sell 75% of products around the hub is never lower than 4.7 for all states in all experiments. In 24 instances the average number of producers who would select this action is greater than 10, or half of the producers . In the experiments where $\alpha = 0.1$, the slowest learning rate,, the learning period lasted until at least time step 300, which corresponds to 6 years. Conversely, when the learning rate is 0.9, the best strategy for producers emerges in fewer than 50 time steps, or less than a year. In experiments where γ is 0.9 (i.e., the agent places high importance on future rewards rather than immediate rewards), the action "sell 75% of products through the hub" emerges as the most popular policy for producers. At time step 1000, the greatest number of producers will choose this action in all instances. In 15 of the 21 instances, the average number of producers selecting that action is greater than 10, or half of the producers. When the discount factor is decreased to $\gamma = 0.1$, the best action becomes more varied for the system, and attempting to sell 75% of products around the hub is less favored.

Since this experiment was performed to tune the values of α and γ for subsequent experimentation, it is important to consider the actual system. In the case study system, it is unlikely that a producer would take six years to decide on their selling policy. This suggests that the learning period should be short. Therefore, $\alpha = 0.9$ is a more realistic learning rate for the model. An appropriate value for the discount factor is less clear. In the case study system, there are producers who do not sell products around the hub or would not consider doing it, so it is unlikely that more than 50% of producers would view selling 75% of their products around as the best action, which occurs when $\gamma = 0.9$ and $\alpha = 0.9$. Thus, a discount factor of 0.9 does not seem valid. The producers are also unlikely to strictly consider their immediate reward from their selling decisions, with no regard for future rewards. Assuming that producers are concerned about their business decisions beyond the short term, a discount factor of $\gamma = 0.5$ seems to be valid. With values of α and γ set to 0.0 and 0.5, respectively, the model is ready to perform experiments to test different food hub management policies.

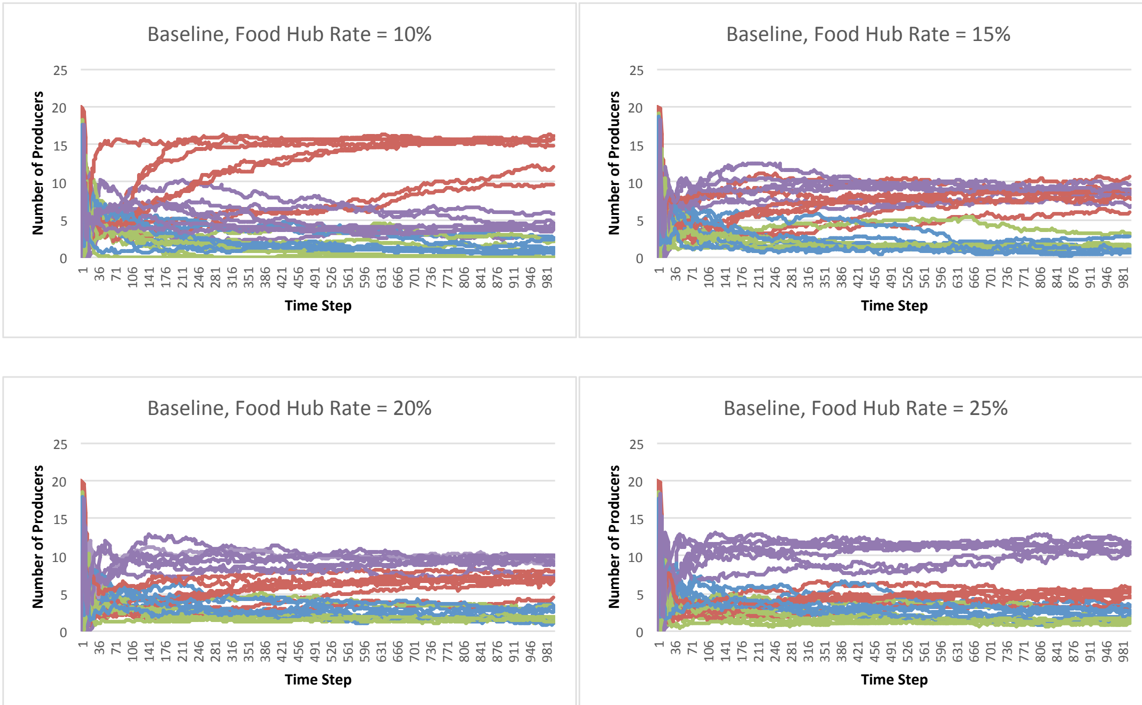
Experiments

Experiment #1: food hub rate & management strategy

The first food hub management strategy experiment is a full factorial experiment consisting of 12 experiments in which the management strategy and food hub service rate are systematically varied. There are three possible management strategies: no strategy (baseline), profit sharing (5%), and producer removal from the food hub. Four food hub rates were used: 10%, 15%, 20% (the case study food hub's actual rate), and 25%. The producer agents will still only sell directly to producers located within 30 minutes driving distance (i.e., 6 units) of their location. The model was run for 1000 time steps and replicated 10 times for each experimental condition. The results of these experiments are described below.

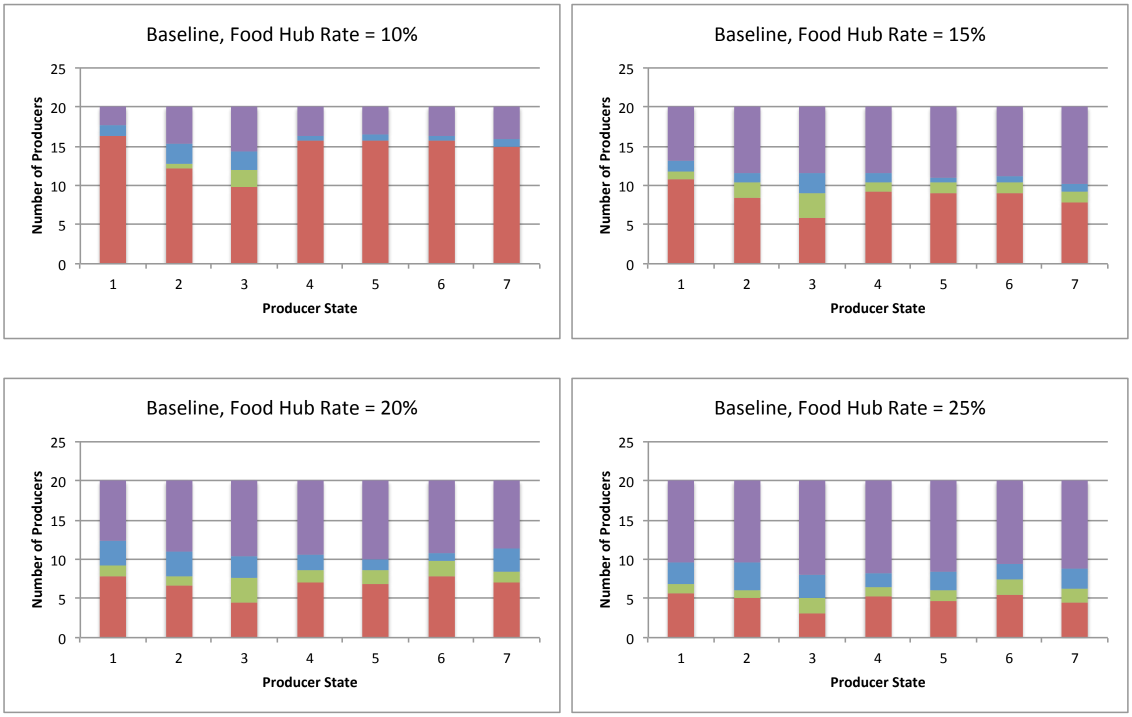
<u>Strategy #1: no strategy (baseline)</u>

The number of producers that selected each of the four actions in each of the seven states when no management strategy was implemented are shown in Figures 5 and 6 for various food hub rate values. Figure 5 shows the average number of producers over 10 replications in each time step over the entire simulation run, while Figure 6 shows the results at the end of the simulation run (i.e., in time step 1000). The results indicate that when the food hub employs no management strategy and uses a 20% rate, at least 38% of the producers will follow the action of attempting to sell 75% of their products around the hub, no matter what their current state is. The next most popular action in all states is to sell all products through the hub, where at least 22% of producers will follow the strategy no matter which state they are in. It seems if producers are going to sell products around the hub, it is beneficial to sell the most they can around the hub. When the hub lowers the service rate to 15%, the two policies become split more evenly, with at least 35% of producers choosing to sell 75% of products around the hub and 30% choosing to sell no producers around the hub in all states. It is only once the hub lowers the service rate to 10% that at least 49% of producers find selling no products around the hub to be the best action to take in any state. Conversely, when the food hub raises its fee to 25%, at least 52% of producers find that attempting to sell 75% of the products around the hub to be the best option in any state.



Color Key for Graphs		
Color	#	Best Action
	0	Sell all items through hub
	1	Attempt to sell 25% items around hub
	2	Attempt to sell 50% items around hub
	3	Attempt to sell 75% items around hub

Figure 5. *Baseline food hub management strategy results over simulation run*



Producer State Key	
State #	State Name
0	None
1	Attempt25-Caught
2	Attempt25-Success
3	Attempt50-Caught
4	Attemp50-Success
5	Attempt75-Caught
6	Attempt75-Success

Color Key for Graphs		
Color	#	Best Action
	0	Sell all items through hub
	1	Attempt to sell 25% items around hub
	2	Attempt to sell 50% items around hub
	3	Attempt to sell 75% items around hub

Figure 6. *Results of baseline food hub management strategy at time step 1000*

In each experiment the q-values and subsequent actions chosen will vary from one producer agent to the next. Since producers have different supply levels and locations, the best action for a given state will be unique to a given producer. Under these experimental conditions, there is no single policy that dominates for every producer. Five producers of various sizes and locations are examined, each showing different preferences. These differences demonstrate how producer size, producer location relative to other producers and customers, and customer buying preferences matter when it comes to what policy will be best for a given producer. This shows that the best selling policy for one producer is not necessarily the best for another producer. Table 8 summarizes the percentage of times each producer agent chose an action over the course of the experiment. Producer 0 mostly prefers to sell products through the hub, while Producer 3 generally prefers to attempt to sell 75% of products around the hub. Producer 15 does not have a very strong preference for any particular action, but it does not prefer to attempt to sell 25% of its products around the hub.

Table 8. *Percentages of actions selected by 5 producers throughout experiment*

	Producer Action			
Producer #	0	1	2	3
0	85%	5%	5%	5%
3	8%	6%	13%	73%
13	6%	6%	6%	82%
15	26%	6%	30%	38%
17	6%	79%	7%	8%

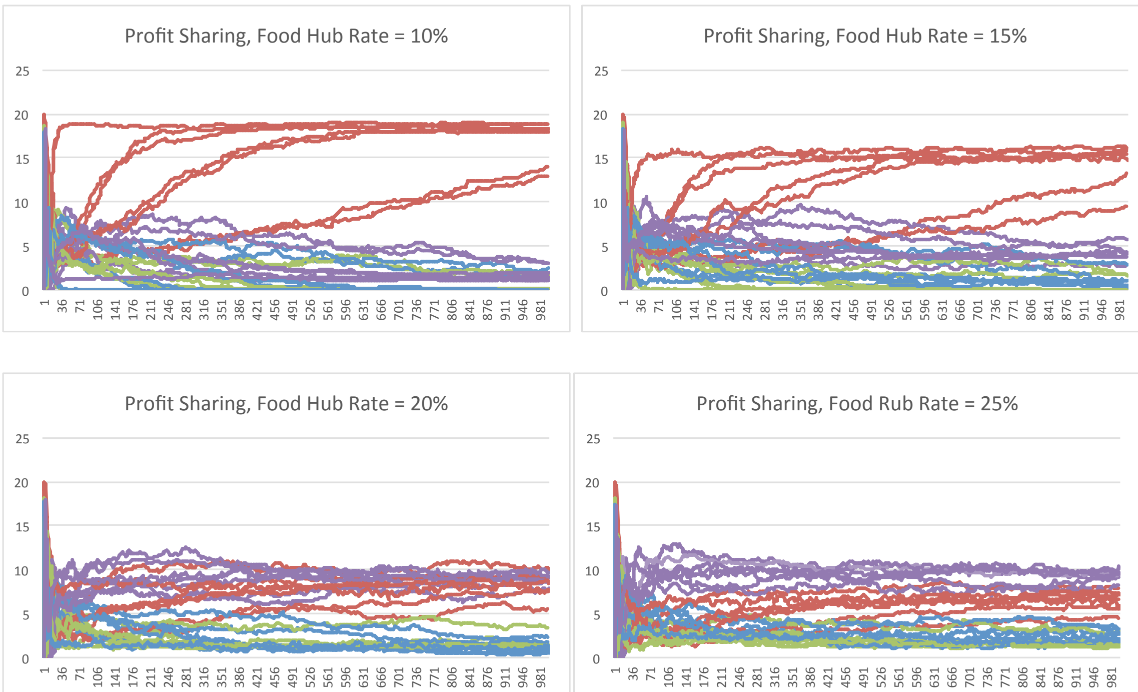
<u>Strategy #2: profit sharing</u>

This section describes the results of the experiments that were performed when the profit sharing management strategy was used and producers received a 5% reduction in the rate that they pay the food hub if they were not detected selling around the hub. Figure 7 shows plots of the average number of producers that followed each possible action/state policy over 10 replications in each time step for the entire simulation run for four different food hub rates. The results of the experiments at the end of the simulation run (i.e., in time step 1000) are shown in Figure 8. When the food hub rate is 10%, selling no products around the hub becomes the best policy for at least 65% of producers in all states, and 90% of producers in five of the seven states. The two states with less than 90% of producers preferring that action correspond to the Attempt25-Caught and Attempt75-Succcess states. In these two states, fewer producers prefer to sell all items through the hub than in other states. The reason behind this discrepancy is that producers quickly realize that selecting to sell all items through the hub is a very good action; therefore, these two states (Attempt25-Caught and Attempt75-Success) are rarely visited. Thus, the producer will only visit either of these states when it selects an action randomly and the corresponding action is selected. Because the producer is rarely in either of the two states, it will take much longer for the producer to develop a stable policy in those states. It is clear that choosing to sell 25% or 75% of products around the hub is never a best strategy for any producers at time 1000.

Similarly, at a food rub rate of 15%, selling all items through the hub emerges as the best policy at time step 1000 for at least 48% producers regardless of current state. Once the food hub rate is increased to 20%, both selling no products through the hub and attempting to sell 75% of products around the hub are the best policy for nearly 41% and 45% of producers respectively with a few producers preferring different actions. Further, once the rate is increased to 25%, attempting to sell 75% of products around the hub edges selling no products around the hub out to be preferred by at least 42% of producers in any state.

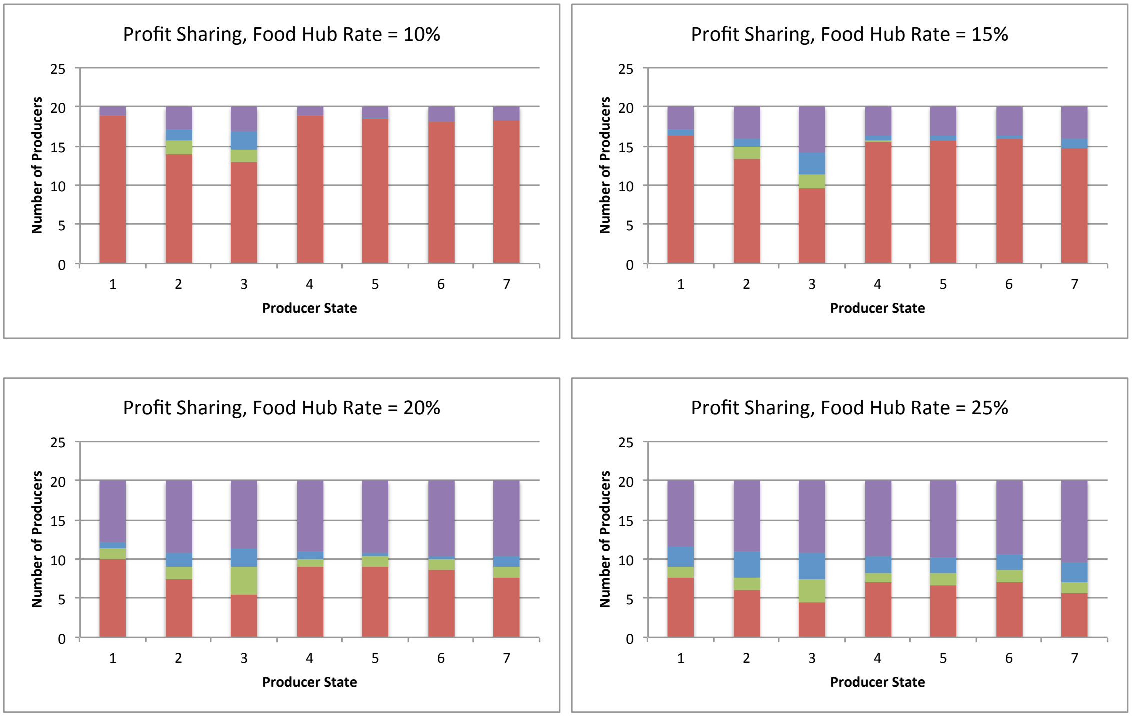
The profit sharing management strategy seems to be only somewhat effective in reducing the number of producer agents that attempt to sell around the hub. When the food hub rate is 15% or lower, a majority of producers choose to sell through the hub. Although the experiment was run when the food hub rate was 15% and 10%, these are not likely to be feasible rates for the actual food hub since the service fee would likely be too low to recoup transportation costs. When the profit sharing strategy is used at food hub rates of 20% and

25%, there is not a lot of improvement from the baseline model. This experiment indicates that if a food hub used the profit sharing strategy to reduce producer disintermediation, the manager would need to carefully assess whether the costs of implementing the strategy would be outweighed by the small reductions in sales around the hub.



Color Key for Graphs		
Color	#	Best Action
	0	Sell all items through hub
	1	Attempt to sell 25% items around hub
	2	Attempt to sell 50% items around hub
	3	Attempt to sell 75% items around hub

Figure 7. *Profit sharing food hub management strategy results over simulation run*



Producer State Key	
State #	State Name
0	None
1	Attempt25-Caught
2	Attempt25-Success
3	Attempt50-Caught
4	Attemp50-Success
5	Attempt75-Caught
6	Attempt75-Success

Color Key for Graphs		
Color	#	Best Action
	0	Sell all items through hub
	1	Attempt to sell 25% items around hub
	2	Attempt to sell 50% items around hub
	3	Attempt to sell 75% items around hub

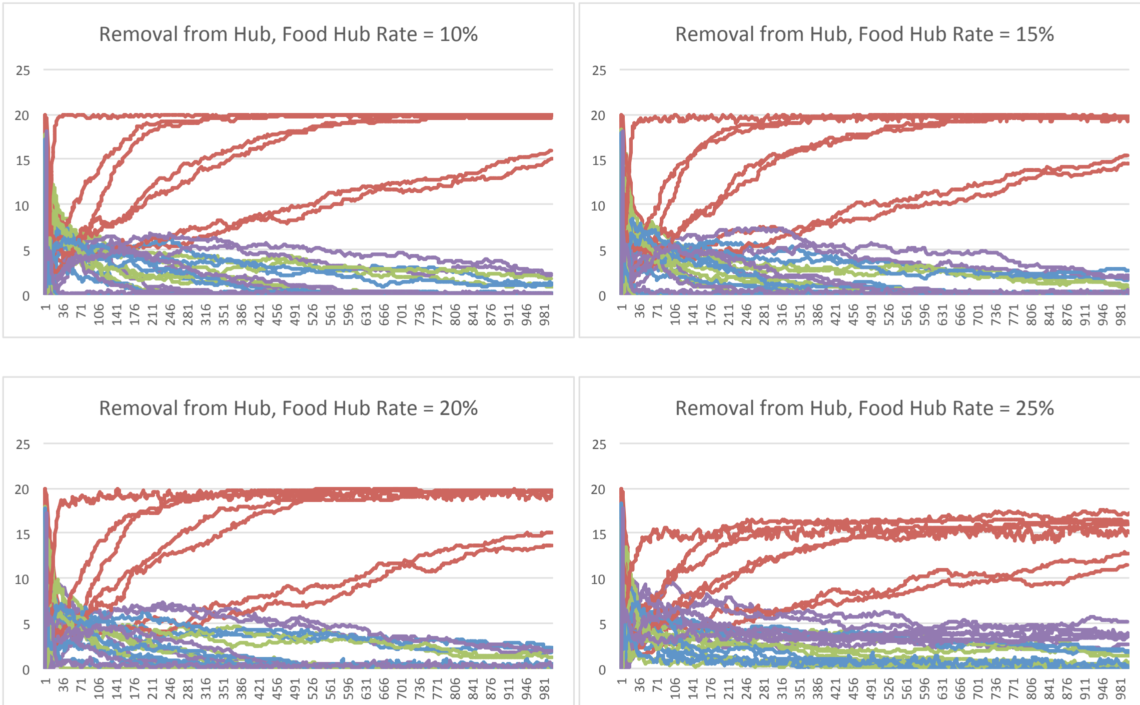
Figure 8. *Results of profit sharing food hub management strategy at time 1000*

<u>Strategy #3: removal from hub</u>

This section describes the results of the experiments in which the food hub removes disintermediating producers from the hub for one cycle. Figures 9 and 10 show the number of producer agents that select each action/state policy in each time step and at the end of the simulation run, respectively, for four different food hub rates. At food hub rates of 20% or lower, selling no products through the hub clearly emerges as the best policy for at least 73%

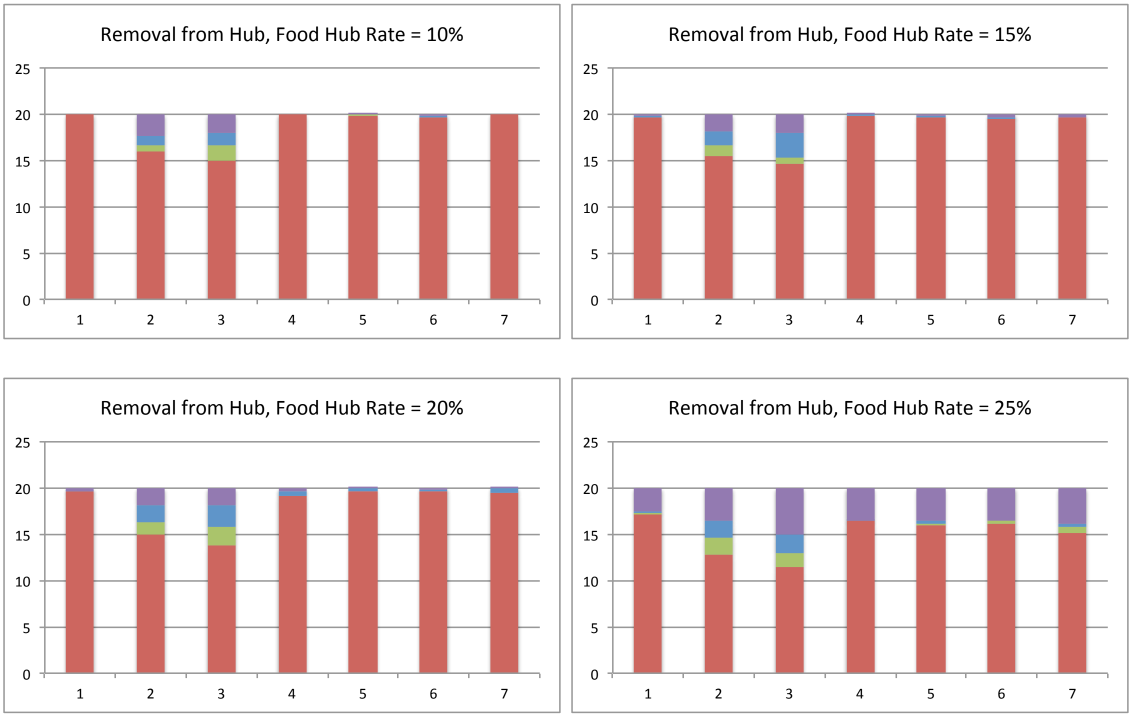
of producers in all cases. When the food hub rate is 25%, selling through the hub emerges as the best policy for at least 64% of producers in all cases. The results of this experiment are similar to the results of the profit sharing experiments where the best strategies of a few states do not stabilize by time step 1000, because producers quickly start selecting one strategy and do not visit those certain states often. It is evident in Figure 9 that the red lines lag corresponding to the two states lag behind the others.

Overall, removing producers from the hub is effective in curbing sales around the hub in this model, more so than the previous management strategies. Even when the food hub rate is 25%, temporarily removing the disintermediating producers from the hub is a better-performing strategy than the case study food hub's current policy, in which there is no preventative management strategy and the food hub rate is 20%.



Color Key for Graphs		
Color	#	Best Action
Red	0	Sell all items through hub
Green	1	Attempt to sell 25% items around hub
Blue	2	Attempt to sell 50% items around hub
Purple	3	Attempt to sell 75% items around hub

Figure 9. *Removal from hub management strategy results over simulation run*



Producer State Key	
State #	State Name
0	None
1	Attempt25-Caught
2	Attempt25-Success
3	Attempt50-Caught
4	Attemp50-Success
5	Attempt75-Caught
6	Attempt75-Success

Color Key for Graphs		
Color	#	Best Action
	0	Sell all items through hub
	1	Attempt to sell 25% items around hub
	2	Attempt to sell 50% items around hub
	3	Attempt to sell 75% items around hub

Figure 10. *Results of removal from hub management strategy at time step 1000*

Experiment #1: discussion

The results of these three sets of experiments show that, regardless of the management strategy that the food hub manager implements, lowering the food hub rate to 10% increases the number of producer agents having a best policy of selling no products around the hub. However, for Western Iowa Food Hub, a 10% rate is infeasible. The food hub must bring in enough revenue to cover its operating costs, and lowering the rate too far will make that impossible. The Western Iowa Food Hub manager has already experienced problems covering transportation costs with a service fee of greater than 10%. Similarly, using a profit sharing strategy when the food hub rate is only 15% is unlikely to provide the food hub with sufficient revenue. Overall, based on the experimental results, the best management strategy for the food hub is to temporarily remove producers from the hub when they are selling around. Not only did this strategy provide the best results, but it is implemented without any financial cost to the hub. Indeed, Local Food Marketplace has recommended that food hubs stop working with producers who sell around the hub (McCann & Crum, 2015). The assumption in this model is that producers would not have the ability to find another source for the items intended for the hub if they are caught, leading to significant lost sales. This assumption would likely not hold in the long term, since a producer who wants to continue to sell products around the hub would work to find other customers for these items or leave the hub completely. Further research on producers' responses to removal from the hub will be necessary to gain a better understanding of the effects of this policy on the case study food hub and producers.

Despite the food hub's management strategies, there are some instances in which producers still find that the best policy is to sell products around the hub. There are always going to be producers who are in a position to sell their products directly to nearby customers, and do not rely on the food hub as much as other producers do. Therefore, the food hub will need to determine how many producers it can tolerate selling products around the hub in conjunction with utilizing an appropriate management strategyto make the most effective decisions.

Experiment #2: producer selling radius

The model was also used to perform experiments to gain an understanding of system behavior when producers alter their business policies. For example, producers might change how far they are willing to drive products directly to customers. In this experiment, the producer selling radius is varied to reflect different producer business policies, assuming that no management strategy is implemented by the food hub and the food hub rate remains at 20%. Three radii are tested: 10 minutes driving (2 units), 30 minutes driving (6 units), and 50 minutes driving (10 units). All radii are one-way driving distances Each experiment is run for 1000 time steps and replicated 10 times, and results are average values over the replications.

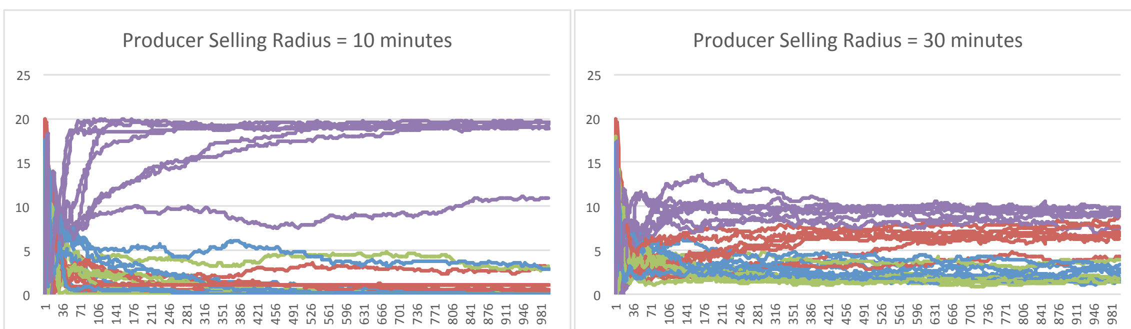
When the selling radius of the producer changes, the number of customers located within the radius also changes accordingly. A larger radius contains more customers than a smaller radius. The distribution of producers by number of customers in their selling radius is shown in Table 9 for the three scenarios.

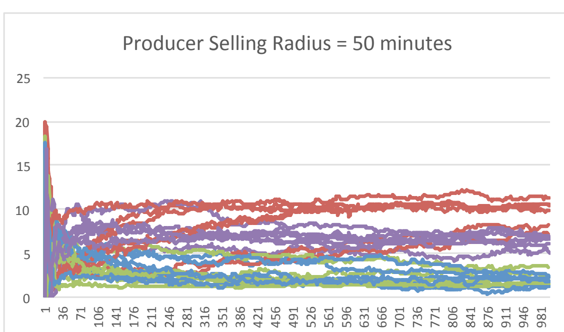
Table 9. *Distribution of producer agents by number of customer agents in radius in producer selling radius experiment*

	Number of customers in selling radius				
Radius	0-5	6-10	11-15	16-20	21-25
2	100%	0%	0%	0%	0%
6	40%	35%	20%	5%	0%
10	0%	30%	25%	40%	5%

The number of producer agents that follow each action/state policy in each time step are shown in Figure 11. Figure 12 shows the results in the final time step. When the selling radius increases from 30 minutes driving to 50 minutes driving, selling all products through the hub is the most popular strategy among the producers, with an average of 49% of producers choosing this strategy at any state. When the producer selling radius is increased, producers that sell products around the hub are more likely to travel further to do so, due to the increased competition among producers selling directly. A greater distance to direct sales customers increases the transportation penalty associated with selling around the hub.

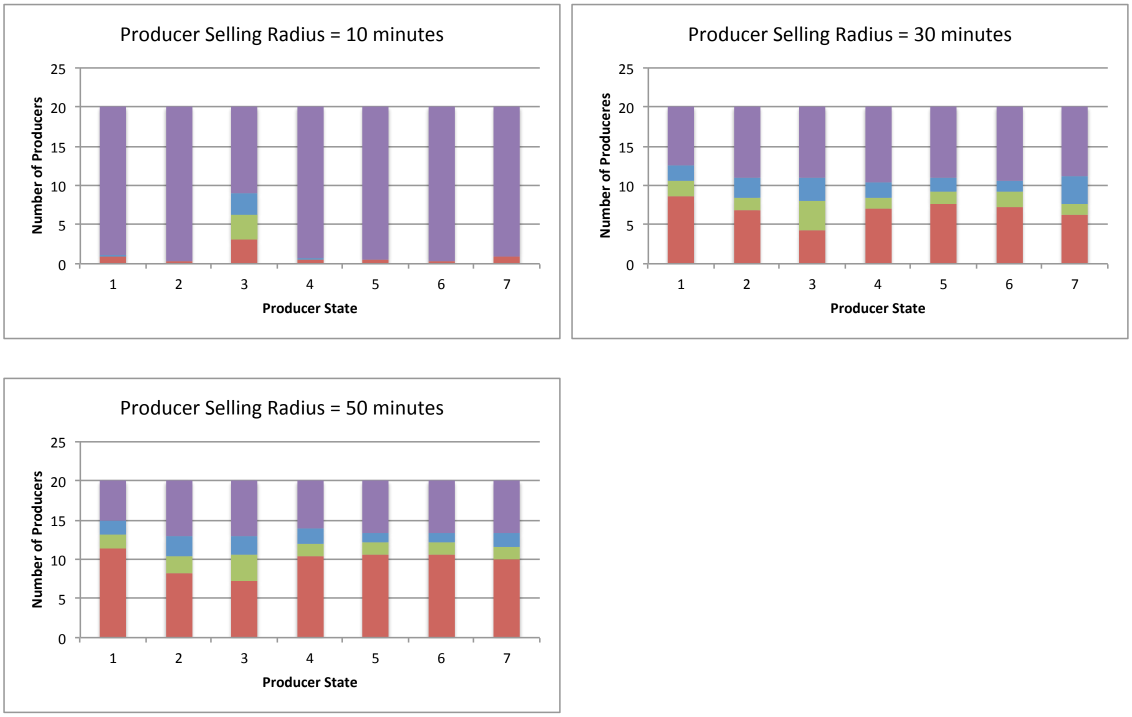
Surprisingly, attempting to sell 75% of products around the hub is overwhelmingly the best policy when the producer selling radius is 10 minutes. Despite the short travel distance to customers, all producers have five or fewer customers within their radius. Having fewer customers in the radius decreases the likelihood that producers are able to successfully sell products around the hub.





Color Key for Graphs		
Color	#	Best Action
	0	Sell all items through hub
	1	Attempt to sell 25% items around hub
	2	Attempt to sell 50% items around hub
	3	Attempt to sell 75% items around hub

Figure 11. *Results of Producer selling radius experiment over simulation run*



Producer State Key	
State #	State Name
0	None
1	Attempt25-Caught
2	Attempt25-Success
3	Attempt50-Caught
4	Attemp50-Success
5	Attempt75-Caught
6	Attempt75-Success

Color Key for Graphs		
Color	#	Best Action
	0	Sell all items through hub
	1	Attempt to sell 25% items around hub
	2	Attempt to sell 50% items around hub
	3	Attempt to sell 75% items around hub

Figure 12. *Results of producer selling radius experiment at time step 1000*

To determine whether producers are actually selling products around the hub, the number of products moving through the hub (hub-supply) was recorded, and the results are shown in Figure 13. As suspected, despite almost all producers preferring to attempt to sell 75% of products around the hub when the radius is 10 minutes, only approximately 25% of total items are actually going around the hub in an average cycle. In fact, even though more producers attempt to sell around the hub when the radius is 10 minutes, fewer products are actually sold around the hub than when the radius is 30 or 50 minutes. The reason for this discrepancy is that in the case where radius is10 minutes, there are a number of producers, who, despite attempting to sell products around the hub have not yet successfully sold any products around the hub and are still aiming to receive the potentially higher margin from those direct sales. These producers are unable to sell directly to customers because there are no customers in their radius, or the customers in their radius will not work with producers directly. Because there is no penalty for approaching customers with direct sales offers or for having zero customers in the radius, these producers will continue to find attempting to sell 75% of their products around the hub to be the best action under no management strategy. Changing the reward equation of the model can prevent this outcome from occurring. If producers incur a cost for approaching customers, it will lower the value of actions involving sales around the hub.

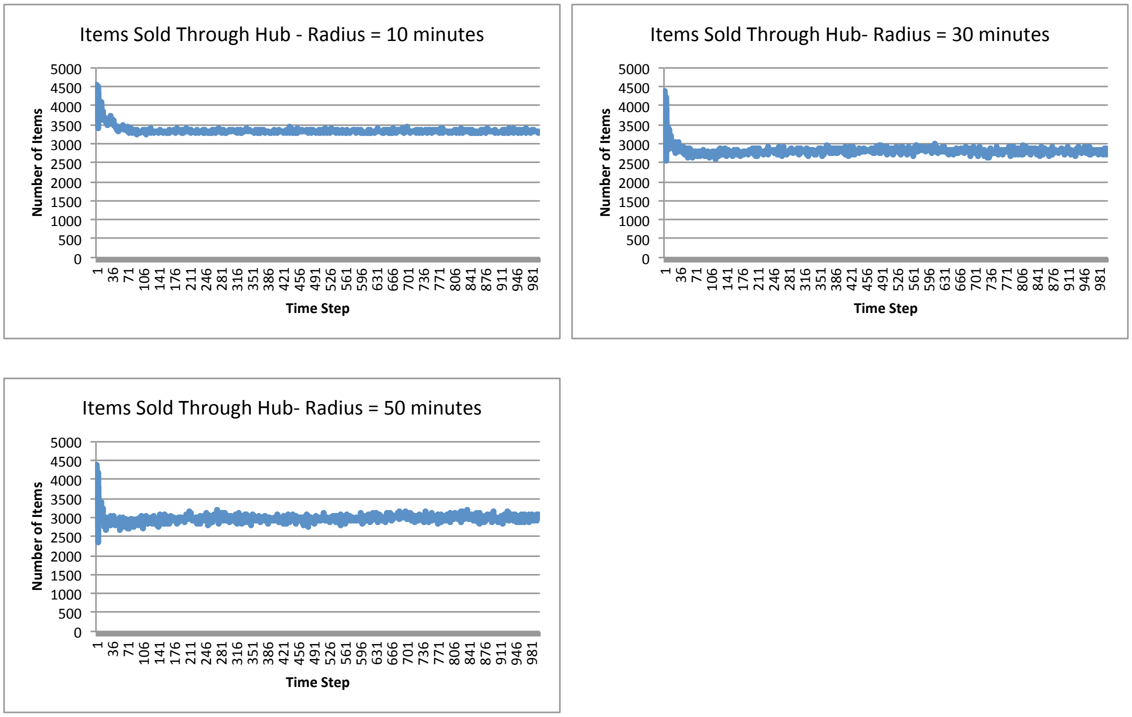


__Figure 13.__ Number of items sold through hub in each time step in producer selling radius experiment

Experiment #3: producer location

The agent-based model is useful for modeling scenarios that are impossible or nearly impossible to test in the real system. The manager can use the model to understand how the system behavior changes when the food hub works with producers in different locations. For example, the food hub manager can test the outcomes of a strategy in which the hub only works with urban or rurally-located producers. A food hub manager could attempt to curb disintermediation by implementing supplier selection policies and this type of model could help inform decisions regarding those policies.

In this experiment, the producer agents are arbitrarily located in urban and rural locations. For the urban locations, the producers are located within one of the two metropolitan areas. Producers in the previous model who were already in an urban location remained in place, and the other producers were moved to random location in the urban area. The customers remain unchanged from the original model. In the rural model, no producers are located in the metropolitan areas. Similar to the urban model, the producers previously located in rural locations remained in place, and other producers were moved to a random location in the rural area. The two models are shown in Figure 14. In this experiment, the standard producer selling radius of 30 minutes (6 units) is used. Because the producers are in new locations, the number of customers located in each producer's selling radius changes. Table 10 shows the distribution of producers in terms of the number of customers in selling radius. In general, the producers have fewer customers to whom they could sell directly when they are located rurally. In this experiment, no management strategy is used and the food hub rate is 20%. Each of the two scenarios was run for 1000 time steps and replicated 10 times. The results of the producer location experiment mimic those of the producer selling radius experiment, and shown in Figures 15 and 16. Despite the short distance to customers, the most popular policy in the urban model is split between selling no products around the hub and attempting to sell 75% of products around the hub. This is explained by the fact that in the urban model, there is increased competition for those direct customers.

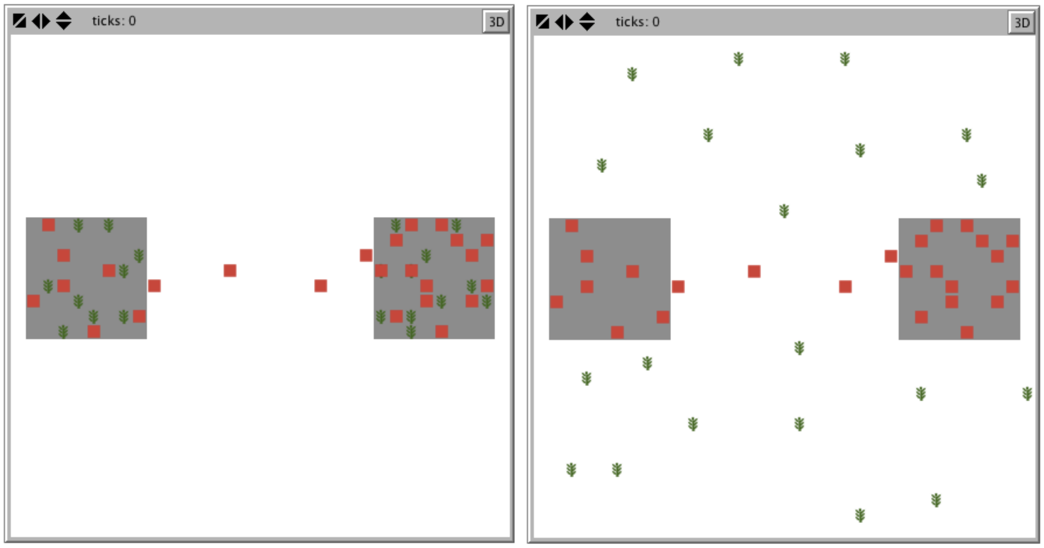
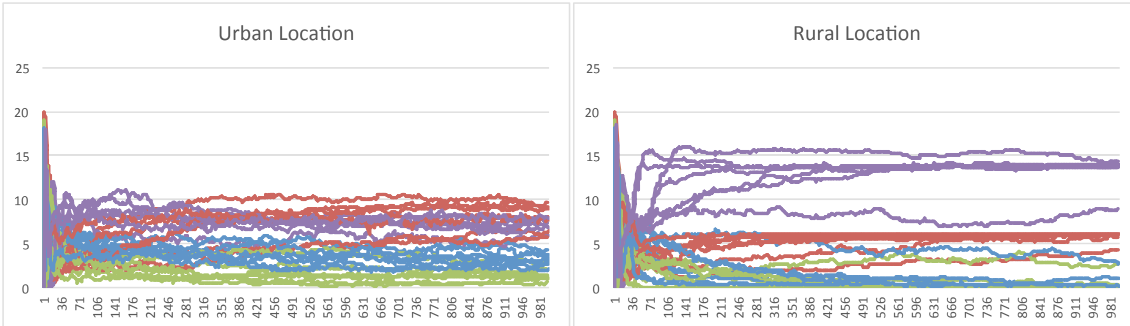


Figure 14. *Urban and rural producer model spaces*

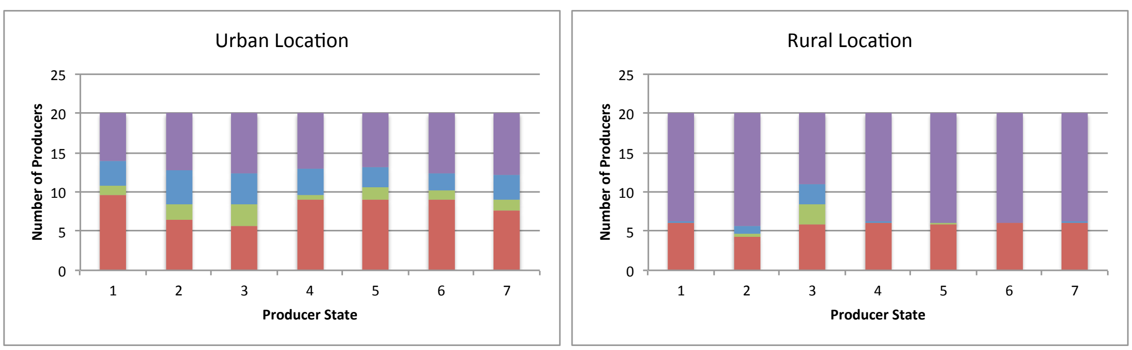
Table 10. *Distribution of producer agents by number of customer agents in radius in producer location experiment*

Location	Number of customers in selling radius				
	0-5	6-10	11-15	16-20	21-25
Urban	10%	45%	40%	5%	0%
Rural	95%	5%	0%	0%	0%



Color Key for Graphs		
Color	#	Best Action
	0	Sell all items through hub
	1	Attempt to sell 25% items around hub
	2	Attempt to sell 50% items around hub
	3	Attempt to sell 75% items around hub

Figure 15. *Producer location experiment results over simulation run*



Producer State Key	
State #	State Name
0	None
1	Attempt25-Caught
2	Attempt25-Success
3	Attempt50-Caught
4	Attemp50-Success
5	Attempt75-Caught
6	Attempt75-Success

Color Key for Graphs		
Color	#	Best Action
	0	Sell all items through hub
	1	Attempt to sell 25% items around hub
	2	Attempt to sell 50% items around hub
	3	Attempt to sell 75% items around hub

Figure 16. *Results of producer location experiment at time step 1000*

As with the producer selling radius experiment in which the radius is 10 minutes, 95% of producers have 5 or fewer customers in their selling radius in the rural model. Again, because there are few viable direct customers, a similar outcome occurs for the rural model. The most common producer action is to attempt to sell 75% of their products around the hub for the rural model; however, the actual number of products going around the hub does not reflect this. The number of products going through the hub in a given cycle (hub supply) is shown in Figure 17. At time step 1000, the rural model has an average of 4350 products being sold through the hub.

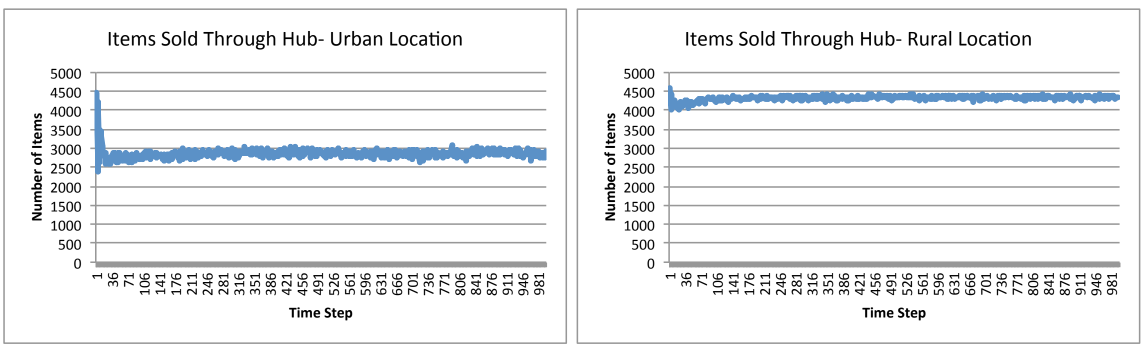


Figure 17. *Number of items sold through hub in each time step in producer location experiment*

In this case more products are going around the hub in the urban scenario than in the rural scenario, where nearly all products are going through the hub. Although many producers prefer to sell products around the hub in the rural scenario, in reality 94% of products end up being sold through the hub regardless of producer intentions. If producers were penalized for approaching customers or for having no customers in their radius, the outcome of the experiment would likely change.

Overall Discussion

In all experiments the producers develop individual selling policies that reflect their unique locations, supply, nearby customers, and competition among other producers. Although theoretical, the model results performed as expected. When the food hub service rate increased, more producers preferred to sell products around the hub, and when the rate lowered, more producers preferred to sell products through the hub. Similarly, more producers preferred to sell products through the hub when the food hub implemented management strategies to punish disintermediation. The management strategy which proved most useful to curbing disintermediation is temporarily removing producers from the food hub in a cycle in which they sold products around the hub.

Using an agent-based model that incorporates Q-learning for each producer agent is effective in generating long-term agent behavior after a learning period. The Q-learning allows producer agents to use a trial and error approach to developing selling policies, and individual producers using reinforcement learning creates emergent system-level behavior which converges in all experiments. The variety of experiments this conceptual model can perform demonstrates its ability to effectively study disintermediation in a regional food supply chain, as well as its usefulness to a food hub manager.

CHAPTER V

EMPIRICAL PILOT STUDY

Methodology

Based on discussions with the manager of the Western Iowa Food Hub, several assumptions were made about producers' disintermediation. The assumptions are as follows:

- Producers (i.e., not customers) are driving the decision to sell products around the food hub.
- The food hub manager's estimate of the percentage of producers selling around the hub is conservative.
- The costs associated with producer deliveries directly to distant customers are high.
- Producers do not disclose their decision to sell products around the food hub to the food hub manager.

The conceptual ABM that was described in the previous section was based on these assumptions. However, these assumptions were not validated by sources other than the food hub manager. To validate these assumptions, and to learn more about the potential impacts of different food hub management strategies on producer disintermediation decisions, an empirical study was developed and was subsequently piloted with food hub producers and customers. The Institutional Review Board (IRB) approved the empirical study in September 2016. Food hub producers and customers were interviewed using the interview protocol in Appendix A to understand more about their perceptions of food hubs and how producers make selling decision. Producers were asked questions regarding their business operations, their perceptions of their food hub and the services it provides, customer service, and their selling decisions. Customers were asked about their business, perceptions of their food hub and the services it provides, and how producers sell products to them.

To gather participants for the pilot study, managers from two Iowa food hubs (including the Western Iowa Food Hub) were asked to send the recruiting email, located in Appendix B, with an attached flyer, located in Appendix C, to their current producers and customers. The food hub managers sent the email, and interested participants responded directly to the research group to maintain confidentiality. Prior to conducting interviews, all participants in the study completed in the consent form in Appendix D. Three producers and two customers participated in the pilot study. All interviews were conducted over the phone.

None of the existing food hub literature focusing on the problem of disintermediation has used data from interview with producers and customers as a method of studying the problem. Since no empirical studies of this kind exist, the interview protocol described in this thesis was based on the same discussions with the Western Iowa Food Hub manager that were used to develop the assumptions of the ABM. Piloting the empirical study with a small number of participants allows the interview protocol to be revised as necessary prior to a conducting a full study.

Results

Producers' business operations

The three producers who were interviewed stated that they sell their products through multiple market channels (e.g., farmer's markets, other food hubs, direct customers). None sells more than half of his/her products through a single food hub. The producers' responses to the first set of interview questions are given in Table 11.

__Table 11.__ Summary of producer business operations responses

Question	Producer 1	Producer 2	Producer 3
Are you able to deliver products to all your customers without the food hub services? Yes or no?	No	Yes	No
How important is building a direct connection to a customer? (1-5)	5	5	4
Has selling directly to customers helped you grow your sales with the customer? Yes or no?	Yes	Yes	Yes
How important is growing your business further? (1-5)	3	5	5

Regarding the ability of producers to deliver their products to all of their customers, one producer noted: “My business would not make money if I had to provide all transportation for my products. The food hub allows me to not have to put capital into transportation”. Two of the producers indicated they would be unable to deliver products to all their customers without food hub services. Although producers rely on food hubs for transportation, producers place high importance on building direct connections with customers. Additionally, all producers believe that selling directly to customers helps them grow their business with that customer. This growth with direct customers is a means by which the producers fulfill their goal of growing their overall business.

When producers were asked how far they are willing to drive to deliver products directly to customers, their answers echoed the previous results that they are unable to deliver products to all customers. All producers interviewed stated that they are willing to drive at most 30 minutes one way to deliver products. These results are shown in Table 12.

Table 12. *Producer direct sales driving distance responses*

How likely are you to sell directly to customers X minutes driving one way to your business? 1-5 scale)			
Distance to customer	Producer 1	Producer 2	Producer 3
Less than 15 minutes driving	4	5	5
Between 15 and 30 minutes driving	3	3	5
Between 30 and 60 minutes driving	1	1	3
More than 60 minutes driving	1	1	2

Producer perceptions of food hubs

The producers responded to questions regarding their perceptions of the food hub and the customer service that it provides. The important responses are summarized in Table 13.

Table 13. *Summary of producer perceptions of food hub responses*

Question	Producer 1	Producer 2	Producer 3
How would you rate the food hub's service level? (1-5)	4	3.5	3
How does your service (customer satisfaction, on time deliveries, product quality at delivery etc.) compare to the food hub's when you sell directly to customers	Better	Better	Better

Two of the producers indicated their rating for the service level of the food hub was low due to poor and inconsistent communication from their food hub. All producers believe that the customer service that they provide is better than the food hub's customer service. Despite communication issues and perception of relatively poor customer service, the food hub does provide services that the producers value. One producer expressed that the food hub has been great for his/her business in regard to marketing: “I can’t afford to advertise, so I like the marketing the food hub offers”.

Producer sales around the hub

Of the three producers interviewed, two claim to have sold products around a food hub under the following definition: a transaction between a producer and customer whose relationship was cultivated by a food hub and the food hub’s services were not used, not including transactions where the food hub cannot provide the services needed for the transaction. A common reason for selling around the hub was that the customer was unhappy with the food hub or food hub services. Specific comments made regarding transactions around the food hub are shown in Table 14.

Table 14. *Producer comments regarding sales around food hub*

Comments Regarding Sales Around Food Hub
“I’ve never intentionally sold products around a food hub. I’ve only sold directly to customers who have stopped working with a food hub”
“I sell directly to food hub customers who have expressed dissatisfaction with the hub and asked me to sell directly”
“I’ve been approached to sell directly to a customer who purchased my products through the food hub. I do not know if this customer is still working with the hub”

None of the producers interviewed stated that they have reached out to customers to sell directly. Two producers explained that they would not know who to reach out to - as producers working with a food hub, they do not know the end customers of their products. All producers interviewed mentioned that they would not lie about selling products around the hub if they were asked, but none said they would or currently do volunteer this information to the hub manager. One producer said: “I wouldn’t lie about selling around the hub if the food hub manager asked me directly”.

Regarding prevention, producers were asked about current food hub contracts and policy, as well as questions to help understand how they might behave if the food hub were to manage them differently. None of the producers know if they’ve signed any sort of contract with the food hub, and all three producers were unaware if selling products around the hub was prohibited or believed that there are no strict policies about it. These questions and their answers are given in Table 15.

Table 15. *Summary of producer responses regarding food hub policies*

Question	Producer 1	Producer 2	Producer 3
Have you signed a contract with the food hub?	No	I don’t remember	No
Does the food hub prohibit producers from selling around the hub? Yes or no?	I don’t know	No idea	There are no strict policies about it

When asked about how profit sharing with producers who are perceived to be loyal to the food hub would influence their decisions, the producers gave mixed responses. One producer said, “Yes. Profit sharing would make me reconsider selling around the hub”, while another responded, “Profit sharing would not be substantial enough for me to change any of my decisions”. Loyalty to the food hub appears not to be a factor influencing producer decision-making. Two of the three producers stated that they feel no loyalty to a food hub. The only producer who has a sense of loyalty to a hub is due to a personal relationship with a food hub employee, rather than loyalty to the food hub business entity.

Customer interviews

Neither of the two customers interviewed admitted to any transactions around the hub, so questions regarding sales around the hub were not applicable. Both customers stated that they use multiple suppliers of local food and do not rely solely on a food hub to fulfill their demand. Overall, the two customers interviewed seemed satisfied with the food hub's service level, each one giving the food hub's customer service a rating of 3.5 and 5 respectively. Each customer valued the food hub differently. One customer liked the time and labor savings the food hub provides them: "I'm okay paying a higher price when buying through the food hub because I don't have to spend as much time managing producers". The other producer values the ability of the food hub to provide specific products: "The food hub will go out of the way to find specific products for us".

Discussion

The responses to the pilot study indicate the existing interview protocol requires revision before it can be implemented as a full study. Some pilot study results were expected, while others were surprising. Nothing from the pilot study is conclusive; however, it provides insight about where subsequent interviews, management strategy development, and modeling efforts should focus.

An important outcome of the study is learning that customers are likely active in initiating disintermediation. This directly contradicts the initial assumption that the producers are primarily driving the disintermediation, while customers are passive participants. Although the two customers interviewed in the pilot study stated that they have never reached out to producers for sales around the hub, it is apparent that there are other customers who are doing so. Two producers stated that they do not know to whom their products are sold by the hub, which suggests that it is difficult for them to initiate any sort of disintermediation. Furthermore, each of the two producers who had sold products around the hub claimed that it was the customer who initiated the transaction. Since the participant sample size in this pilot study is small, it is not certain that customers alone are driving disintermediation. However, these preliminary results suggest that producers should not be assumed to be driving the disintermediation entirely.

The results of this pilot study indicate that producers prefer direct sales to customers whenever possible. Producers expressed that direct sales earns more for them than selling through the food hub. The interviewed producers stated that they value the perceived improvements in customer service and the benefits a direct relationship brings their business. Producer loyalty is unlikely to prevent producers from acting against the interests of the hub, which should be considered when developing future interview questions and developing potential food hub management strategies.

Based on the results of this pilot study, it appears that the food hub manager has not made her policies about disintermediation sufficiently clear to the producers. None of the producers interviewed knew if selling products around the hub was acceptable or prohibited by the food hub. Communicating this policy to producers could be a first step in preventing this behavior. Furthermore, there was no consensus by the producers on whether profit sharing would impact their selling decisions. No producers seemed particularly enthusiastic about such a program. Losing the hub as a supply chain partner appears to be more important, particularly for the two producers who would be unable to deliver products to all of their customers. Studying this further will help ensure that the ABM captures the effects of management strategies effectively.

For the food hub manager, it seems that determining and communicating the value that the food hub provides to its producers and customers could be more effective in preventing disintermediation than developing a specific management strategy (i.e., incentives or punishments). Based on the results of this study, there appear to be many different reasons that a producer or customer chooses to the use the food hub's services. Studying the value that the Western Iowa Food Hub provides and the perceptions of that value by the producers and customers would be worthwhile future research. When asked about why they liked the food hub, some of the commonly cited benefits of food hubs were never mentioned by any of the producers. One producer was pleased with the marketing the food hub offers, and another noted a dependency on its transportation services. No producers, however, mentioned enjoying any other food hub benefits that are cited by the USDA. These services are listed below (Barham, Tropp, Enterline, Farbman, Fisk, & Kiraly, 2012):

- Packaging Services
- On Farm Pick up
- Cold and Dry Storage
- Liability Insurance
- Actively Linking Producers and Customers

Although Western Iowa Food Hub provides these services, they appear to be undervalued by the producers. Better communication regarding the benefits of working with a food hub could help to prevent producer disintermediation.

CHAPTER VI

CONCLUSIONS AND FUTURE WORK

After demonstrating the capabilities of the computational model and completing the empirical pilot study, several important conclusions can be drawn. Firstly, combining reinforcement learning and agent-based modeling is effective in demonstrating the system-level behavior of the producers of a food hub. Producers in a real regional food system do not and cannot have perfect information when making business decisions. The reinforcement learning allows the producer agents to start with no knowledge and learn information as they test different behaviors, which likely better reflects reality. The computational model is able to incorporate interactions between producers and customers and the actions of the food hub in response to producer behavior. The model allows for producer agents that develop their individual selling preferences when using reinforcement learning to make decisions. The model provides a food hub manager with a system-level view of the regional food supply network under various management strategies. Although the model is useful for demonstrating producer behavior, the current model is not fully validated, and therefore it is not ready to be used to make specific conclusions regarding the case study system.

Because there is not enough existing empirical data, this model cannot be validated for the case study system. This model is flexible and can incorporate more empirical data from the case study system in place of the theoretical model assumptions. Once empirical data is incorporated into the model and the model is validated, it will be ready to test actual management strategies the Western Iowa Food Hub manager is considering.

Based on the results from the pilot interviews with producers and customers of the case study food hub, it appears that some of the initial assumptions regarding the case study system may be incorrect. If so, the model must be changed to reflect the behavior of the real system prior to using it to draw any valid conclusions. The conceptual model and empirical study interview protocol assumed that the producer alone is driving the disintermediation. This assumption was made based on conversations with the food hub manager. However after conducting the pilot study, it seems likely that the customers take some part in driving sales around the hub. This finding contradicts the original assumption that producers alone drive the disintermediation, and suggests that more research is necessary before the ABM can be validated for the case study regional food system.

Although the conceptual ABM and the results of the pilot empirical study do not allow for any specific conclusions regarding the Western Iowa Food Hub disintermediation problem to be made, the unexpected results from the pilot empirical study suggest many possibilities for future work. One of the most important directions for future work is to determine whether it is the producer, customer, or both who are driving disintermediation in the system. By interviewing additional producers and customers, this can be better understood. Furthermore, the customers should be asked more questions regarding buying products around the hub. After determining the driver of disintermediation, this logic should be incorporated into the producer and customer agents in the ABM. Customer agents likely require more complex decision-making logic and should take a more active role in the ABM.

Another direction for future work is to study the actual and perceived value that the food hub provides before concentrating on developing management strategies. There are many services that the food hub provides that were never mentioned by the pilot study producers as something they valued about working with the food hub. Future work should focus on determining if the producers are undervaluing the food hub services, or if these services are not being properly communicated to producers. Additionally, determining whether different types of producers have different perceptions of value may prove useful. Since the focus of the empirical study interviews was on the producers, future interviews should focus equally on the customer. The customers should be asked additional questions to quantify the type and amount of value that the hub provides to them. Further, if producers and customers do not undervalue food hub services, additional research can focus on finding new ways for the food hub to provide the value that producers and customers are seeking.

It is also important to gather additional empirical data to understand how the producers would respond to a given management strategy. There are assumptions in the conceptual ABM regarding producer responses to management strategies that have not yet been validated. Also, the current model does not allow producers to leave the food hub completely. It is important to understand if that could be a potential consequence of implementing a given management policy. Accurately predicting the producer response to potential management strategies is imperative to decision-making in the system. Once the empirical data has been gathered and incorporated into the ABM, the ABM can be validated and used for decision-making purposes.

Lastly, the Western Iowa Food Hub is currently in a stage of growth and is adding new producers. This is a phase that more established food hubs have already experienced. Interviewing and researching these established food hubs, which exist elsewhere in the United States, could provide insight into how best to manage growth. Growing the food hub effectively could reduce the prevalence of disintermediation and possibly prevent its occurrence in the future.

Combining reinforcement learning with agent-based modeling is not only useful for studying regional food systems, but this method can also be used to study system-level behavior of other systems in which agents make decisions without perfect knowledge. Disintermediation is not the only problem that this computational model framework is capable of studying; it can study other problems where autonomous entities are making decisions in a system. Managers of non-supply chain systems can find this model useful for understanding how their actions affect individual decision-making and how those individual decisions influence system-level behavior.

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APPENDIX A

INTERVIEW QUESTIONS

Questions for Producers

Basic questions about your business

What products do you sell? What percentage of your sales is each product?

- Produce
- Meat
- Dairy
- Dry goods
- Other

How long is the drive from Des Moines to where you are located?

How long is the drive from Omaha to where you are located?

What types of transportation modes do you have available to you to deliver products?

- Refrigerated truck?
- Non-refrigerated truck?
- Pickup truck?
- Van?
- Car?
- Other?

What kind of customers do you sell to? What percent do each make up?

- Grocery stores-small
- Grocery store-large
- Restaurants
- Institutions (Schools, hospitals etc)
- Direct consumers
- Other

How much revenue does your farm/processing facility generate in a year?

Are all your products available through the food hub? What other channels do you use to sell your products?

What percentage of your products do you sell through the food hub? How much revenue comes from the food hub?

Is your business growing? Are you trying to grow your business, If yes, how?

- Growing business with current customers
- Growing business within current customer metropolitan areas
- Growing business beyond current metropolitan areas
- Other

How important is growing your business further?

- 1-Not important
- 2-Mostly unimportant
- 3-Neutral

- 4-Mostly important
- 5-Completely important

How long have you been using the food hub's services?

Are you able to deliver products to all your customers without the food hub services? Yes or no? Would you business be profitable if you had to deliver products to all your customers? Would you lose customers?

Do you think the food hub's rate is fair/ appropriate? Explain. If not, what should it be?

<u>Questions about customer service</u>

Does the food hub provide all services you want? What is missing?

On a scale of 1 to 5, how would you rate the food hub's service level? Explain

- 1-Completely unsatisfied
- 2-Mostly unsatisfied
- 3-Neutral
- 4-Mostly satisfied
- 5-Completely satisfied

Do you like the food hub? Why? For what purposes?

How does your service (customer satisfaction, on time deliveries, product quality at delivery etc.) compare to the food hub's when you sell directly to customers?

- Better
- The same
- Worse

How important is building a direct connection to a customer?

- 1-Not important
- 2-Mostly unimportant
- 3-Neutral
- 4-Mostly important
- 5-Completely important

<u>Questions about selling decisions</u>

Selling around the hub definition: A transaction between a producer and customer whose relationship was cultivated by a food hub and the food hub's services were not used. It does not include transactions where the food hub cannot provide the services needed for the transaction

Do you sell products around the hub? If you sell products directly to customers, do you charge a different price than through the food hub?

- If yes, do you charge more or less?
  - More (50% or more higher)

    - More (less than 50% higher)
    - Less (less than 50% lower)
    - Less (50% or more lower)

If you don't sell around the food hub, have you considered it?

- How likely are you to do this?
    - 1- Very unlikely
    - 2- Somewhat unlikely
    - 3- Neutral
    - 4- Somewhat likely
    - 5- Very likely

How frequently do **customers** request you sell around the hub to them?

- Never
- Less than once a month
- Twice a month
- Weekly
- Daily

If a customer requests you sell around the hub to them, do you ever decline their request?

- Always
- Most of the time
- Half of the time

- Some of the time
- Never

When **you** offer to sell around the hub to a customer, how often do they accept the offer?

- Always
- Most of the time
- Half of the time
- Some of the time
- Never

How likely are you to sell around the hub to customers located less than 15 minutes driving one way to your business?

- 1- Very unlikely
- 2- Somewhat unlikely
- 3- Neutral
- 4- Somewhat likely
- 5- Very likely

How likely are you to sell around the hub to customers located between 15 and 30 minutes driving one way from your business?

- 1- Very unlikely
- 2- Somewhat unlikely
- 3- Neutral

- 4- Somewhat likely
- 5- Very likely

How likely are you to sell around the hub to customers located between 30 and 60 minutes driving one way from your business?

- 1- Very unlikely
- 2- Somewhat unlikely
- 3- Neutral
- 4- Somewhat likely
- 5- Very likely

How likely are you to sell around the hub to customers located greater than 60 minutes driving one way from your business?

- 1- Very unlikely
- 2- Somewhat unlikely
- 3- Neutral
- 4- Somewhat likely
- 5- Very likely

Has selling directly to customers helped you grow your sales with the customer? Yes or no?

If you sell products around the hub, how secretive are about your selling decision?

- 1-Not secretive

- 2-Mostly not secretive
- 3-Neutral
- 4-Mostly secretive
- 5-Completely secretive

If you sell products around the food hub, has the food hub discovered your behavior? Yes or no?

Do you feel disloyal to the food hub if you sell products around the hub? Yes or no? Explain.

Do you consider selling a high sales amount around the hub more disloyal to the hub than selling only a small amount around the hub? Yes or no?

Does the food hub prohibit producers from selling around the hub? Yes or no? Explain.

Have you signed a contract with the food hub?

- Yes
- No
- I don’t remember

If you’ve signed a contract a contract with the food hub, do you view it as legally binding?

- Yes
- No

- Not sure

If you don't view the contract as legally binding, what would need to change in order for you to view it that way? If you do view it legally binding already, what changes would make other producers view it seriously?

If you were caught selling around the hub, would there be any legal repercussions? Yes or no? Explain.

Do you tell other producers if you sell around the hub? Yes or no?

How would other producers view your business if you choose to sell around the hub?

- Positively
- Neutral
- Negatively

Would you reconsider selling around the hub if that choice was shared with other producers? Yes or no?

If the food hub were to share profits with producers who are not caught selling around the hub, would it dissuade you from selling around the hub or reconsider if you have not sold around the hub? Yes or no?

<u>Questions about your recent selling decisions</u>

Did you sell any products around the food hub?

- Last week?
- 2 weeks ago?
- 3 weeks ago?
- 4 weeks ago?
- 5 weeks ago?

For each time you sold around the food hub, what percentage of your sales do you estimate went AROUND the food hub?

- 1%-33%
- 34%-66%
- 67%-99%

For each time you sold around the food hub, how close (one way) were the customers you sold to from your business? Select all that apply.

- Less than 15 minute drive
- 15-30 minute drive
- 30-60 minute drive
- Greater than 60 minute drive

For each time you sold around the food hub, did the food hub manager know you sold around the hub?

- Yes
- No

Questions for Customers

What type of customer are you?

- Grocery stores-small
- Grocery store-large
- Restaurants
- Institutions (Schools, hospitals etc)
- Direct consumers
- Other

Do producers who previously sold to you through the food hub ever offer to make sales to you directly?

- If a producer offers to sell directly, do you accept?

Do you ever request that producers who previously sold to you through the food hub sell to you directly?

Do you pay a lower price when a producer sells directly to you? Explain.

On a scale of 1 to 5, how would you rate the food hub’s service level? Explain.

- 1-Completely unsatisfied

- 2-Mostly unsatisfied
- 3-Neutral
- 4-Mostly satisfied
- 5-Completely satisfied

Does the food hub provide all services you want? What is missing?

Do you like the food hub? Why? For what purposes?

APPENDIX B

EMAIL TEMPLATE

Dear Food Hub Producer,
I am a graduate student at Iowa State University, in the Department of Industrial and Manufacturing Systems Engineering. I am working with assistant professor Dr. Caroline Krejci on her research involving regional food distribution and food hubs. The objective of this research is to help regional food systems become more resilient, with the aim of increasing their ability to support social, environmental, and economic sustainability in communities.
As part of this research, Dr. Krejci and I are performing a study to assess regional food hub producers' selling decisions. The knowledge gained from this study will help to inform and support the decision making of regional food hub managers, enabling them to develop effective strategies to maintain and grow of their supply network and their customer base. As such, the beneficiaries of this information include not only food hub producers and food hubs, but also consumers who would like to gain or increase their access to regional food. Because you are a producer for a regional food hub, customer for a regional food hub or food hub manager, we invite you to participate in this study. We will be conducting interviews with regional food hub producers beginning in September. If you are interested in participating in this study or have any questions, please contact Teri Craven to set up an appointment for an interview at a time that is convenient for you.

Teri Craven
Phone: 515-294-4867
Email: tjcraven@iastate.edu

Caroline Krejci
Phone: 515-294-4867
Email: ckrejci@iastate.edu

APPENDIX C

FLYER

Iowa State University is currently conducting a study regarding selling decisions of producers in a regional food supply network.
You are being invited to participate in this study because you are a producer for a regional food hub, customer of a regional food hub or food hub manager. You should not participate if you are under age 18. If you agree to participate, you will be asked a variety of questions about your business operations and decisions in an interview.
Records identifying participants will be kept confidential to the extent permitted by applicable laws and regulations and will not be made publicly available.
If you are interested in participating in the study, if you have any concerns, or if you would like additional information about this study, please contact Teri Craven tjcraven@iastate.edu

APPENDIX D

CONSENT FORM

CONSENT FORM FOR: ASSESSING MANAGEMENT STRATEGIES FOR INTERMEDIATED REGIONAL FOOD SUPPLY NETWORKS

This form describes a research project. It has information to help you decide whether or not you wish to participate. Research studies include only people who choose to take part—your participation is completely voluntary. Please discuss any questions you have about the study or about this form with the project staff before deciding to participate.

Who is conducting this study?

This study is being conducted by Teri Craven and Dr. Caroline Krejci

Why am I invited to participate in this study?

You are being asked to take part in this study because you are a producer for a regional food hub, customer of a regional food hub or food hub manager. You should not participate if you are under the age of 18.

What is the purpose of this study?

The purpose of this study is to gain a better understanding of the decision making of producers participating in food distribution via a regional food hub. This knowledge will help food hub managers ensure they provide distribution services that meet the needs of small and mid-sized producers. It will also help regional food researchers in creating regional food supply chains that deliver regional food efficiently to consumers. As such, the beneficiaries of this information include not only food hub producers and food hubs, but also consumers who would like to gain or increase their access to regional food.

What will I be asked to do?

If you agree to participate, you will be asked to respond to a variety of interview questions on the following topics:

- Demographic information about your business
- What you value about local food
- Your business operations
- Your business and selling decisions
- Views on food hub services

Your participation will last for approximately one hour.

What are the possible risks or discomforts and benefits of my participation?

Risks or Discomforts— There is a slight risk of disruption of personal relationship to the participants due to the fact that some of them have personal relationships with the food hub manager. This risk will be mitigated by performing interviews in private rooms, not identifying the participants by name, and by keeping interview data in a secure location. It's important to note that the manager will not be in the interview room and the interview information shared with the manager will be de-identified. The type of information that may be shared with the manager is the average response to an interview question or distribution of responses to an interview question.

Benefits—you may not receive any direct benefit from taking part in this study. We hope that this research will benefit society by supporting the development of socially, environmentally, and economically sustainable and resilient regional food systems, which benefits all people who depend on food for their livelihoods and health.

How will the information I provide be used?

The information you provide will be used to perform statistical analyses to assess the relationships between regional food hub producer attributes/preferences and their selling decisions. These statistical relationships will then be used to develop computer simulation models of a regional food supply network.

What measures will be taken to ensure the confidentiality of the data or to protect my privacy?

Records identifying participants will be kept confidential to the extent allowed by applicable laws and regulations. Records will not be made publicly available. However, federal government regulatory agencies, auditing departments of Iowa State University, and the ISU Institutional Review Board (a committee that reviews and approves research studies with human subjects) may inspect and/or copy study records for quality assurance and analysis. These records may contain private information.

To ensure confidentiality to the extent permitted by law, all collected information will be placed in a locking briefcase and transported to 3031 Black Engineering Building, where it will be placed in a locking filing cabinet for which only the PI and Co-PIs will have a key to access. Electronic data will be stored on an encrypted Iowa State cloud storage or on a devoted external hard drive with encryption that will itself be stored in the locking file cabinet.

No meaningful identifying information (for example, your name or business name) will be associated with the interview data at any point in time. This will ensure that your identity will be kept confidential when study results are disseminated.

Will I incur any costs from participating or will I be compensated?

You will not have any costs from participating in this study. You will not be compensated for participating in this study.

What are my rights as a human research participant?

Participating in this study is completely voluntary. You may choose not to take part in the study or to stop participating at any time, for any reason, without penalty or negative consequences. You can skip any questions that you do not wish to answer.

If you have any questions *about the rights of research subjects or research-related injury*, please contact the IRB Administrator, (515) 294-4566, IRB@iastate.edu, or Director, (515) 294-3115, Office for Responsible Research, 1138 Pearson Hall, Iowa State University, Ames, Iowa 50011.

Whom can I call if I have questions about the study?

You are encouraged to ask questions at any time during this study. For further information, please contact Teri Craven or Caroline Krejci:

Teri Craven
Email: tjcraven@iastate.edu
Phone: 515-294-4867

Caroline Krejci
Email: ckrejci@iastate.edu
Phone: 515-294-4867

Consent and Authorization Provisions

Your signature indicates that you voluntarily agree to participate in this study, that the study has been explained to you, that you have been given the time to read the document and that your questions have been satisfactorily answered. You will receive a copy of the written informed consent prior to your participation in the study.

Participant's Name (printed) ____

____ ________________________

Participant's Signature Date