An agent-based approach to modeling sustainable sociotechnical systems

by

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DEDICATION

To my parents, and all my teachers
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ABSTRACT

A gradual evolution in the food and energy sectors towards decentralized decision-making is requiring participant organizations to consider new approaches to the design of policies and processes. Increasing consumer preference for food sourced from small-scale regional farmers has led to changing logistics requirements. Similarly, as consumers have become conscious of the impacts of climate change on the environment, they have begun to adopt renewable sources to meet their energy needs. Moreover, the emergence of new technologies has enabled consumers to generate their own energy. Such shifts in decision-making power to consumers necessitates the consideration of their perspectives and preferences when designing policies and business structures. In food and energy systems, which can be considered sociotechnical systems, the role of human behavior influences system dynamics as strongly as the technical artifacts. This dissertation utilizes an agent-based modeling approach to study such sociotechnical systems. Although agent-based modeling (ABM) has demonstrated the potential to understand and predict the dynamic behavior of sociotechnical systems, the biggest barriers in implementing ABM widely are its replicability and validation. This dissertation aims to address these two issues by developing empirical ABMs for applications in regional food supply chains and renewable energy systems. The applications of the ABMs in this dissertation are motivated by United Nations Sustainable Development Goals, specifically those goals that are focused on the objectives of responsible consumption and production, climate action, and affordable and clean energy for all.
CHAPTER 1. GENERAL INTRODUCTION

In 2015, the United Nations adopted 17 Sustainable Development Goals that call for a better quality of life for all. Two key focus areas are food and energy, which are two of the most important requirements for sustainable development. The United Nations emphasizes that, in addition to providing nutritious food for all, it is necessary to rethink existing policies and practices associated with globalized food supply chains, with an aim of supporting people-centered rural development and protecting the environment. Furthermore, the Sustainable Development Goals highlight the importance of enabling universal access to energy through efficiency gains and renewable sources in order to create more sustainable and inclusive communities with increased resilience to the effects of climate change.

Consumers have lately started to recognize the importance and urgency of sustainable development and the role they can play at individual level by altering their choices of food and energy sources. They have started to show an increased preference for regionally-produced food (food that is produced in a given geographical proximity and travels shorter distance to reach consumers as compared to conventional supply chains) and support for local farmers in community as well as an inclination towards renewable sources for their energy needs. This enhanced perspective of consumers makes them an important stakeholder in the food and energy systems. Therefore, when designing policies that seek to encourage sustainable development it has become imperative to study these two systems in a manner that incorporates heterogeneous individual consumer motivations and behavior.

Decentralized food systems

The global food supply system is witnessing a transition from a supply chain with centralized control to regionalized supply networks with a more decentralized control.

The
globalized food supply chains provide consumers with convenient and consistent access to an extraordinary variety of food, irrespective of season or locale. Despite these benefits, consumers are increasingly seeking alternatives to the global system. In particular, demand for regionally-produced food has increased tremendously among the consumers due to its perceived benefits that include: lower prices, food that is fresher, safer, and/or more nutritious than conventionally-produced food, reduced reliance on long-distance transport and fossil fuel consumption, and the ability to support the local economy [1 – 3]. Many consumers also value the ability to have face-to-face interactions with the farmers who produce their food. Such interactions facilitate transparency and trust-based relationships between producers and consumers [4, 5].

To cater to this increased preference for regionally produced food by consumers and also support small farmers, ‘food hubs’ have emerged as a popular intermediary in the U.S. These food hubs have experienced tremendous growth in popularity over the last decade. The USDA defines a food hub as “a business or organization that actively manages the aggregation, distribution and marketing of source-identified food products primarily from local and regional producers to strengthen their ability to satisfy wholesale, retail and institutional demand” [6]. The primary objective of food hubs is to support local economies by providing market opportunities for small-scale producers and treating them as valued business partners, rather than interchangeable suppliers [7]. These food hubs typically operate at a regional level and supply within a limited geographical proximity. As such, the food crosses less distance to reach end consumers and via lesser number of entities involved, in contrast to a conventional supply chain system. The decision making at the food hub is locally influenced, i.e., much more decentralized. However, food hubs in the U.S. are not profitable on average [8]. In fact, the highest performing (i.e., top 25%) food hubs earn only a 4% profit margin, and the average across all food hubs is -
2% [9]. Many food hubs fail because they lack systematic supply chain management structures [10]. Therefore, to be able to support long-term economic, environmental, and social sustainability in regional food systems, food hubs should consider implementing the kinds of efficiency-enhancing supply chain management techniques that have been adopted by conventional FSCs [11]. Unlike conventional distributors, however, most food hubs have a strong social mission that guides their strategic, tactical, and operational decision making. For some food hubs, this mission involves supporting small and midsize food producers; others focus on providing consumers with affordable access to healthy food. As a result, both producers and consumers become significant stakeholders in the operation of these food hubs. These participants have diverse motivations, bring in diverse perspectives, and exhibit diverse behavior. Unfortunately, reconciling socially motivated and financial objectives due to increased number of roles and actions of various stakeholders has proved to be very difficult for them to effectively and efficiently manage the supply chains.

**Decentralized energy systems**

Due to an increased share of renewable sources, the energy sector is experiencing a shift from a centralized production and distribution network to a more decentralized network. Energy consumers are now becoming energy generators, leading to a shift in decision making power from an organizational level to an individual level, thereby increasing the number of actors involved in the energy market. This changing business environment, in which more power lies in the hands of consumers, has made it necessary for policymakers, utilities and other private players such as solar installers to consider consumer behavior when making predictions, developing business strategies, and framing policies.
For example, residential energy consumers in the U.S. have demonstrated an increased interest in solar-based electricity at home, resulting in increased adoption of distributed solar on the rooftops of owner-occupied residences (typically known as rooftop PV). However, in the U.S., only 57% of all residential buildings are suitable for rooftop PV installation [12]. In addition, renters and apartment owners who do not own the installation space are not able to take advantage of this technology. These barriers have led to equity concerns among policymakers, particularly because publically-funded rebates for PV system installation are only being distributed to a small number of U.S. households. Moreover, as the number of consumers who generate their own energy using rooftop PV increases, utilities’ revenues decline.

Alternative renewable energy models, such as community solar and green pricing programs, offer a potential solution to these challenges. These models involve both consumers and utilities as stakeholders. For example, community solar enables a customer to subscribe to a portion of a shared renewable energy facility (much like a resident may invest in a community garden) located elsewhere in the community. As such, consumers choices are becoming increasingly important in this system, as opposed to the conventional energy sector, which was dominated by decisions made at the central level by utilities and policymakers. Therefore, it is important to understand how heterogeneous individual customers would respond in the presence of different renewable energy models and what the impacts of these individual decisions would be on the long-term success of the overall system. In particular, when consumer energy choices are driven by perceived benefits such as financial savings and increased convenience, they are also often socially motivated.

1.1 Sociotechnical Systems

In the context of organizational policy development and decision making that affect the long-term well-being and resilience of society, taking individual behaviors into account is
extremely important. This is especially relevant where decision making is decentralized and is influenced by social interactions of consumers and where a transition from the conventional system is being observed. This organizational landscape can be defined as a sociotechnical system that consists of two subsystems – a social network of actors and a physical network of technical artifacts [13]. In a sociotechnical system, autonomous entities interact with each other and with their environment directly or indirectly, make decisions, and take actions to achieve their objectives. Over time, these individual interactions and decisions can lead to a system-wide behavior that is difficult to understand and predict. At the same time, it is important to study these systems and work towards designing efficient policies and business landscape such that the ultimate objectives of the United Nations Sustainable Development Goals can be achieved.

1.2 Agent-based Models

Agent-based modeling (ABM) is a powerful computational tool that enables quantitative analysis of system-wide behavior that emerges from individual behaviors, interactions, and adaptations over time. This dissertation describes new applications of ABM to the study of sociotechnical systems that are focused on improving social and environmental sustainability for the benefit of society. Although ABM has demonstrated potential to understand and predict the dynamic behavior of sustainable sociotechnical systems, the biggest barriers in implementing ABM widely across industrial applications are its replicability and validation [14]. This dissertation aims to address these two issues using the ABM methodology by developing empirical ABMs for applications in regional food supply chains and renewable energy systems.

Agent-based Model of Regional Food Systems

Logistics best practices from conventional supply chains have the potential to improve the efficiency of regional food supply chains (RFSCs). Therefore, to further understand how best practices in conventional food supply chains can be implemented in RFSCs, a structured and in-
depth review of the existing literature on RFSC logistics was conducted as described in Chapter 2. The review concluded that the logistics decisions in RFSCs are typically made on an ad-hoc basis, because RFSC practitioners usually have very little background in business planning and supply chain management. Therefore, there exists a need to develop data-driven decision tools based on quantitative evaluations to help RFSC practitioners make smart logistics management decisions.

Chapter 3 describes the development of a novel hybrid simulation modeling framework that addresses this concern. The model evaluates the degree to which efficiency-enhancing practices adopted by conventional FSCs can be integrated into RFSC operations. Secondly, it demonstrates the value of incorporating empirically informed human decision making and behavior in a simulation model of warehouse operations. Existing simulation models of warehousing operations fail to incorporate the effects of human behavior and decision making on efficiency-enhancing operational policy changes. The hybrid simulation model described in this chapter leverages the combined capabilities of ABM and discrete-event simulation to incorporate empirical human behavioral data into a process-oriented model of warehouse inbound operations for a regional food hub in central Iowa.

Agent-based Models of Residential Renewable Energy Systems

Chapter 4 describes a conceptual ABM that is used to predict the effect of the availability of different distributed renewable energy models in creating a successful zero energy community (ZEC). The U.S. DOE defines a ZEC as an “energy-efficient community where, on a source energy basis, the actual annual delivered energy is less than or equal to the on-site renewable exported energy” [15, p. 4]. Specifically, this study seeks to evaluate design trade-offs for a community solar program and determine how to maximize total renewable energy generation.
through consumer participation. As the concurrent presence of multiple different renewable energy models (e.g., rooftop PV, community solar, and green pricing programs) can affect participation, it is important to model these options simultaneously.

Chapter 5 describes an agent-based approach to modeling consumer adoption behavior in the presence of competing renewable energy models, such that the impacts on multiple stakeholder objectives can be understood. The conceptual ABM described in this chapter is a novel approach to designing urban residential renewable energy systems that equitably satisfy consumer demand while maintaining solar installers and utility revenues. Thus, the proposed modeling methodology can help to inform design decisions of distributed solar energy models that avoid benefiting some stakeholders at the unnecessary expense of others. Fulfilling the conflicting and competing objectives of these key stakeholders will support the overarching goal of greater renewable energy deployment in the energy sector.

Chapter 6 describes a structured approach to identifying the key behavioral and social factors that should be drawn from a set of empirical data in order to parameterize an ABM. This approach will be used to develop an empirically validated ABM of residential consumer solar adoption in the City of Livermore in California. Behavioral and social factors are critical in accurately predicting demographic and spatial patterns of residential solar diffusion [16]. However, existing ABMs of solar diffusion are parameterized using a subset of potential factors that seem to have been selected on an ad-hoc basis. Therefore, these models do not include certain behavioral and social factors that are known to play an important role in consumers’ decisions to adopt solar.

One approach to factor selection is the use of established behavioral theories, such as the Theory of Planned Behavior, Value-belief Norm Theory and Theory of Innovation Diffusion
This chapter suggests a systematic approach to deriving a set of behavioral factors to parameterize agents’ solar adoption decision logic, with an aim toward balancing model fidelity and parsimony. Chapter 7 concludes the dissertation.

References


CHAPTER 2.  LOGISTICS BEST PRACTICES FOR REGIONAL FOOD SYSTEMS: A REVIEW

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2.1 Abstract

The modern industrial food supply system faces many major environmental and social sustainability challenges. Regional food systems, in which consumers prefer geographically proximate food producers, offer a response to these challenges. However, the costs associated with distributing food from many small-scale producers to consumers have been a major barrier to long-term regional food system success. Logistics best practices from conventional supply chains have the potential to improve the efficiency and effectiveness of regional food supply chains (RFSCs). This paper provides a structured and in-depth review of the existing literature on RFSC logistics, including recommended and implemented best practices. The purpose of the review is to provide RFSC researchers and practitioners with convenient access to valuable information and knowledge derived from years of experimentation and research. This information will help to inform practitioners’ implementation decisions and to increase researchers’ awareness of the existing work on RFSC logistics, the unmet needs of practitioners, and topics that have not been fully explored, yielding insights into potential future directions for RFSC research. The overarching aim of the paper is to facilitate improvements in RFSC logistics, thereby improving regional food system viability.
Keywords: logistics; supply chain management; regional food systems; food hubs; sustainability

2.2 Introduction

The global food supply system provides consumers with convenient and consistent access to an extraordinary variety of food, irrespective of season or locale. Despite these benefits, consumers are increasingly seeking alternatives to the global system. In particular, demand for regionally produced food has increased tremendously. In 2015, food that was produced and sold regionally by U.S. farms yielded $8.7 billion in sales [1]. Some regionally produced food is sold directly to consumers through farmers’ markets, but most is distributed to consumers through retailers. In fact, the results of a 2015 survey indicate that 87% of consumers choose a supermarket based on its regional food offerings [2]. Consumers’ motivations for buying regional food vary widely and are based on perceived benefits that include: Lower prices, food that is fresher, safer, and/or more nutritious than conventionally-produced food, reduced reliance on long-distance transport and fossil fuel consumption, and the ability to support the local economy [3]–[5]. Many consumers also value the ability to have face-to-face interactions with the farmers who produce their food. Such interactions facilitate transparency and trust-based relationships between producers and consumers [6], [7].

Increased demand for regional food has the potential to greatly benefit small-scale farms (i.e., farms with annual income <$75,000), which account for 85% of all regional food providers [8]. In particular, direct-to-consumer sales (e.g., via farmers’ markets) allow small-scale producers to offer lower volumes and set higher prices than mainstream distributors would accept. As a result, many federal, state, and local policymakers have begun to incorporate regional foods into programs designed to support small farmers and rural economies [9]. However, the scale and efficiency of direct-to-consumer marketing channels can be limiting—
many consumers prefer the convenience of shopping for food at retail stores, and many farmers struggle to afford the high marketing and transportation costs associated with distributing their products at multiple farmers’ markets [8], [10].

For regional food systems to achieve their full potential, regional food producers must find ways of scaling up their operations to allow them to distribute their products to a greater number of consumers via institutional and retail channels. Such opportunities are increasingly available, with retailers, school districts, universities, healthcare facilities, and corporate cafeterias committing to sourcing more regionally-produced food [11]–[13]. The recent emergence of scale-appropriate logistics infrastructure for regional food systems has helped some producers to take advantage of these opportunities. In particular, regional food hubs provide logistics services to connect small-scale producers and institutional/retail buyers. A regional food hub is “a centrally located facility with a business management structure facilitating the aggregation, storage, processing, distribution, and/or marketing of locally/regionally-produced food products” [14]. A primary objective for food hubs is to support local economies by providing market opportunities for small-scale producers and treating them as valued business partners, rather than interchangeable suppliers [14].

However, most regional producers and food hubs do not have robust systems in place to support large-scale processing, aggregation, and distribution, and they often lack the necessary expertise, capital, and access to credit to acquire and implement these systems [15], [16]. This lack of adequate logistics infrastructure has been a huge barrier to regional food system growth and success. Efforts to overcome this barrier have been primarily led by grassroots community groups, food policy councils, and local planners, who often have little expertise in food distribution logistics [17].
One approach to facilitating scaled-up logistics in regional food supply chains (RFSCs) is to implement best practices that have yielded high levels of efficiency and effectiveness in large-scale supply chains. Such practices include relationship development and coordination across the supply chain, efficient utilization of transportation and logistics infrastructure, implementation of accurate and reliable systems for food traceability, and data-driven demand planning and inventory management. Recommendations and guidance on logistics best practices for RFSCs are available in an extensive body of literature [18], but this literature is scattered and fragmentary. Most of the research on RFSC logistics has been communicated through case studies and technical reports written by various university extensions, non-profit organizations, and state and federal agencies. As a result, regional food practitioners have reported being overwhelmed by the continually growing body of knowledge [19].

There have been some efforts to organize and consolidate this research in reviews of recommended best practices and barriers to success, as well as examples of successes and failures [18]–[21]. Additionally, several bibliographies of publications on regional food systems have been compiled in an attempt to improve information accessibility for researchers [22]–[24]. However, the systematic study of RFSCs is still in its early stages [4], [25]. As such, no systematic review has been conducted that integrates the available information on recommended RFSC logistics best practices, implementation examples of these practices by RFSC practitioners, and the associated benefits and challenges.

In an effort to fill this gap, this paper provides a structured and in-depth review of the existing literature on RFSC logistics. The purpose of the review is to provide researchers and practitioners with convenient access to valuable information and knowledge derived from years of experimentation and research. Practitioners will benefit from a greater awareness of logistics...
best practices that are available to them, as well as associated advantages and disadvantages, based on the experiences of other RFSC practitioners. Understanding these tradeoffs can help to inform their own decisions, for example, whether to buy or lease a truck (or perhaps neither). Furthermore, the analysis performed in this paper aims to increase researchers’ awareness of the existing work on RFSC logistics, the unmet needs of practitioners, and topics that are not yet well understood and have not been fully explored, which may yield insights into potential future directions for RFSC research. The overarching aim of the paper is to facilitate improvements in RFSC logistics, thereby improving regional food system viability.

The paper is organized as follows: Section 2 describes the challenges associated with RFSC logistics management, with a focus on transportation, warehousing, and inventory management. These challenges were identified through a detailed review of peer-reviewed journal articles, technical reports by university extensions, conference papers, and book chapters. Section 3 summarizes best practices recommended in the mainstream supply chain literature to address the challenges described in Section 2. Section 4 describes the standard review method adopted in this paper. Using the best practices described in Section 3 as a framework, Section 5 provides a systematic review of recommended and implemented RFSC logistics best practices, as evidenced by case studies, university extension reports, and scholarly literature. Section 6 summarizes and analyzes the review and then discusses potential future directions for RFSC logistics research. Finally, Section 7 provides overarching conclusions from the review.

2.3 Challenges in Regional Food Logistics

Various definitions of the terms “logistics” and “supply chain management” exist in the literature. According to the Council of Logistics Management, logistics is a function that is contained within supply chain management and is defined as “that part of the supply chain process that plans, implements, and controls the efficient flow and storage of goods, services,
and related information from the point of origin to the point of consumption in order to meet customers’ requirements” [26]. According to [27], logistics includes warehousing, transportation, management of materials and information, and integration of logistics operations for the entire supply chain, whereas supply chain management merges marketing and manufacturing with distribution functions to improve competitive advantage. With respect to agriculture and food systems, logistics includes production planning and the movement of food products from producers to consumers, including processing, storage, handling, and packaging [28].

Based on the accepted definitions available in the existing literature, this paper broadly defines the scope of logistics to include transportation, warehousing, and inventory management [29]–[33]:

**Transportation**: The movement of inventory from point to point in a supply chain.

**Warehousing**: Activities involving the physical locations where inventory is stored, retrieved, assembled, and packed for distribution.

**Inventory management**: Monitoring and deciding how much inventory to stock, what is in stock, and how inventory should be stored.

Effective logistics management requires sufficient infrastructure to support consistent deliveries of the right product, in the right quantity, in the right condition, to the right place, at the right time, for the right cost [34]. However, the logistics infrastructures of food supply chains are often not as developed as the supply chains of other industries, such as automotive or electronics [35]. This is especially true for RFSCs, in which distribution tends to be fragmented and less efficient than the centralized distribution networks of conventional food systems [28]. As a result, RFSCs commonly struggle with a variety of challenges in transportation, warehousing, and inventory management.
2.3.1 Transportation

Supply chains in every industry face a variety of transportation-related challenges, including capacity shortages, empty backhauling, issues with security and contamination, and concerns over environmental impacts and non-renewable energy consumption [36]. While regionally-produced food travels much shorter distances from farm to consumer than food that is distributed via conventional supply chains, RFSC transportation is typically much less efficient, due to the economies of scale that can be achieved with long-distance freight movement of full truckloads [37]. In fact, gains in fuel efficiency per unit of product hauled can cancel out the effects of longer transport distances [9]. This is particularly true for producers of specialty crops and niche food products—managing their movement from farm to market is much more complex and expensive than distributing conventional farm products. The smaller volumes and the necessity of keeping niche products separate from bulk commodities add to the cost of handling and shipping [38].

Many of the greatest logistical inefficiencies associated with regional food freight occur at the beginning and end of the supply chain, where numerous short but indirect first/last-mile hauling routes increase the per-unit hauling cost [37]. Small farmers often use their personal trucks or vans, rather than commercial carriers, for this purpose [39]. This requires the use of many small vehicles transporting low volumes, for which the balance between fuel used and volume transported is not favorable [40]. For example, a study on an RFSC in Sweden found that the average load rate was less than 50% [41].

RFSCs are also typically disaggregated and not vertically integrated [42], which can lead to coordination challenges. For example, a lack of coordination between transportation providers and small producers can cause problems when products are not packed and ready for a scheduled pickup, or when there is no one available at the farm to load products on the truck. Poor
transportation coordination can also be problematic for producers who provide their own transportation. For example, when deliveries to a retailer or food hub warehouse are not properly scheduled, numerous producers may arrive at the same time, causing traffic congestion and delays [37].

2.3.2 Warehousing

The wide variety of products that are distributed through RFSCs presents a tremendous warehousing challenge. In particular, safely and efficiently handling and storing a large number of stock keeping units (SKUs) that may have product-specific cold storage requirements and varying degrees of perishability can be very difficult and expensive [43]. However, small-scale farmers and food hubs generally do not have access to sophisticated physical warehousing infrastructure (i.e., washing, cooling, packing, and storage facilities) [44]. Moreover, the physical infrastructure developed to facilitate high-volume transactions through conventional food supply chains can be inefficient and impractical when applied to regional food distribution. Unfortunately, infrastructure that is at an appropriate scale for small-scale producers is largely unavailable, which is a major challenge for RFSCs [45]–[47]. Therefore, new RFSC-specific warehousing infrastructure and supply chain models are needed to support efficient logistics for larger volumes of regional food products [48]–[50].

Warehousing labor availability is another major operational challenge for RFSCs. Out of 79 U.S. regional food hubs surveyed, 41 indicated labor availability as a barrier to growth [17]. Nine of these food hubs also emphasized that dependence on volunteer labor was a significant challenge. While volunteer labor helps to reduce costs, operational efficiency and consistency tend to suffer, due to a lack of training and inconsistent commitment [51].
2.3.3 Inventory Management

Balancing demand and supply is a major challenge for RFSCs. In fact, this was the most frequently cited challenge in interviews with U.S. food hub operators, primarily because demand is greater than what their regions are able to supply [52]. Regional food retailers in Michigan and Illinois have indicated that a lack of consistent supply has negatively impacted their sales [53], [54]. This imbalance in supply and demand is partly a result of poor coordination between marketing and crop production, with respect to demand planning and inventory management [42]. Seasonal fluctuations in regional food availability are another major factor; in many regions, there is a shortage of supply in the winter months [55].

Another major inventory management challenge for RFSCs involves food traceability. One of the greatest perceived advantages of RFSCs is their ability to provide customers detailed information about product sourcing and production methods, due to their comparatively shorter supply chain structure [56]. Simply labeling products as ‘regional’ is insufficient, because customers often want to know which specific farm produced the food that they are purchasing. However, food hubs often struggle to maintain farm identity along the supply chain [52], because small-scale farmers will often combine their products with those of other farmers to make processing and shipping more economical [4].

2.4 Logistics Best Practices

Much of the existing research on RFSCs suggests that they should adopt conventional supply chain practices for their long-term growth and sustainability [57]. Such practices have the potential to reduce warehousing and transportation costs and improve the ability of RFSCs to meet growing consumer demand for regionally produced food. In general, best practices in logistics are applicable to a wide variety of organizations, irrespective of industry, channel position, or size [58]. However, it is not clear how readily these practices translate to RFSCs.
This section describes best practices that have been recommended for mainstream supply chains to address the logistics challenges that RFSCs commonly face, as described in Section 2.

2.4.1 Transportation

Best practices for maximizing transportation efficiency in supply chains include efficient vehicle utilization, reducing empty backhauling, appropriate vehicle selection, frequent and timely deliveries, leveraging the services of third-party logistics providers, and developing transportation collaborations.

2.4.1.1 Efficient Vehicle Utilization

Increasing vehicle load rate is one of the most important activities that an organization can undertake to reduce its carbon footprint, increase its logistics efficiency, and reduce transportation cost, since most shipments are less-than-truckload [29], [59]. Maximizing vehicle load rates requires optimal routing and scheduling [60]. For example, by consolidating delivery routes and reducing the number of required stops, Kraft Foods improved its company-wide fuel efficiency by seven percent [29]. Similarly, a study in Serbia identified that optimizing delivery vehicle routing could yield a 20% reduction in transportation costs and associated emissions [61]. However, a systems view of the problem is essential—a case study on waste collection in Finland demonstrated that significant cost savings could be achieved by optimizing the routes and schedules of the entire fleet, rather than individual vehicles [62]. Strategic design of the distribution network structure is also critical. For example, having customers pick up their orders at a designated location can improve vehicle load rate, but providing last-mile delivery can be nearly as efficient if customer orders are sufficiently large [63].

Efficient vehicle utilization can be achieved through the use of a transportation management system (TMS) [59]. TMS software automates many key transportation functions, including optimal carrier selection, load building, fleet management, routing and scheduling, and freight
audit payment. Although expensive, the return on investment for a TMS is generally less than a year, depending on the size and revenue of an organization [59]. For example, Coca-Cola implemented a TMS to determine optimal vehicle loads and routes, given distributors’ volume, frequency, and delivery time window constraints. This system yielded an annual savings of $45 million and significant improvements in customer service [64].

2.4.1.2 Backhauling

Backhauling, which involves carrying goods on return trips, rather than returning with empty trucks, can significantly improve vehicle load rates [65]. For example, after delivering products to a distributor, an empty truck can be routed to a nearby vendor to pick up raw materials [29]. By reducing the number of empty trips, backhauling increases overall fleet efficiency and reduces transportation costs for suppliers and customers, as well as help reducing environmental impacts [29], [66].

2.4.1.3 Vehicle Selection

Fleet management (i.e., determining fleet size and vehicle types, sizes, and ownership) significantly affects the percentage of empty hauls and overall transportation efficiency [67]. In particular, fuel consumption depends on vehicle type—large and/or refrigerated vehicles tend to have very low fuel efficiency [68]. Therefore, selecting appropriate vehicle types and sizes to meet supply chain objectives is critical. Adopting vehicles that use alternative or hybrid fuel technology can also reduce transportation costs and adverse environmental impacts [29], [69].

Vehicle ownership is another major determinant of transportation efficiency. Leasing a vehicle allows organizations to avoid up-front investment. However, purchasing a vehicle can be less costly in the long run, depending upon the terms and conditions of the leasing contract (e.g., interest rate, down payment, and payment period) [70]. Maintenance costs, which tend to
increase sharply after three years of vehicle usage, are an important consideration, as well as the risk of mechanical breakdowns, which can result in lost sales and dissatisfied customers [71]. In this regard, leasing can be beneficial, because it is generally the responsibility of the leasing company to provide alternate arrangements while the leased vehicle is being serviced [72].

2.4.1.4 On-Time and Frequent Deliveries

Customers highly value on-time deliveries, which tend to encourage repeat business [73]. On-time deliveries also facilitate effective and efficient cross docking by reducing waiting times for outbound trucks [74]. Additionally, frequent deliveries benefit customers by increasing product availability and freshness. However, frequent deliveries of small quantities can depress vehicle load rates, creating a financial burden for suppliers and distributors [66].

2.4.1.5 Third-Party Logistics (3PL)

A third-party logistics provider (3PL) is an organization that manages one or more logistics processes or operations (typically transportation or warehousing) for another company [33]. 3PL providers integrate multiple customer loads using sophisticated software to improve load rates and enable product traceability [75], [76]. 3PLs can also provide aggregated information for many small suppliers in a single location, thereby reducing customers’ search costs and eliminating the need for suppliers to invest in information infrastructure [31]. Many organizations have successfully outsourced some or all of their logistics operations to 3PLs, including Kimberly-Clark, which used a 3PL to satisfy retailers’ delivery frequency requirements and significantly reduced its distribution costs [77].

2.4.1.6 Transportation Collaboration

Successful supply chains rely on long-term strategic collaborations that enable participants to work together to create an effective and efficient transportation system [78]–[80]. A survey of
286 companies revealed that collaboration was the most important transportation practice in driving their supply chain improvement [59]. There are two types of collaboration in logistics: horizontal and vertical.

**Horizontal collaboration**—Horizontal collaboration occurs between organizations in different supply chains to better utilize assets and reduce overall costs [81], [82]. In horizontal collaboration, organizations cluster their logistics activities and assets (e.g., through shared transportation and processing facilities) to improve efficiency and reduce environmental load [33]. Examples of horizontal collaboration in transportation include shared consolidation centers, joint trucking routes, and optimization of the entire transportation network across multiple competing supply chains for maximum transportation efficiency [82]. Effective horizontal collaboration between Nestle and United Biscuits resulted in fewer empty truck runs and eliminated 280,000 truck kilometers from the roads, reducing fuel consumption and CO₂ emissions by 85,000 liters and 223 tons, respectively [77]. However, effective horizontal collaboration requires organizations to overcome significant challenges, including technological barriers and insufficient trust between coordinating partners [83].

**Vertical collaboration**—Vertical collaboration occurs between entities belonging to the same supply chains, either upstream (i.e., with suppliers), downstream (i.e., with customers), or internally across functions in an organization [82]. It can be facilitated through information exchange via interconnected system between successive partners in a supply chain [33]. Vertical collaboration in transportation is necessary to optimize a supply chain’s transportation network, thereby reducing costs, improving service levels, and improving supply and delivery reliability [30], [81], [82]. For example, real-time sharing of information between distributors and retailers...
will enable them to identify delivery problems as they occur. This will improve the retailers’
customer service levels and the distributors’ transportation network planning.

2.4.2 Warehousing

Best practices for maximizing warehouse/distribution center productivity include effective
labor utilization, optimized facility location selection, adequate infrastructure development,
efficient and effective storage, picking, and packing policies, and collaboration and resource
sharing within and outside the supply chain for warehousing activities.

2.4.2.1 Effective Labor Utilization

Inadequate employee training can result in a variety of negative outcomes, including poor
man-hour utilization, worker frustration, and frequent turnover [84]. Therefore, implementing
effective training programs is critical to success in warehousing operations. Properly training
warehouse employees yields increase in operational efficiencies, as well as improved service
levels [59], [85]. In particular, cross-training workers to enable them to undertake a wider variety
of tasks improves labor scheduling flexibility and can also lead to increased worker satisfaction
and retention [86], [87].

2.4.2.2 Facility Location

Determining the optimum number and locations of warehouses is critical for logistics
efficiency [59]. While transportation and inventory decisions can be changed relatively
frequently without negative consequences, location decisions are often long-term and directly
affect labor costs, transportation costs, and inventory holding costs, as well as many indirect
costs, such as taxes [88]. Facility location decisions depend on access to markets and suppliers,
competitor locations, government and tax regulations, environmental factors, labor availability,
and transportation and utilities services [89]. Service quality and customer responsiveness are
also important considerations—being located near major customer bases enables warehouses to provide just-in-time, smaller, and more frequent shipments to customers [90].

2.4.2.3 Infrastructure Development

Best-in-class companies invest significantly in infrastructure (e.g., technology and facilities) to improve the performance of their supply chains [91]. For food supply chains in particular, inadequate infrastructure can result in variable product quality, unreliable supply, and insufficient storage capacity [92], whereas investment in appropriate infrastructure (e.g., refrigeration) can improve product handling and storage, which reduces post-harvest losses [93].

2.4.2.4 Efficient Warehousing Policies

Order picking from warehouse storage locations to fulfill customer orders is labor-intensive and is therefore the costliest activity in most warehouses [94]. Therefore, an optimal warehouse layout and the use of effective and efficient storage and picking policies can significantly reduce material handling costs [59]. Designing a warehouse layout involves decisions regarding the relative locations of departments (e.g., receiving, picking, storage, sorting, and shipping), the appropriate number of picking blocks, and the length and width of aisles in each block, with an objective of minimizing overall warehouse operating costs [95].

Packaging provides opportunities for cost savings and improved sustainability throughout the supply chain [96]. Optimal packaging and pallet patterns can reduce materials usage, increase space utilization in the warehouse and on trucks, and reduce the amount of material handling required. The result is less packaging waste, greater vehicle load rates, and improved handling in the warehouse. This efficiency directly translates into less impact on the environment [97]. In the fresh food supply chain, the development of modified-atmosphere packaging lengthens the best-
before-date and is often combined with sensors and tracking devices to facilitate traceability [33].

2.4.2.5 Warehousing Collaboration and Resource Sharing

*Horizontal collaboration*—Sharing warehousing and/or production capacity with other organizations can significantly reduce operational costs in a supply chain [81]. Horizontal collaboration in warehousing can also be extended to joint infrastructure development, which can reduce the need and risk of high up-front investment cost.

*Vertical collaboration*—Vertical collaboration in warehousing is important for reducing errors in inventory placement and order assembly, as well as facilitating cross-docking [98]. Cross-docking involves moving inbound material directly from receiving to shipping without placing it into storage locations. The items are unloaded, sorted by destination, and then reloaded onto outbound trucks. By eliminating storage and picking, cross-docking significantly reduces inventory and operational costs [59]. Cross-docking also prevents overstocking and reduces the risk of loss and damage of stored goods [99]. For example, Goodyear’s transition from traditional warehousing to cross-docking increased their service levels to 96% and decreased operational costs by more than 12% [100]. However, successful cross-docking requires synchronization of the arrival times and capacities of inbound and outbound trucks. Many organizations use a hybrid combination of warehousing and cross-docking to take advantage of both approaches [101].

2.4.3 Inventory Management

Best practices in inventory management include implementing warehouse inventory management systems, using inventory tracking systems, matching supply with demand through demand forecasting, improving supplier reliability, and collaborative inventory management.
2.4.3.1 Warehouse Inventory Management Systems

An inventory management system allows buyers to coordinate with suppliers and accurately evaluate, order, and update inventory. In particular, e-sourcing—the use of electronic marketplaces for purchasing, rather than emails and spreadsheets—improves the speed and efficiency of procurement [59]. Furthermore, integrating the inventory management system with a buyer’s material requirements planning (MRP) system can assist in making efficient long-range demand planning, purchasing, scheduling, and inventory management decisions [102].

2.4.3.2 Inventory Tracking and Food Traceability

Inventory tracking within a warehouse is best performed through the use of a warehouse management system (WMS). A WMS is a software application that interfaces with supply chain planning, order management, enterprise resource planning, and the TMS. It tracks the location of items by purchase order, bar code, lot number, or other identification system, such as RFID [59]. RFID tags have recently been introduced in the food supply chain by many large retailers (e.g., Walmart, Tesco, and Metro) at the pallet level. Using such tags provides significant logistical benefits, since the tracking of those items does not require human intervention [33]. In food supply chains, product traceability is critical for food safety, enabling timely product recalls and determination of liability [103].

2.4.3.3 Demand Forecasting

Accurate demand forecasting is one of the most important and most challenging measures of supply chain proficiency [59]. Demand planning involves collecting and analyzing historic sales and inventory data and then sharing this forecast information upstream and downstream in the supply chain [104]. Collaborative forecasting and replenishment reduce inefficiencies that result from multiple uncoordinated forecasts (i.e., the bullwhip effect) [105]. However, establishing
sufficient trust between organizations and implementing appropriate technology for information sharing can be significant barriers [105].

2.4.3.4 Improved Supplier Reliability

Consistent supplier reliability is critical for supply chain success, because inventory availability significantly impacts customer satisfaction and loyalty [106,107]. Reducing supply uncertainty through improved supplier reliability can help organizations to match supply and demand, thereby increasing inventory availability and supply chain responsiveness. This is particularly important with suppliers of perishable goods [108]. Technological advances can help to improve supply reliability. For example, Gillette adopted RFID technology to monitor the flow of its products from distribution centers to retail stores and found that sales from RFID-enabled stores were 19% higher than stores that did not use it due to less out-of-stocks [109].

2.4.3.5 Collaboration and Resource Sharing for Inventory Management

*Horizontal collaboration*—Group purchasing is a typical method of horizontal collaboration in inventory management [81]. Group purchasing can potentially lead to lower prices of products for collaborating organizations due to economies of scale, as well as give them an access to purchase goods which they could have not done alone due to volume constraints.

*Vertical collaboration*—Upstream vertical collaboration in inventory management includes supplier development and planning, production scheduling, and vendor managed inventory (VMI). Downstream vertical collaboration includes customer relationship management, collaborative demand planning, and demand replenishment [83]. Strong vertically collaboration and information sharing throughout the supply chain (both upstream and downstream) can help organizations reduce demand variability, improve forecast accuracy, and reduce inventory levels [30,110]. Because owning inventory involves carrying costs, keeping inventory levels to a
minimum is critical for supply chain success. Inventory levels can be significantly reduced through the use of just-in-time (JIT), in which items are replenished just as they are required [111]. In particular, implementation of an electronic data interchange (EDI) system facilitates continuous electronic flow of consumer sales data and inventory management information between retailers and suppliers [112]. For example, Walmart shares real-time demand information electronically with its suppliers, who use this information to replenish inventory. The system results in less inventory, lower costs, and the ability to pass on these savings to customers [34].

2.5 Review Method

A standard three-step process was followed to conduct the systematic literature review, including planning the review, conducting the review, and reporting and dissemination [113]. In the planning stage, the Leopold Center for Sustainable Agriculture was contacted to obtain information about institutions and research centers in the U.S. that are conducting research on RFSCs. Information from the Leopold Center helped to establish connections with coordinators from the Sustainable Agriculture Research and Education (SARE) Program and researchers at the Wallace Center at Winrock International, which is a non-profit organization that is focused on social, agricultural, and environmental issues in the U.S. Based on recommendations from SARE coordinators, the Regional Food Systems group at Michigan State University and the Center for Environmental Farming Systems at North Carolina State University were contacted, as well. The inputs from these research centers and institutions helped to determine 12 major sources of technical reports in the area of regional food system logistics, as shown in Table 2.1. The technical reports from these organizations were written by notable regional food system researchers, and many have been peer reviewed. Therefore, these reports are considered to be
nationally credible. Reports available through March 2016 from the sources listed in Table 2.1 have been considered for review in this paper.

Table 2.1 Sources of technical reports.

<table>
<thead>
<tr>
<th>Source</th>
<th>URL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural Sustainability Institute, University of California, Davis</td>
<td><a href="http://asi.ucdavis.edu/resources/asi-publications">http://asi.ucdavis.edu/resources/asi-publications</a></td>
</tr>
<tr>
<td>Center for Environmental Farming Systems, North Carolina State University</td>
<td><a href="https://cefs.ncsu.edu/publications/">https://cefs.ncsu.edu/publications/</a></td>
</tr>
<tr>
<td>Center for Integrated Agricultural Systems, University of Wisconsin Madison</td>
<td><a href="http://www.cias.wisc.edu/category/local-food/">http://www.cias.wisc.edu/category/local-food/</a></td>
</tr>
<tr>
<td>Center for Regional Food Systems, Michigan State University</td>
<td><a href="http://foodsystems.msu.edu/resources/">http://foodsystems.msu.edu/resources/</a></td>
</tr>
<tr>
<td>Leopold Center for Sustainable Agriculture, Iowa State University</td>
<td><a href="https://www.leopold.iastate.edu/resources">https://www.leopold.iastate.edu/resources</a></td>
</tr>
<tr>
<td>National Center for Freight and Infrastructure Research and Education, University of Wisconsin Madison</td>
<td><a href="http://www.wistrans.org/cfire/research/completed-research/">http://www.wistrans.org/cfire/research/completed-research/</a></td>
</tr>
<tr>
<td>National Good Food Network</td>
<td><a href="http://www.ngfn.org/resources/ngfn-database">http://www.ngfn.org/resources/ngfn-database</a></td>
</tr>
<tr>
<td>North Carolina Cooperative Extension</td>
<td><a href="https://content.ces.ncsu.edu/catalog/category/11/local-foods">https://content.ces.ncsu.edu/catalog/category/11/local-foods</a></td>
</tr>
<tr>
<td>United States Department of Agriculture</td>
<td><a href="https://www.ams.usda.gov/resources">https://www.ams.usda.gov/resources</a></td>
</tr>
<tr>
<td>Wallace Center at Winrock International</td>
<td><a href="http://www.wallacecenter.org/resourcelibrary/">http://www.wallacecenter.org/resourcelibrary/</a></td>
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<tr>
<td>Wholesome Wave</td>
<td><a href="https://www.wholesomewave.org/resources/publications">https://www.wholesomewave.org/resources/publications</a></td>
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</tbody>
</table>

Peer-reviewed journal articles published between 2006 and 2016 (through February) that discuss best practices in RFSC logistics were also reviewed. The Scopus database was used to search for journal articles using a specific set of keywords, which are listed in Table 2.2. Scopus covers a broad range of journals and is widely accepted by the scientific community for
structured literature reviews [114]. Articles were shortlisted based on combinations of keywords, a technique that is widely practiced in literature reviews that are published in reputed journals [115]–[117]. Every possible combination of keywords was used, resulting in an exhaustive search process. Table 2.2 provides the logic that was used to generate these combinations.

Table 2.2 Keyword set used for shortlisting journal articles in the Scopus database (‘*’ is used as an operator for truncated search process).

<table>
<thead>
<tr>
<th>Keyword 1</th>
<th>Boolean</th>
<th>Keyword 2</th>
<th>Boolean</th>
<th>Keyword 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food</td>
<td>AND</td>
<td>region*</td>
<td>AND</td>
<td>supply chain</td>
</tr>
<tr>
<td></td>
<td></td>
<td>local</td>
<td></td>
<td>logistics</td>
</tr>
<tr>
<td></td>
<td></td>
<td>sustainab*</td>
<td></td>
<td>value chain</td>
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</table>

In all, total 672 technical reports, journal articles, and case studies were reviewed. A total of 106 technical reports and 28 journal articles were determined to be the most relevant, and they were included in this paper. The flowchart in Figure 2.1 shows the literature search and screening process adopted in this study as per PRISMA guidelines.

2.6 Best Practices in Regional Food Systems Logistics

This section provides a systematic review of the literature on recommendations and implementation examples of logistics best practices in RFSCs. The focus of this review is restricted to the best practices that have been shortlisted in Section 3.

2.6.1. Transportation

This sub-section describes recommendations on the six transportation best practices by RFSC researchers, as well as implementation examples of these practices by RFSC practitioners.
2.6.1.1. Efficient Vehicle Utilization

*Recommended practices*—Route optimization and vehicle load rate maximization can help RFSC participants to reduce their fuel consumption and benefit from economies of scale [118]. Although regional food is not transported over long distances, RFSC transportation can consume more fuel than conventional food supply chains, as a result of inefficient collection and delivery processes [4], [8], [119]. RFSCs have low “food miles”, but product aggregation to achieve large load sizes is necessary to yield highly fuel-efficient distribution systems [9], [120].

The Michigan Food Hub IT Platform Feasibility Study recommends the use of routing software that provides distribution route visibility, schedules, and product availability along each
route and enables the creation of new routes [121]. To maximize load rates, RFSCs should also consider implementing Global Data Synchronization (GDS), which provides universal product codes and information-sharing standards for suppliers, distributors, and customers [122]. GDS improves the accuracy of information (e.g., product weights) throughout the supply chain. Having accurate product weights allows trucks to be filled as fully as possible without exceeding Department of Transportation weight limits. Although route planning is easier with software, the associated costs can be prohibitive for small organizations, which have fewer trucks and stops to consider [123]. Therefore, increased availability of affordable routing software that is tailored to the specific needs of RFSCs could greatly benefit such organizations [124]. However, if affordable software are unavailable, simple guidelines that leverage expert judgment may be appropriate. For example, in order to run cost-efficient routes with fully-loaded trucks, food hubs should plan their deliveries according to seasonal supply and focus on serving nearby customers when supply is low [125].

*Implemented practices*—Because they are generally small-scale organizations, most RFSC participants do not use sophisticated software for transportation routing. Instead, they tend to rely on expert knowledge and informal heuristics. For example, the employees of Local Harvest Supply, a regional food distributor in Coralville, Iowa, use their personal knowledge of roads, traffic, and past transportation decisions to plan their deliveries [123]. To maximize its load rates, Keewaydin Organics, a farm and regional food distributor in Viola, Wisconsin, uses small trucks to deliver products to an aggregation point and then makes long/large market hauls with a larger truck [126]. Keewaydin also uses Google Maps and regional knowledge to determine the most efficient routes [123]. The Purchase Area Aquaculture Cooperative, a farmer cooperative in Kentucky, also uses different types of vehicles for different kinds of deliveries. Their system
uses a leased truck to make small deliveries directly to customers, and distributors are hired to handle large deliveries [127]. Some RFSCs have also increased vehicle utilization through distribution network design. All Natural Beef Cooperative, a natural beef co-op in Kansas, sells regionally-produced beef to Balls Food Stores, a grocery retailer in Kansas [128]. Originally, the cooperative shipped products from its processing facility to individual Balls Food’s retail outlets, which required the use of multiple refrigerated trucks and labor to load and transport the meat. To address these issues, Balls Food now operates a hub-and-spoke distribution network in which products are brought from various regional producers to a central warehouse, where they are unloaded, repacked, and reloaded onto trucks and are then shipped to individual stores. This new network structure has reduced the number of deliveries to the grocery stores, thereby decreasing overall operational costs. It has also helped farmers reduce their transportation costs by providing them with a single delivery point [128]. However, Balls Food’s central warehouse lacks sufficient cold storage capacity for All Natural Beef Cooperative’s products, so the cooperative decided to open its own regional meat distribution facility [128].

A food hub in the UK uses a different strategy—it requires its customers to pick up products from conveniently-located distribution sites, which significantly reduces the number of delivery stops for the food hub’s delivery vehicles [129]. The Iowa Food Cooperative, a food hub in central Iowa, follows a similar distribution model, in which customers pick up products from one of seven distribution sites. Similarly, Fifth Season Cooperative, a regional food cooperative in Viroqua, Wisconsin, and Common Market, a regional food distributor in Philadelphia, have multiple aggregation points for regional producers [130], [131]. Having sufficient cold storage and a loading dock at these locations has been critical, as well as quality inspections to ensure that products meet the food hubs’ standards. Full Circle, a food hub in Washington, divided its
delivery area into three regions and supplies its customers with products from farmers located within the customers’ region [132]. New North Florida Cooperative in Marianna, Florida, cultivated a customer base within a specific geographic region to establish economically-efficient delivery routes [133]. The cooperative also makes efficient use of truck capacity by pairing deliveries to high-volume/low-price customers (e.g., grocery stores) with low-volume/high-price customers (e.g., schools).

The Iowa Food Hub, located in West Union, Iowa, offers hauling services to its producers, in addition to transporting their products to the hub’s warehouse [134]. By providing this additional service, the truck is filled with a more complete load and receives additional income from charging hauling fees to producers. Similarly, Potato King, a produce wholesaler and transporter in Wisconsin, maximizes the loads on its trucks by providing a hauling service for regional companies that have shipments to be delivered near Potato King’s existing customers on its established routes [126]. However, they avoid taking on any extra deliveries that would interfere with their ability to serve their customers.

Some regional food organizations have implemented software for route optimization and load rate maximization. For example, the implementation of a simple vehicle routing tool significantly reduced transportation costs for a regional food delivery company in Mexico [124]. Similarly, the Purchase Area Aquaculture Cooperative implemented a basic program that plans efficient routes, rather than a complex interactive model [127]. Bix Produce, a regional food distributor in Minnesota, uses two different routing systems to create efficient routes [123]. Bix’s routing system creates an initial set of fixed routes, and a UPS Logistics Technologies system fine-tunes those routes based on the actual loads and specific stops.
2.6.1.2 Backhauling

**Recommended practices**—To reduce system transportation costs, RFSC organizations should work together to incorporate backhauling into their distribution routes [37], [135]. For example, a food hub could offer a pick-up service for producers along its regular customer delivery route, thereby eliminating delivery trips for the producers and additional pick-ups for the food hub. Similarly, a food hub can partner with a larger regional food distributor by having it pick up products from the food hub during its regular delivery routes [136]. An innovative and efficient distribution model, known as the Farmers’ Market Hub, was proposed to increase regional food access for customers in the Greater Los Angeles area [137]. With this model, products from multiple farmers would be aggregated at the farmers’ market. Before returning home from the farmers’ market, the farmers’ empty trucks would be filled with the aggregated product, which would be used to fulfill wholesale orders in their respective regions. Backhauling can also facilitate the use of reusable shipping containers [123]. While this requires up-front investment and additional storage space, regular usage can lead to cost savings and improved environmental sustainability in the long run.

**Implemented practices**—Although backhauling can reduce RFSC transportation costs, implementation has proved to be challenging, because backhauling increases transportation route complexity and requires additional planning. For example, Bix Produce reported that it often struggles to arrange backhauls [123]. Nevertheless, several regional food organizations have reported successful implementation of backhauling into their distribution routes. Both Cherry Capital Foods, a regional food distributor in Traverse City, Michigan, and La Montanita Co-op in Albuquerque, New Mexico, orchestrate transportation to ensure that whenever possible, all of their trucks backhaul products on their return trips [138], [139]. This has led to increased
transportation efficiency and a reduced carbon footprint. Edina Couriers, a regional distributor in Minnesota, modifies its core routes to backhaul whenever possible, adding freight to avoid empty and less-than-full trucks [123]. Since one major customer defines most of Edina’s delivery routes, the routes remain relatively consistent, which reduces the amount of planning and coordination that is necessary for backhauling. Several food hubs in the Hudson Valley have extended their delivery reach by backhauling with distributors and retail stores [56].

2.6.1.3 Vehicle Selection

*Recommended practices*—For an RFSC organization that provides transportation, choosing the best type of vehicle to meet its needs is essential. If an organization delivers fresh produce, a refrigerated truck that can maintain a consistent temperature is recommended [140]. However, if the organization faces significant financial constraints, a creative vehicle solution may be best. For example, a donated city bus can allow an organization to expand its services and provide a mobile market [18]. Other vehicle options include mobile carts, renovated postal or commissary trucks, and boats. Replacing old vehicles with energy-efficient vehicles can aid in food hub success and sustainability [140]. If a food hub is distributing products nationwide, it might consider utilizing multi-modal freight options to reduce costs, increase fuel efficiencies, and avoid traffic congestion [37]. For example, barges could be used for food distribution to cities along the Mississippi River [37]. When purchasing a truck, food hubs are advised to look for vehicles that are common in their area, so that replacement parts can be obtained quickly. This can help a food hub to reduce truck downtime and avoid financial losses due to missed deliveries [134].

Once the appropriate vehicle type has been established, the next decision that an RFSC organization must make is whether to buy or lease a vehicle. To determine whether buying or
leasing is more cost-effective, organizations should have a good understanding of all of the relevant costs, including rental costs for a leased vehicle, loan payments for a purchased vehicle, fuel costs, maintenance costs, insurance payments, and taxes [125]. A hybrid strategy, in which some vehicles are purchased, and others are leased, can provide flexibility without significant capital investment. For example, a food hub can lease additional vehicles to supplement its purchased fleet during busy seasons [51]. In [134], a detailed overview of the tradeoffs of renting and purchasing a delivery truck has been provided, and the National Good Food Network provides a buy-versus-lease cost comparison tool on its website to assist food hubs in making this decision [141]. Another important decision in vehicle selection is selecting the appropriate vehicle size, based on the maximum load requirements during the peak season. This is an important decision, because fuel efficiency differs significantly for different vehicle sizes. For example, for a semi-trailer, mid-size truck, and pick-up truck, the respective amounts of fuel required to move one ton of product are one, two, and eleven gallons [119]. Vehicles that use alternative fuels are another option; for example, a group of producers can set up a biodiesel operation and reduce their fuel costs significantly [142].

*Implemented practices*—Several regional food enterprises in the U.S. have retrofitted buses and trucks for cost-effective transportation [143]. Capay Valley Farm Shop in Esparto, California, decided to purchase (rather than lease) its two refrigerated box trucks to avoid lengthy trips to the leasing agency for maintenance [139]. Co-op Partners Warehouse, a regional organic food distributor based in St. Paul, Minnesota, transports products from its warehouse to its customers using one leased truck and six self-owned trucks. The leased truck is used for daily deliveries to its biggest customer, which mitigates risk: The leasing company is obligated to provide a replacement truck if a mechanical problem occurs, so this critical route will always be
covered [133]. La Montanita Co-op decided to lease a truck to avoid high upfront purchase costs, and this truck is used to pick up products from many small-scale regional producers and deliver them to multiple stores in Albuquerque and Santa Fe [144]. Organically Grown Company, an organic produce distributor in Eugene, Oregon, has converted its trucks to bio-diesel in an effort to reduce fuel costs [145]. Goodness Greeness, a regional produce distributor in Chicago, Illinois, explored multi-modal options and is now using short line rail to ship carrots instead of a truck [37]. This Old Farm in Colfax, Indiana, has two delivery vehicles: One serves as a primary delivery vehicle, while the other provides flexibility in accommodating emergency and seasonal deliveries [139].

2.6.1.4 On-Time and Frequent Deliveries

*Recommended practices*—To ensure that customers receive the freshest food possible, it is strongly recommended that RFSC participants make an effort to deliver on time to meet buyers’ needs [4], [47], [146]–[148]. Institutional buyers often prefer to have multiple deliveries each week to avoid stock-outs and to minimize the loss of perishable items [149], [150]. Regional Access, a food hub operating in upstate New York, surveyed its customers and found that 33% of them would increase their purchases if the food hub increased product variety, provided more frequent deliveries, and reduced the time between order placement and delivery [151]. Similarly, survey data from 126 restaurant owners in Iowa indicated that RFSC participants must be highly responsive and offer frequent deliveries to be successful [152].

*Implemented practices*—Ninety-eight percent of Edina Couriers’ deliveries are on time, which allows them to deliver in the small time windows necessary for cross-docking with other distributors [123]. Potato King maintains a perfect on-time delivery rate by routing its trucks around adverse weather [126]. Other organizations have focused on providing frequent
deliveries. Appalachian Harvest, a local food organization in Abingdon, Virginia, created a single brand to represent all of its producers, which allows them to ship twice per week to a small number of large customers [125]. Co-op Partners Warehouse offers daily deliveries of small volumes, which has attracted restaurants and has helped them differentiate themselves from other organic food distributors in the area [133]. They also deliver on Sundays and offer “short delivery calls” for in-town customers, in which orders received by 10:00 a.m. can be delivered the same day for no extra charge. In an effort to increase sales, Grown Locally, a food hub in northeast Iowa, delivers products twice a week during the growing season [153]. Similarly, Oklahoma Food Cooperative, a regional food cooperative in Oklahoma City, decided to increase the frequency of its deliveries from once to twice per month [133]. However, sales did not increase as expected, because the co-op did not have enough supply to meet the resulting increase in demand. HomeGrown Wisconsin, a marketing cooperative of 25 family farms from southern Wisconsin, regularly updates its product availability list and delivers to restaurants twice a week [144]. Western Montana Growers Cooperative in Arlee, Montana, delivers twice each week in summer and once a week in winter to ensure convenient service for its customers [154].

2.6.1.5 Third-Party Logistics (3PL)

*Recommended practices*—Contracting with a reasonably priced 3PL provider can be a good way to ensure on-time deliveries [125]. 3PLs can distribute products very efficiently, allowing food hubs to focus on their core competencies [129]. Using a 3PL is highly recommended for food hubs that are in the early stages of their development [154], [155]. In some cases, 3PL services may be less expensive than in-house distribution; therefore, [37] recommend that food hubs accurately calculate and compare in-house distribution costs with 3PL fees. The authors
specifically recommend using regional 3PLs, which are best suited to accommodating the needs of regional food distribution. However, shipper associations, freight forwarders, and common carriers can provide economies of scale for RFSCs, and they can arrange customs clearance [38].

**Implemented practices**—The use of 3PL providers has varied among different RFSC organizations. Some organizations hire regional 3PLs to help them manage their transportation. Grass Run Farms, a beef producer collective in the Midwest, selected regional distributor Edina Couriers to distribute all of its products to its customers [123], [126]. Small food businesses and producers in Central Oregon have contracted with Cascade Couriers, a regional distributor, for pick-up and delivery services [154]. Keewaydin Organics reported cost savings from working with Edina Couriers and Nottestad Trucking, which contracts with Organic Valley (an organic dairy cooperative in Wisconsin) and allows Keewaydin to piggyback on its deliveries [123]. A food store in Ohio uses a regional 3PL to coordinate procurement efforts with small-scale local farmers and to assist with developing efficient pickup and delivery routes [156]. New North Florida Cooperative outsourced its entire order fulfillment operation to a third-party community-based non-profit organization [147]. This organization receives customer orders and coordinates with the farmers to fill and deliver the orders. Ojai Pixie Growers, a food hub in Ojai, California, uses local contractors to haul, organize, and sell their products [157]. Fifth Season Cooperative has partnered with Reinhart Foodservice for transportation, including backhauling the co-op’s products from several Wisconsin farms [139]. By setting Fifth Season up as a vendor, Reinhart has also been able to connect the co-op with a pool of potential new customers.

By contrast, some organizations use large-scale national 3PL providers [143]. Good Earth Farms, a producer in Wisconsin, uses a combination of a national parcel service and a regional delivery service for its products [158]. Similarly, This Old Farm contracts with less-than-
truckload carriers for non-local sales and works with a regional produce company to arrange backhauling [139]. Farmers in New England contracted with UPS to ship their products to restaurants in New Hampshire, such that farmers can simply drop off products and a chef 200 miles away will receive them the next day. The farmers receive discounts of up to 33% if enough farmers use the program in a given week [144]. High Desert Foods, a small processor of sustainably-grown food located in Durango, Colorado, typically relies on conventional courier services to distribute its products across the U.S. [138]. Organic Valley also uses 3PL providers to distribute products nationwide [159]. Red Tomato, a food hub in Massachusetts, improved operational efficiencies by distributing products via multiple transportation service providers. These providers incorporated their products on existing routes, thereby filling their trucks more completely [122], [131].

Other organizations use a 3PL to manage a portion of their deliveries, while distributing the rest themselves. For example, Tuscarora Organic Growers, a cooperative in Pennsylvania, contracts with a trucking company to complete one-third of its deliveries [160]. Often, an organization will deliver to nearby customers and hire a 3PL provider for distant deliveries, thereby increasing its delivery radius. In fact, nearly all of the 11 most successful food hubs in the U.S. use company-owned trucks for local deliveries and outsource long-distance hauling [139]. These relationships help the trucking companies fill partial loads and provide efficient transportation for the food hubs. Full Circle uses two produce distributors to provide long-haul deliveries beyond the reach of their own trucks, which only deliver products locally [132]. Co-op Partners Warehouse makes its own local deliveries and contracts with common carriers to deliver products more than 100 miles away [161].
A 3PL provider can be a practical solution for a regional food organization that is in the early stages of its development, before it develops logistics expertise and is able to invest in distribution infrastructure. For example, a grass-fed beef company in Minneapolis initially used the distribution services of a local food cooperative before gradually developing its own transportation and distribution network [9]. However, the benefits of using a 3PL provider do not always outweigh the costs. The Purchase Area Aquaculture Cooperative originally used a 3PL provider to handle distribution but found that the numerous fees charged by their provider were too expensive [127]. Additionally, using a 3PL resulted in longer delivery times, because the products were routed through a distribution center, rather than being delivered directly to customers. Using a 3PL can also reduce food traceability. In an effort to efficiently provide its customers with regionally-produced food, Sysco, one of the leading food distributors in the U.S., contracted with a 3PL [162]. However, the farmers supplying Sysco were unhappy that their products were commingled with products from other farms, thereby reducing their ability to build their farm’s brand.

2.6.1.6. Transportation Collaboration

*Recommended practices (Horizontal Collaboration)*—Horizontal collaboration among RFSC participants can greatly improve the efficiency of a regional food system and can expand the RFSC’s logistics capabilities. For producers in particular, collaboration can be critical to success, allowing them to pool their resources and efforts, rather than trying to do every job on their own [144], [163]–[165]. Collaboration among multiple producers can also help to mitigate their risk through shared benefits and losses [166]. For example, producers can collectively invest in a shared delivery truck [163], [167]. Collaborative logistics can also provide producers with better access to processing facilities and distribution networks, thereby improving market
access for their products [9], [168]. A study on regional food organizations in Sweden indicated that coordinated transportation has the potential to reduce the number of routes, driving distance, and total transportation time by 68%, 50%, and 48%, respectively [39]. A similar study in Bagolino, Italy, demonstrated how small cheese producers could benefit from strategic transportation collaborations [169]. However, implementing traceability systems (e.g., farm-level labeling) would be necessary to enable each product’s origins to be identified [4].

While horizontal collaboration can reduce costs for RFSC participants, it can potentially increase their business risk, and it can also slow decision making, since decisions are made by a group rather than individuals [140]. However, the amount of risk incurred depends upon the level of collaboration between the participants. Collaboration is broadly described into three different levels, based on the amount of information exchanged between the collaborating organizations: Cooperating, coordinating, and collaborating networks [170]. As the level of collaboration increases (from cooperating to collaborating), participating members become more interdependent, and there is a greater level of investment and reallocation of resources across the network. To reduce risk and increase the likelihood of successful collaboration among regional food organizations, a contract specifying the responsibilities of each involved party is recommended [171] and parameters for membership of the network should be clearly defined [157]. While network members should share information to maintain transparency, they should avoid information sharing that is too frequent or irrelevant.

*Recommended practices (Vertical Collaboration)—*While the conventional food supply system is largely vertically integrated, vertical collaboration is a relatively new concept in RFSCs [144]. However, collaboration between participants at different echelons of an RFSC can help small producers to survive and compete [8], [172], while insufficient vertical coordination
can potentially lead to inefficiencies and mistrust. For example, the careless handling of products by other RFSC members can be frustrating for producers, creating concerns about end customers’ perceptions of their brand [173]. By contrast, building strategic partnerships with upstream and downstream RFSC members can greatly benefit food hubs and producers [123], [156], [174]. For example, vertical collaboration can facilitate drop shipping, wherein food hubs deliver producers’ products directly to customers for a fee. Drop-shipping programs benefit both the food hub, which receives extra revenue, and the producer, which is able to reach wider markets while maintaining its relationships with customers [138].

Additionally, information sharing throughout the RFSC, in conjunction with joint problem solving, can enable increased efficiency and adaptability. However, encouraging information sharing can be challenging, due to the competitive nature of the relationships between supply chain members [173]. Successful implementation of vertical collaboration in RFSCs requires that participants treat each other as partners and engage in regular and effective communication. Regular meetings to evaluate and discuss supply chain performance can help resolve difficulties and bottlenecks in the supply chain [174]. These meetings also allow regional food organizations to assess whether their core business principles are being upheld throughout the supply chain.

*Implemented practices (Horizontal Collaboration)*—Many regional food producers have reported that they have benefited from horizontal transportation collaboration. Driftless Organics, a farm in Wisconsin, shares distribution efforts with nearby producers and holds regular meetings to share ideas about ways to further increase efficiency [123]. The producers of Grass Run Farms combine their deliveries to increase efficiency, as well as sharing their production, marketing, and administrative expertise with the entire group [123]. By sharing trucking with another company for their long hauls, Eden Natural, a pork producer in Iowa,
saved $0.08 per mile in transportation costs, an annual savings of over $25,000 [175]. Good Natured Family Farms, an alliance of local farmers in Kansas, collaborated to combine deliveries to the Balls Food Stores warehouse and share transportation costs [176]. Regional food producers in western France became more economically and environmentally efficient once they began coordinating transportation with one another [177]. New North Florida Cooperative developed multiple autonomous farmer distribution networks to help their farmers to collaborate with one another [133].

Food hubs have also benefited from horizontal transportation collaboration. Southeast Minnesota Food Hub Network, which consists of over 90 producers, collaborates with Co-op Partners Warehouse in St. Paul, Minnesota, to distribute to locations outside the 90-mile range from their main distribution point [130].

**Implemented practices (Vertical Collaboration)**—Vertical transportation collaboration between food hubs and upstream supply chain members (i.e., producers) has yielded benefits for both parties. For example, Organic Valley wanted to deliver its milk to restaurants, institutions, and grocery stores throughout New Mexico. However, these customers are located outside major U.S. freight routes. To address this challenge, Organic Valley entered into a partnership with La Montanita Co-op in which La Montanita delivers Organic Valley’s weekly milk orders to buyers across the state. This partnership helped La Montanita to develop statewide routes for its delivery business and also led to better truck utilization [131]. Similar partnerships with other producers have helped them to develop a strong statewide distribution system for regionally-produced food.

Vertical transportation collaboration can also occur downstream in an RFSC, between a food hub and regional food buyers. Co-op Partners Warehouse developed a drop-shipping program for small producers, allowing them to sell their products directly to customers but have Co-op
Partners Warehouse make the deliveries [161]. Co-op Partners Warehouse fits the drop-ship deliveries into its regular delivery schedule and bills the producer for the service. Farmigo, an online farmers’ market, in Palo Alto, California, connects customers with producers to arrange drop shipping at convenient locations, such as workplaces or churches [18]. La Montanita Co-op maintains a vertically integrated RFSC by holding team meetings with its retail store staff and its distribution center to determine which products should be routed through the distribution center and which should be marketed directly through the retail store [133]. The distribution center also coordinates with producers to directly deliver their products to their customers under their own invoice for a fee.

2.6.2. Warehousing

This sub-section describes recommendations for the five warehousing best practices by RFSC researchers, as well as implementation examples of these practices by RFSC practitioners.

2.6.2.1. Effective Labor Utilization

Recommended practices—Maintaining a professional and skilled workforce is critical to running a successful food hub operation [133], [155], [157]. Effective labor management, including employee training, workload balancing, and appropriate staffing, can help to reduce turnover [17]. Because most regional food hubs in the U.S. employ part-time and/or volunteer workers [139], their labor management strategies must account for the inherent variability of volunteer labor [178]. While the use of volunteer labor reduces operational costs, it can be problematic for efficiency and consistency due to frequent staff turnover [51], [139]. In particular, sustaining consistent volunteer labor over long periods of time can be difficult, particularly as their initial enthusiasm diminishes. Additionally, volunteers may lack the necessary skills and experience to take on leadership roles and longer-term responsibilities, which can inhibit a food hub’s development [129], [139]. Food hub managers should
systematically track volunteer activities, such that they can identify who performed certain tasks at particular points in time [178]. This will help managers to plan for future staffing needs as the business grows. Also, it is important to develop training materials which can help in faster and efficient on-boarding of new employees [139]. In particular, training employees to load delivery vehicles properly (e.g., loading the last delivery first) is important for regional food distribution efficiency [125].

If a food hub pays its employees, labor efficiency is critical to its financial sustainability. Tracking labor costs and efficiency with appropriate metrics (e.g., sales per worker equivalent) will enable a food hub manager to make informed decisions with respect to labor management [178]. In general, research indicates that high-performing hubs pay their employees more. The performance benefits that are derived from a motivated and loyal workforce tend to outweigh the costs [178].

*Implemented practices*—To improve labor efficiency, Oklahoma Food Cooperative has made efforts to streamline its sorting processes [133]. Its members built an efficient storage system with dedicated locations for refrigerated, frozen, and nonperishable food items. This system has increased order-processing efficiency, such that the number of volunteer workers has remained steady even as throughput has increased. Other food hubs have discovered that personnel attributes and work culture significantly impact labor efficiency. Much of the success of La Montanita Food Co-op can be attributed to recruiting the right combination of skilled and experienced warehouse staff [133]. Their staff members have extensive backgrounds in warehousing, delivery, management, and operations. The farmers who are members of the Appalachian Harvest network are trained in efficient and effective post-harvest handling methods, including washing, grading, picking, and packing [125]. By contrast, one of the
greatest challenges faced by Co-op Partners Warehouse, a Minnesota-based distributor of organic products, has been a lack of experienced staff. Their management also suspect that a lack of professionalism in the warehouse’s work culture has contributed to lost business opportunities [133]. Greenmarket Co., New York, a wholesale food hub, employed a mix of permanent and seasonal staff to avoid giving volunteers responsibility for key operations [139]. The food hub believes that their employees’ institutional knowledge is important for its growth and success.

2.6.2.2. Facility Location

Recommended practices—To minimize transportation time, expense, and emissions, regional food aggregation facilities should be located near major transportation routes and as close to customer bases and growers as possible, particularly when handling perishable goods [53], [119], [155], [157], [179]. The decision to locate a facility in a rural or more populous area depends on whether the facility serves primarily growers or urban customers. Locating distribution hubs far from main thoroughfares may serve the immediate aggregation needs of a cluster of producers, but such hubs will struggle to tap into external freight transport systems and leverage existing transportation infrastructure [123]. A strong customer base can also justify selecting an aggregation site that is further from producers [154]. A survey of food hubs across the U.S. reported that food hubs that were not located near a metropolitan area had higher-than-average dependence on grant funding [17].

While proximity to demand is important, there are other factors to consider when selecting facility location, including the availability of a large pool of people with the necessary skills for employment [175]. Food hubs should also co-locate with existing food markets so that each can benefit from the other’s existence [180]. For example, a feasibility study conducted in London recommended that food hubs work closely with existing infrastructures, particularly the
wholesale markets that already serve much of the city [180]. A facility may have special requirements that can also impact the choice of location. For example, processing facilities require large quantities of water for their operations, so a location that provides access to an abundant supply of water is crucial.

Another factor that may influence a regional food facility location decision is the presence of underserved areas [157]. Food Desert Map created by United States Department of Agriculture shows areas that lack access to fresh and healthy food, based on proximity and accessibility to full-service retail grocery stores [181]. Investors that are interested in developing regional food distribution systems can use the map to determine where to focus sales to improve consumers’ access to fresh food. The Wallace Center is also adding food hub locations to an existing online map of regions in the United States that have low access to supermarkets [181].

To assist in facility location decisions, a mathematical model has been developed that can determine the optimal locations for food hubs in the U.S. The model’s overall objective is to minimize transportation costs, subject to upper bounds on allowable transport distances and food hub capital costs/capacity, as well as road conditions [182].

*Implemented practices*—The Virginia Department of Agriculture and Consumer Services determined the locations of four new packing houses based on input from different regional stakeholder groups, including farmers [140]. Proximity to major markets has been an important driver for the success of Smucker’s Meat, a small-scale regional meat processing facility in Mount Joy, Pennsylvania [46].

2.6.2.3. Infrastructure Development

*Recommended practices*—The foundation of an RFSC is the aggregation and distribution infrastructure it has available to move products from farms to markets, in the form required by
buyers [125], [183]. Thus, the development of sufficient infrastructure capacity is necessary to make RFSCs a vital complement to the global food system [4], [45], [154]. However, an organization’s level of investment in infrastructure should match its stage of development and its marketing capacities [133]—a food hub should use its storage space and material handling equipment efficiently and not invest in capacity that it does not have plans to use [181].

Relatively small investments in infrastructure, such as establishing new or improved loading docks, can offer substantial benefits to regional food producers and distributors [143]. Other recommended infrastructure includes pallet lifters, forklifts, and banding and wrapping equipment, all of which can reduce labor costs and speed up operations at loading docks [184]. The size of a food hub’s warehouse should be based on projected peak season weekly pounds sold [119]. To determine this value, a food hub should frequently monitor its space and equipment usage (e.g., the proportion of space occupied in cold storage each week).

Alternatively, warehouse size can be based on the farm acreage that supplies it (e.g., five square feet per acre), while allowing for future growth and expansion [148], [179].

A food hub might also consider investing in infrastructure that would enable it to provide some basic food processing capabilities (i.e., sorting, trimming, and washing fresh produce) [119], [167]. If funding for acquiring a new facility is unavailable, alternatives (e.g., repurposing existing facilities such as that of a food bank) should be examined [143], [185]. Paying for access to existing supply chain infrastructure or leasing options can also eliminate up-front investment costs [139], [155], [186], [187]. A handbook has been published to help RFSC participants find channels for addressing capital and resource challenges [188].

**Implemented practices**—Some food hubs have reported making significant investments in infrastructure and capacity, often in response to projected or actual demand increases. To
accommodate increased sales and anticipated future growth, Co-op Partners Warehouse significantly expanded its warehouse and trucking capacity [133]. This investment strategy has helped them become one of the biggest distributors of organic products in the upper Midwest. In some cases, however, innovative solutions can reduce the need for investment. For example, a local food distributor in Vermont had its producers dip their eggplants in ice water before loading them on the truck to the warehouse to reduce spoilage [150]. Adopting this strategy eliminated the need for investing in a refrigerated truck.

2.6.2.4. Efficient Warehousing Policies

*Recommended practices*—Standardized methods for product storage, picking, and packaging are critical to the success of regional food hubs [164]. The use of consistent and high-quality packaging methods is particularly important to food buyers [54], [140], [147], [155], [183], [184], [189]–[192]. A survey of local food retailers in Michigan found that inconsistent product labeling and packaging by regional producers was a major reason for decreased regional food sales [54]. Therefore, buyers typically require standardized packaging materials and consistent sizing and grading methods [156]. In particular, restaurants are accustomed to working with large-scale food distributors that use standardized packaging, which is designed for shipping and handling, refrigeration, extended shelf life, and user-friendliness [163]. Therefore, regional food hubs must work with producers to ensure that packed products meet all buyer requirements [45]. In particular, they should select appropriate containers that do not break down when exposed to water, allow for ventilation, and fit in customer storage facilities and displays. A food hub may also need to repack items from small-scale producers to reach a customer’s desired order size [4].

Efforts should also be made to reduce packaging and to use recyclable packaging materials [120]. A study comparing cardboard boxes and reusable plastic containers concluded that
cardboard is a better packaging option (both economically and environmentally) for short food supply chains [193]. On the contrary, a similar study conducted in Emilia-Romagna, Italy, concluded that reusable plastic containers will reduce environmental impact [194]. However, increased transportation and labor handling costs associated with reusable containers could result in overall product cost increases.

*Implemented practices*—Many regional food hubs and producers have made efforts to standardize their packaging methods. The owners of JenEhr Family Farm in Wisconsin visited the kitchens of area restaurants to gain a better understanding of the chefs’ preferences, which helped them to improve their picking and packaging policies [146]. Similarly, a group of farmers in Ohio gained insights from a personnel at a regional grocery chain to learn about customers’ packaging requirements [156]. Members of HomeGrown Wisconsin standardized their packaging and delivery methods to meet the needs of their restaurant customers [144]. An aggregator for small farmers in northern Virginia packs products differently for different customers: Products for retailers are packed in cases, whereas products for processors are packed in bulk [179].

Balls Food Stores provides packing supplies at cost to their regional food suppliers and educates them on how to appropriately pack and deliver products [131], [176]. Winter Harvest, an online regional food buying club based in Philadelphia, sends all of the shipping labels for each delivery date and site to participating farmers at the beginning of the growing season [195]. They also assemble individual orders at each delivery site, rather than at the time of picking or at the beginning of a delivery route, which has helped them reduce delivery errors. An organic potato packing plant in Minnesota provides custom packaging by implementing sorting and packing technologies that are used in conventional food supply chains [38]. An automated screen
sizer is used to remove small potatoes, and an expanding roll sizer sorts out larger sizes to meet consumer needs. Similarly, Coop Partners Warehouse offers custom-sized packs that are smaller than cases to satisfy the requirements of their restaurant clients [133]. Sysco has successfully incorporated apples grown by small and midsize farms near Grand Rapids, Michigan, into its mainstream supply chain [162]. They customized volumes and pack sizes to meet customer requirements, which led to increased sales to convenience stores and hotels.

Some regional food distributors have made efforts to develop environmentally sustainable packaging systems. For example, Organically Grown Company uses reusable plastic bins instead of waxed boxes [145]. Good Earth Farms is working with FedEx to develop a box with insulating foam that can be returned and recycled [158]. Packaging at Red Tomato uses sustainable materials and is designed to feature local farms’ growing practices and to protect perishable products [131],[132], [196].

2.6.2.5. Warehousing Collaboration and Resource Sharing

*Recommended practices (Horizontal Collaboration)—*Collaborative warehousing activities can reduce RFSC costs and improve distribution efficiency [197]. For example, producers can purchase packaging materials as a group [163]. Producers can also share storage facilities to reduce warehousing costs in the post-harvest season [148], [167], [198]. Retailers and food hubs often prefer to pick up products at common aggregation points to address the challenge of managing too many vendors [156]. Therefore, multiple producers selling to the same food hub or retailer should consider forming collective aggregation points at one of their farms, which can enable a more consistent volume and frequency of supply, require fewer transactions for the retailer/food hub, and reduce transportation costs [4], [9], [51], [147], [154], [156], [199], [200].
Food hubs should also consider collaborative warehousing; new food hubs in particular can benefit from partnering with existing distributors or organizations [18], [56]. For example, a food hub can lease warehouse space to other organizations to generate additional revenue [51], [129], [140]. Collaboration between food hubs can facilitate inter-hub brokerage and increase each hub’s access to infrastructure and technical assistance [157]. In [201], an overview has been provided on how the capacities of regional food hubs can be increased by partnering with other food hubs in proximity. The report also provides information on important attributes that food hub stakeholders should consider before establishing a food hub collaborative network.

**Recommended practices (Vertical Collaboration)—**Cross-dock consolidation centers allow small-scale farmers to aggregate their products without incurring the high capital and operational costs of a full-service food hub [202]. Cross-docking can also help full-service food hubs improve their logistics operations without requiring additional capital investment [136], [148]. For example, an analysis of the distribution network of a food hub in North Carolina determined that expanding its service to an additional grocery store would require collaborative cross-docking with the grocery’s regional distribution center [136]. A feasibility study for the development of a network of food hubs in California recommended that the food hubs pay to use the existing distribution infrastructure and cross-docking services of food banks [157].

**Implemented practices (Horizontal Collaboration)—**In a survey of 143 food hubs in the U.S., more than half (52%) reported that they were engaged in either a formal or an informal collaboration, and several had increased their revenues by renting space to other businesses in their region [44]. Some food hubs share extra space in their warehouses with other regional food organizations to bring in additional revenue. For example, Co-op Partner’s Warehouse leases space to Featherstone Farm and Equal Exchange when the space is not needed for its own
operations [133], [161]. Local Food Hub in Charlottesville, Virginia, serves as an aggregating hub for many specialty food distributors in the region [52]. Working with the Local Food Hub has helped Keany Produce, a regional produce distributor in Landover, Maryland, source a greater volume of locally grown produce for its customers than how much it could otherwise have managed independently.

Implemented practices (Vertical Collaboration)—Some farms and food hubs have reported successfully incorporating cross-docking into their operations. For example, Full Circle has developed several small cross-docking facilities in Idaho and eastern Washington to facilitate local deliveries [132]. Others have partnered with larger distributors. Good Natured Family Farms, integrated cross-docking into its distribution network by leveraging the distribution infrastructure of a large grocery chain [174]. Farmers’ products are delivered to the grocery’s central warehouse, where they are aggregated by Good Natured Family Farms personnel and then distributed to retail stores via the grocery’s trucks.

2.6.3. Inventory Management

This sub-section describes recommendations for the five inventory management best practices by RFSC researchers, as well as implementation examples of these practices by RFSC practitioners.

2.6.3.1. Warehouse Inventory Management Systems

Recommended practices—Implementing systematic inventory management procedures will significantly increase the likelihood of a food hub’s success. In particular, the use of inventory management technology can increase the speed of information exchange and therefore enhance RFSC efficiency [174]. A good inventory management system will keep track of which products are in stock, on order, and on backorder, and which products have been sold to customers [181]. It will also support the use of first-in-first-out inventory control to ensure that products are sold
within their shelf life. If an organization manages a large number of SKUs or has a retail location, it may be necessary to implement a system that supports barcode labeling and scanning [51].

An inventory management system can also serve as an interface that facilitates ordering and information sharing with buyers [156]. For example, Local Dirt (localdirt.com) provides a software platform that allows buyers to quickly and easily assess product availability and order items that are currently in stock, although its usefulness relies on prompt and accurate inventory updates [119]. Alternatively, Local Orbit provides food hubs with all the necessary software tools required to run their business along with customized sales portals, marketing support, and payment processing services [52]. If both producers and distributors/retailers implement inventory management systems and EDI, they can co-manage their inventory through continuous surveillance of electronic purchases, which is a common practice in conventional food supply chains. Implementing inventory management systems will also help producers better manage their record keeping and improve their overall farm management [203]. Ideally, a food hub’s inventory management system should also be able to share inventory information with other nearby aggregators that can extend its distribution services beyond its current distribution radius [121].

Food hubs can use either an Excel-based inventory management system, which is highly dependent on manual data entry, or an enterprise resource planning (ERP) system, which automates data exchange as transactions are performed [204]. While inventory management software can be very useful for RFSCs, the price of the software can be prohibitive [123]. Open-source software would eliminate this cost barrier, but a lack of quality and reliable support could be problematic. If a food hub decides to develop its own proprietary inventory management
software, this software should be customized using inputs from stakeholders who are familiar with the food hub’s operations [139]. An overview of software solutions for RFSC inventory management has been provided in [204].

**Implemented practices**—Some food hubs have reported successfully implementing warehouse inventory management systems. Ecker’s Apple Farm in Wisconsin currently records its inventory transactions on paper and transfers this data to QuickBooks, with an eventual goal of adopting inventory management software and eliminating manual record keeping [126]. Bix Produce currently uses an inventory management system that requires manual data entry for order picking but plans to upgrade this system to include electronic scanning [123]. A regional food business in Iowa invested $1 million to develop the sophisticated tracking and inventory systems required to work with Sysco [205]. Sysco has worked with the Wallace Center to develop new ordering codes and an inventory management system to support regional food distribution in Grand Rapids, Kansas City, and Chicago [162]. Capay Valley Farm Shop uses a combination of CSAware software, Excel, Google Documents, and QuickBooks for order management and internal tracking [139]. This Old Farm uses custom-designed software to manage traceability, bar-coding, labeling, and order fulfillment [139]. Greenmarket Farmers Markets in New York used QuickBooks to manage orders and inventory in the initial phase of the business’s development but then switched to software designed by Food Connex [139]. Oklahoma Food Cooperative uses Local Food Cooperative Software, an open source platform. Though the software make some assumptions on the operational structure of a food hub like weekly delivery cycle, it acts as a cost-effective option for the food hub, especially in their starting phase [52].
2.6.3.2. Inventory Tracking and Food Traceability

*Recommended practices*—The ability to track inventory as it moves throughout an RFSC is very useful (and often necessary) for producers, distributors, and retailers [9], [142], [183], [197], [206]. In particular, the ability to identify which product (i.e., crop type, originating farm, harvest date) was ordered by which customer on what day is essential to successfully manage recalls [204]. Additionally, many consumers want to know the story of the farmers whose products they are buying, including geographic information, and processing methods [47], [150], [152], [167], [174], [190]–[192], [207]–[210]. Providing this story can add to regional products’ perceived value, such that customers are sometimes willing to pay more [211]. Some consumers also want precise information on production methods, agrochemical treatments, frame-size and breed of animals (for meat products), transport and storage methods, the number of hands through which the products have passed from farm to fork, and harvest dates of the products they are buying [157], [203], [212], [213]. Therefore, it is important for RFSCs to implement inventory tracking systems that will help them to build customer trust and comply with legal traceability requirements [173], [214]. Producers and intermediaries that share this information with their customers via labels and packaging make their products more competitive in the market [154], [168], [185]. However, the cost and inconvenience associated with implementing inventory tracking systems may require that producers be incentivized to participate, such as being awarded with long-term contracts [215].

Regional food organizations can use software to track a bill of lading, accept delivery confirmation, and support food recalls [121]. Inexpensive applications developed using tools like MS Office can also be used to improve traceability [215]. Accounting software can provide both inventory tracking and accounting functions in the same system. For example, The Leopold
Center for Sustainable Agriculture published a how-to guide with step-by-step instructions for tracking inventory using QuickBooks [216]. For organizations that process food products, the software system should also be able to track lot numbers throughout the production line and the supply chain [181]. To meet food safety requirements, temperature tracking on the production line is also very important for food processors [204]. Temperature tracking is also often required in cold chains [140].

To expedite the inventory tracking process, regional food organizations can replace manual methods with an electronic bar coding system, or an RFID system if selling to wholesale customers [126]. Although RFID tags are more expensive than printed barcode labels, RFID is more efficient, because the tags do not need to be visible to be scanned, and multiple items can be scanned at once. Labels with QR codes allow consumers with smartphones to access product and traceability information to learn about the farm or region where the product originated [126]. However, producers can provide this information to their customers without scanning technology by adding information about their products on signage, cases, and PLU codes [155].

*Implemented practices*—Systems that enable inventory tracking and food traceability have proved to be beneficial to RFSCs. Grass Run Farms and Edina Couriers have both implemented electronic scanning and software systems to track the movement of their products and to provide other supply chain members with accurate inventory data [123]. However, Grass Run Farms found that consumers did not value QR codes enough to justify the cost of implementation [126]. Cherry Capital Foods has ensured food safety by implementing traceability systems throughout their supply chain [131]. Organic Valley implemented its own inventory tracking system that has the ability to trace and recall every case of products [159]. Similarly, every item sold by All Natural Beef Cooperative and Niman Ranch can be traced back to its source [47], [128].
FarmLogix, a Chicago-based technology platform, and Fifth Season Cooperative worked together to develop an inventory tracking system that would provide product origin information to consumers [217]. An Irish organic meat brand provided their customers with an access code that can be entered on the distributor’s website to access the location of the source farm and how the livestock was raised [218].

Food hubs that aggregate and commingle products from multiple producers are typically unable to identify the specific source of each item they distribute. However, they may still be able to offer some degree of traceability. Red Tomato maintains product traceability by allowing apples from only one producer in each tote, along with the name and description of the farm [133]. By contrast, Bix Produce knows from which two or three farms each product originated and provides customers with information on all of these farms to consumers, thereby maintaining farm identity but avoiding overburdening their operations [123]. Appalachian Harvest addressed this issue by building a single brand that represents all of their farmers and farming methods, rather than maintaining individual farmer identities [125].

2.6.3.3. Demand Forecasting

*Recommended practices*—Matching regional food supply with demand is a major challenge [17], [148]. In fact, it is the most cited challenge for food hub growth, based on responses to two U.S. food hub surveys [17], [44]. Therefore, it is recommended that all RFSC participants have a detailed understanding of supply and demand across their region [121], [167]. If producers, aggregators, and buyers are all able to monitor the RFSC’s production capacity, quantities purchased, and any unmet demand, they can improve future planning efforts and potentially increase productivity over time. This allows producers to plan their production accordingly and lower their business risk [185]. Therefore, food hub managers should conduct pre-season crop
planning with both buyers and producers to more consistently match supply and demand throughout the season [119], [155], [190]. Ideally, food hub managers should have a core group of dedicated producers that participate in crop planning, as well as relationships with a broader range of producers to help fill in any gaps caused by unplanned events [154]. Additionally, setting up informal intent-to-buy agreements with buyers will yield standing orders that make demand patterns more predictable [219].

Market research can provide food hubs with useful demand information and assist them in choosing which products to procure [143]. The granularity of this information varies, from rough overall demand estimates to information on specific customer demand. For example, New Venture Advisors provides a free tool called Local Food MarketSizer, which assists regional food organizations in determining the demand for local food in a particular metropolitan area or state [181]. This tool is unable to provide demand information for specific products, but it can roughly estimate the demand for a class of products (e.g., fruits and vegetables). Alternatively, food hubs and other regional food organizations can go directly to their customers to gather demand information. This can be accomplished through online surveys, tracking ordering habits, and speaking with customers about their needs [143].

**Implemented practices**—Many producers simply track their sales and watch for demand trends for each product that they sell, and they use this information to help plan for the following season [220]. Some food hubs work with buyers to determine their needs and forecast demand. For example, Common Market developed strong customer relationships with several school districts and hospitals that provide them with data on the volumes and types of products demanded by consumers [221]. Oklahoma Food Cooperative also surveys its customers to
determine their preferences and then shares the survey results with their producers to support crop planning [133].

Other organizations work closely with producers to manage supply. Balls Food Stores works with the local farmers to have them grow new crop varieties based on customer demand [176]. Alba Organics, a food hub in Salinas, California, develops a crop plan with its producers based on historic sales volumes. This plan is updated periodically as new crops are added and removed, based on customers’ requests and producers’ constraints, respectively [157]. However, information management has been a challenge for them—the available software in the market is either too sophisticated or costly, or not sophisticated enough. Tuscarora Organic Growers coordinates crop planning with all its farmers to meet weekly market demand based on a historical database for each produce item sold [52]. At HomeGrown Wisconsin, each grower has a pre-season meeting with the co-op manager to review production and sales data from the previous season and examine projected sales for the coming season. While this meeting helps producers with production planning, there is no sales contract between the co-op and its members [144]. Country Natural Beef begins communicating demand requirements to producers 18 months before cattle are needed on farms to ensure that demand is met for special events and holidays [222]. Southeast Minnesota Food Hub Network works with buyers and producers before the growing season to ensure that there is sufficient supply [130]. Organically Grown Company practices extensive production planning with its producers, working with them to create crop plans and production estimates [223]. Appalachian Harvest found that allocating 10–20% more supply than expected demand was a good strategy, since some producers do not meet their production projections [125].
Some organizations have begun using software to facilitate more accurate and efficient demand management. Keewaydin Farms is developing software to manage its inventory, match supply with demand, and approximate the volumes that each of its producers is able to sell [123]. Local Harvest Supply, a local food distributor in Iowa, also uses software to analyze customer purchasing patterns in an effort to balance supply and demand [123].

2.6.3.4. Improved Supplier Reliability

*Recommended practices*—Improving supplier reliability can significantly reduce a food hub’s exposure to risk, since delivering products in desired quantities at the promised times is critical for maintaining customers [54], [146], [154]. However, this can be a challenge when the food hub and the producers have different objectives. Producers may prefer to primarily sell directly to customers and only sell surplus products to the food hub, whereas food hubs prefer a consistent supply [173], [224], [225]. To maintain a consistent supply of products for their customers, food hubs should work with producers to determine how much they are able to supply and how frequently, and they should consider offering producers incentives to increase consistency and loyalty [51]. Establishing long-term relationships with a few strategic suppliers will ensure consistent pricing, higher quality, and steady product availability [122].

To reduce overall risk, food hubs should buy products from several suppliers, rather than relying on one producer to fulfill their entire demand [226]. This is particularly important for food hubs with wholesale customers, which require consistent deliveries, contract pricing, and volumes [156], [174]. To maintain a consistent year-round supply of products for its buyers, food hubs should consider carry both regional and non-regional foods [225]. The food hubs in California have been advised to collectively monitor the supply and demand of individual hubs.
to facilitate sales across member hubs and to reduce problems that arise due to seasonality of their growers [157].

Producers and food hubs can also help to ensure that they have a consistent supply by adding post-harvest management technologies (e.g., food processing and preserving capabilities) to their facilities [47], [52], [118], [120], [148], [152], [167], [206], [227]. Processing (e.g., freezing, canning, drying) can extend the season for fresh foods, allowing farmers to produce greater volumes during the growing season and then store and sell products year-round without compromising quality [197]. The convenience of processed food is also appealing to many buyers—it is easy to store, ready to use, and less perishable than fresh products [140], [221]. Thus selling processed food products can help farmers capture better prices [228]. Processing can also increase the utilization of cosmetically imperfect food products [18]. For example, a farmer may be unable to sell imperfect fresh tomatoes, but with the proper equipment and certifications, he/she could process the tomatoes into tomato paste, which can be sold profitably to foodservice customers. Nearly 43% of surveyed farmers in Minnesota stated that they would be more likely to sell their products through a local food hub that had facilities for processing and value-added activities [119]. However, the up-front costs of purchasing equipment and facilities, as well as daunting certification and licensing requirements, may prevent many growers and food entrepreneurs from producing and selling processed food items [140]. Another possibility is the use of mobile processing units [46]. These may require less up-front investment than a fixed-location unit; however, operating costs may be greater, due to fuel and maintenance.

Implemented practices—Idaho Bounty, a food hub in Idaho, manages risk by using a small group of large-scale producers to fill its wholesale customers’ orders [229]. These producers are capable of meeting the quality and quantity requirements of wholesale markets. To maintain
consistent availability of regional produce for its customers throughout the year, a local food co-op in Ohio developed relationships with farmers that can supply both fall and spring crops [156]. Similarly, Red Tomato leverages producer networks across the state to extend seasonal availability for its customers [131]. Country Natural Beef has increased the reliability of its supply by paying higher prices to farmers who are willing to breed calves in difficult calving seasons, as well as having farmers breed more cattle in these difficult periods to serve as insurance [222].

Common Market expanded its year-round supply of products by including frozen regional products sourced from its own producers or partner processors [131]. Similarly, Fifth Season Cooperative offers a line of frozen and value-added vegetable blends to extend their season [139]. The co-op also acts as a broker for frozen and refrigerated meat, to avoid inventory holding costs. Originally, each rancher member of the All Natural Beef Cooperative was responsible for producing, processing, and distributing their beef [128]. To reduce its members’ costs and increase overall efficiencies, the co-op purchased and renovated an existing processing facility, which has also helped it to maintain a steady supply of beef throughout the year and meet increasing demand [128]. Good Natured Family Farms owns a state-inspected meat processing plant and has found that processing both chicken and beef in the plant maximizes facility and distribution system utilization [230]. They also plan to have the plant become a federally-inspected facility to enable them to distribute their products across state lines [231]. Developing processing facilities has allowed Colorado Homestead Ranches, a distributor of natural beef products raised by family ranches in Gunnison, Colorado, to establish greater economic control of its supply chain and to provide processing capacity to other meat producers in the region [185]. Lorentz Meats in Cannon Falls, Minnesota, is able to efficiently run its
processing unit by keeping its three key customers in constant communication with them about scheduling [46]. Anna Marie Seafood in Louisiana developed a cost-effective method of flash freezing shrimp onboard their fishing vessels [232].

2.6.3.5. Collaboration and Resource Sharing for Inventory Management

**Recommended practices (Horizontal Collaboration)**—RFSC participants are highly interdependent, and “coopetition”—cooperation with competitors—among them is a collective strategy that can expand markets and support prices [53], [155]. For example, food hubs can reduce their inventory management costs by sharing deliveries, taking advantage of group purchasing, and purchasing pooled insurance policies [139], [154], [157], [174].

**Recommended practices (Vertical Collaboration)**—Collaboration between upstream and downstream RFSC participants can facilitate frequent just-in-time (JIT) deliveries and inventory reduction. Although holding inventory helps RFSC participants to buffer against supply and demand uncertainties [184], adopting frequent JIT deliveries and systems that support inventory tracking and demand forecasting can reduce the need for excess inventory and large warehouse spaces [51], [183]. Food hubs, which have limited cash flows, will benefit from keeping their inventory levels low and ensuring rapid inventory turnover [233]. However, the high level of coordination that is needed to support JIT deliveries requires significant information sharing between RFSC participants, which can be challenging if they are competitors [173].

**Implemented practices (Horizontal Collaboration)**—Stonyfield Farm, a dairy company in New Hampshire, has benefited from collaborating with Organic Valley to aggregate and process organic fluid milk [159]. Both companies jointly market the milk, and Wisconsin-based Organic Valley benefits from Stonyfield’s strong brand presence in the Northeast region. La Montanita Co-op realized that developing a strong regional supply base would require partnering with
competitors, such as Whole Foods [133]. Sysco has encouraged its regional operators to share both information and suppliers, thereby extending its geographic radius of regional food distribution [162].

*Implemented practices (Vertical Collaboration)*—Vertical coordination in RFSCs for inventory management is practiced by successful food hubs in the U.S. through the development of strategic relationships between upstream and downstream participants [20]. For example, Iowa Food Hub was able to reduce its inventory levels by ordering products more frequently from producers [233]. This also allowed the food hub to make more frequent deliveries, which helped their customers to avoid shortages and to reduce their own inventory levels. Capay Valley Farm Shop uses a JIT system to purchase and pick up products from producers and immediately deliver them to their customers [139]. Grass Run Farms manages its inventory using Excel spreadsheets and has been able to reduce its week-to-week inventory to just a few boxes of product [126]. Country Natural Beef participates in a vendor-managed inventory system in which its customers own six warehouses and purchase the products, but Country Natural Beef manages the inventory for them [222].

Vertical information sharing has increased the effectiveness of many RFSC collaborations. For example, Walsma and Lyons and Sysco Grand Rapids, two food distributors in Michigan, regularly visit producers to learn about their operations and to build trust [174]. Over a three-year period of building relationships, they have doubled the amount of regional produce that they distribute, and they have helped producers expand their delivery reach. Sysco maintains a vertically integrated supply chain by establishing a communication channel between Sysco’s staff, local aggregators, and farmers, as well as connecting farmers with customers at the beginning of the season [162]. Kansas City retail chain Balls Food Stores has been able to source
more regional food by partnering with Good Natured Family Farms [131]. The grocery managers regularly visit the producers to gain a better understanding of their production practices, and the producers visit stores to showcase products and engage customers. This strategic partnership has yielded $3 million in sales for the cooperative and has helped to maintain consistent supply to the stores, even in slow seasons [128], [174]. Similarly, a large-scale food distributor in Ohio maintains relationships with regional growers by visiting their farms, inspecting their facilities and growing standards, and conducting soil tests [156]. If the producers meet the distributor’s required standards, they become an approved supplier; otherwise, they are dropped as a vendor.

2.7 Summary of Findings

This section provides a summary of the works cited, identifies several gaps in the existing research on RFSC logistics management, and recommends directions for future research. This paper summarized and analyzed 106 technical reports (published between 2002 and 2015) and 28 journal articles (published between 2007 and 2016) that provided recommendations and/or examples of implementation with respect to logistics best practices in RFSCs. A summary of the references reviewed in Section 5 for each best practice is provided in Table 2.3. The RFSC implementation examples are make reference to 67 different regional food practitioners (e.g., farms, cooperatives, food hubs).
Table 2.3 Summary of reviewed literature on RFSC logistics best practices (technical reports; journal articles).

<table>
<thead>
<tr>
<th>Best Practice</th>
<th>Recommended</th>
<th>Implemented</th>
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<tbody>
<tr>
<td>Efficient Vehicle Utilization</td>
<td>[4], [8], [9], [119] – [123], [125], [118], [124]</td>
<td>[123], [126] - [134]; [124]</td>
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<tr>
<td>Backhauling</td>
<td>[37], [123], [135] - [137]</td>
<td>[56], [123], [138], [139]</td>
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<tr>
<td>Vehicle Selection</td>
<td>[18], [37], [51], [119], [125], [134], [140] – [142]</td>
<td>[37], [133], [139], [143] – [145]</td>
</tr>
<tr>
<td>On-time and Frequent Deliveries</td>
<td>[4], [47], [146] – [149]; [150] – [152]</td>
<td>[123], [125], [126], [133], [144]. [153], [154]</td>
</tr>
<tr>
<td>Third-party Logistics (3PL)</td>
<td>[37], [38], [125], [129], [154], [155]</td>
<td>[9], [122], [123], [126], [127], [131], [132], [138], [139], [143], [144], [147], [154], [156] - [162]</td>
</tr>
<tr>
<td>Transportation Collaboration</td>
<td>Horizontal collaboration - [4], [9], [140], [144], [157], [163], [164], [166], [167], [170], [171], [39], [165], [168], [169] Vertical collaboration - [8], [123], [138], [144], [156], [173], [174]; [172]</td>
<td>Horizontal collaboration - [123], [130], [133], [175], [176]; [177] Vertical collaboration - [18], [131], [133], [161]</td>
</tr>
<tr>
<td>Effective Labor Utilization</td>
<td>[17], [51], [125], [129], [133], [139], [155], [157], [178]</td>
<td>[125], [133], [139]</td>
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<tr>
<td>Facility Location</td>
<td>[17], [53], [119], [123], [154], [155], [157], [175], [179], [180], [181]; [182]</td>
<td>[46], [140]</td>
</tr>
<tr>
<td>Infrastructure Development</td>
<td>[4], [45], [119], [125], [133], [139], [143], [148], [154], [155], [167], [179], [181], [184], [188]; [183], [185] – [187]</td>
<td>[133]; [150]</td>
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<tr>
<td>Efficient Warehousing Policies</td>
<td>[4], [45], [120], [140], [147], [155], [156], [163], [164], [184], [189] – [192]; [54], [183], [193], [194]</td>
<td>[38], [131] – [133], [144] – [146], [156], [158], [162], [176], [179], [195], [196]</td>
</tr>
<tr>
<td>Warehousing Collaboration and Resource Sharing</td>
<td>Horizontal collaboration - [4], [9], [18], [51], [56], [129], [140], [147], [148], [154], [156], [157], [163], [167], [197], [198], [201]; [199], [200] Vertical collaboration - [136], [148], [157], [202]</td>
<td>Horizontal collaboration - [44], [52], [133], [161] Vertical collaboration - [132], [174]</td>
</tr>
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<td>Warehouse Inventory Management Systems</td>
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<td>[52], [123], [126], [139], [162], [205]</td>
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Table 2.3 (continued)

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<th>Best Practice</th>
<th>Recommended</th>
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<tr>
<td>Inventory Tracking and Food Traceability</td>
<td>[9], [47], [121], [126], [140], [142], [154], [155], [157], [167], [174], [181], [190] – [192], [197], [203], [204], [207] – [211], [213], [216]; [150], [152], [168], [173], [183], [185], [206], [212], [214], [215]</td>
<td>[47], [123], [125], [126], [128], [131], [133], [159], [217], [218]</td>
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<tr>
<td>Demand Forecasting</td>
<td>[17], [44], [119], [121], [143], [148], [154], [155], [167], [181], [190], [219]; [185]</td>
<td>[52], [123], [125], [130], [133], [144], [157], [176], [220] – [223]</td>
</tr>
<tr>
<td>Improved Supplier Reliability</td>
<td>[18], [46], [47], [51], [52], [119], [120], [122], [140], [146], [148], [154], [156], [157], [174], [197], [221], [224], [226], [228]; [54], [118], [152], [173], [206], [225], [227]</td>
<td>[46], [128], [131], [139], [156], [222], [229] – [232]; [185]</td>
</tr>
<tr>
<td>Collaboration and Resource Sharing for Inventory Management</td>
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<td>Horizontal collaboration - [133], [159], [162]</td>
</tr>
<tr>
<td></td>
<td>Vertical collaboration - [51], [184], [233]; [173], [183]</td>
<td>Vertical collaboration - [20], [126], [128], [131], [139], [156], [162], [174], [222], [233]</td>
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This substantial literature reflects the growing importance of logistics in regional food system research over the past decade. Figure 2.2 shows the publication trend of the reviewed literature over time, which demonstrates significant growth in the number of publications in this domain from 2006 through 2014. However, there was a significant decrease in publications in 2015. This paper reviewed journal articles that were available online as of February 2016 and technical reports available as of March 2016, which may be the reason for the significant drop in the number of publications published that year.
Figure 2.2 Publication trend of the reviewed literature.

An analysis of this literature indicates that majority of the research on RFSC logistics is being performed in specific geographic areas. Figure 2.3 shows the geographic dispersion of authors of the literature reviewed in this study. Most of the journal articles on RFSC logistics have been published by researchers in Europe (46%), and United States (46%). The remaining (8%) articles were from either Mexico or Canada. For shortlisting the technical reports, only research centers in the U.S. were considered. Therefore, reports originated mainly from the U.S., with two reports from the United Kingdom. In the U.S., the research is concentrated on the East Coast, the upper Midwest, and California.

Figure 2.3 Geographic dispersion of reviewed literature.
In the reviewed literature, the most frequently recommended best practice for RFSCs is inventory tracking and food traceability, with 35 publications mentioning its importance. Having detailed information about a food product’s origin is very important to most regional food consumers, and an inventory tracking system can help producers, distributors, and retailers to preserve and share this information as the product moves along the RFSC. Moreover, a high degree of traceability helps RFSCs differentiate themselves from the conventional food system, which serves as a competitive advantage.

After inventory tracking and food traceability, the next most frequently recommended best practice for RFSCs is horizontal collaboration, which can be applied to transportation, warehousing, and inventory management (recommended in total by 32 publications). The potential to reduce operational and overhead costs makes horizontal collaboration particularly promising for RFSC participants, who typically lack access to capital. Horizontal collaboration can also facilitate the implementation of other highly recommended best practices. For example, partnerships among RFSC practitioners can be leveraged to develop new shared infrastructure (recommended in 19 publications), such as food processing and cold storage facilities, and to improve the reliability and off-season supply of regional food (recommended by 28 publications). Such partnerships can also enable the creation of a common vehicle fleet that can support efficient vehicle utilization (recommended by 11 publications), backhauling (recommended by 5 publications), and frequent and on-time deliveries to customers (recommended by 9 publications).

The third most frequently recommended best practice is supplier reliability improvement (recommended by 28 publications). This is unsurprising, given that the irregular supply of products is one of the major reasons for food hub failure and closure in the U.S. [234].
By contrast, the most frequently cited implementation of RFSC logistics best practices was the use of 3PLs (19 examples). Because most RFSC organizations lack the financial capability to invest in infrastructure development, hiring a 3PL to support their logistics operations is a logical choice. The second most frequently cited examples of implementation were from efficient vehicle utilization (16 examples) followed by vertical collaboration (13 examples).

Based on the review of the RFSC logistics literature, three major gaps in the research were identified. These gaps suggest potential avenues for future research to address the biggest logistics challenges faced by RFSC practitioners.

**Research Gap #1: Appropriately tailored implementation of logistics best practices**—The regional food community is highly diverse. Regional producers’ logistics management requirements vary widely, based on their production capacity, the types of food they are producing, the location of their farm, and seasonal weather conditions at their location. Similarly, regional food distributors and food hubs have unique logistics requirements and capabilities. For example, there are approximately 302 regional food hubs in the U.S., and no two have the exact same business structure. They are characterized by a variety of different capacities, financial models, ownership structures (e.g., non-profits, farmer groups, private entities) and business missions (e.g., maximizing producer profits, providing healthy food to underserved areas, supporting environmentally friendly agricultural practices). There are also many different food hub operational structures and strategies, including farm-to-school distribution, retail grocery stores, acting as a 3PL provider for regional producers, farm-to-wholesale distribution, as well as hybrid combinations of these structures.

For this reason, it is very difficult to identify from the existing literature which logistics approaches are most appropriate for a specific RFSC entity, and at what level they should be
implemented. An examination of best practices at a more targeted level (e.g., by closer examination of food hubs with similar social goals) would greatly help RFSC participants make informed decisions. For example, horizontal collaboration is one of the most widely discussed logistics best practice in the literature. However, none of these publications addressed the need for a framework for successful RFSC collaborations. Such a framework could provide guidance on how to efficiently build and manage the collaboration, how to decide on adding a new member to a preexisting network of collaborating members, how to assign roles and responsibilities to each member (including leadership), and how the benefits of collaboration will be shared among members. There is a large body of literature on collaboration in conventional supply chains [81], some of which focuses on small and midsize enterprises in the agri-food industry [235]. However, many RFSC participants are values-based organizations with strong social and environmental components in their business missions [236], [237], and the existing profit-focused frameworks on horizontal collaboration may conflict with RFSC objectives [238]. Also, RFSC participants typically face financial constraints that prevent them from adopting sophisticated supply chain technologies that are typically recommended to facilitate horizontal collaboration in conventional supply chains [239]. Therefore, the development of an appropriate framework to provide RFSC practitioners with guidance on how to collaborate that is aligned with their structures and missions is needed.

**Research Gap #2: Economically viable logistics solutions**—Infrastructure development (recommended by 19 publications), maintaining a professional and skilled workforce (recommended by 9 publications), making frequent and on-time deliveries (recommended by 9 publications), and deploying traceability tools (recommended by 35 publications) and warehouse inventory management systems (recommended by 11 publications) are highly recommended for
RFSCs to help them grow and successfully compete with conventional food supply chains. These best practices will help RFSCs to preserve farm identity throughout the supply chain and make frequent deliveries of fresh food to customers, which are capabilities that differentiate RFSCs from conventional food systems and are necessary to fulfill customers’ requirements for product traceability and freshness. However, these best practices require significant financial investment for implementation, which prevents most RFSC participants from adopting them. Many RFSC practitioners are heavily dependent on external funding and grants to survive, particularly in the early stages of their business development. Because of this, technologies for food traceability and inventory management that have been widely adopted by conventional food supply chains are out of reach for RFSCs.

Unfortunately, research on cost-effective strategies for implementing these technology-based best practices in RFSCs is lacking. RFSCs would greatly benefit from the development of innovative and economically viable versions of the tools used by conventional supply chains. For example, a low-cost and low-maintenance inventory tracking system was developed for collaborating food hubs and farmers in Iowa [240]. This system includes an Excel-based label generator interface for the farmers and a mobile application for the food hub managers and truck drivers to track the movement of the farmers’ products through the supply network in real time.

**Research Gap #3: Data-driven decision support**—Transportation cost has been cited as a major logistical barrier for RFSCs. To overcome this barrier, RFSC participants are advised to use the efficient services of a 3PL provider, or to tap into the existing distribution networks of conventional supply chains to transport products to their customers (recommended by 6 publications). This best practice is the most highly cited implementation (19 examples). However, decisions about adopting these practices are typically made on an ad-hoc basis,
because RFSC practitioners usually have very little background in business planning and supply chain management [44], [197].

Therefore, data-driven decision tools based on quantitative evaluations should be developed to help RFSC practitioners make smart logistics management decisions, such as determining the maximum delivery distance for which they should use their own transportation network and the appropriate terms and conditions for a third-party contract. Such decision support tools can help producers decide which costs (i.e., transportation, warehousing, processing) to absorb and which to pass on to their customers [47]. For example, a computer simulation model was developed to enable food hub managers to understand the effects of various scheduling policies on the efficiency of their warehouse operations [241]–[243].

2.8 Conclusions

This paper presented a structured review of the literature on logistics management in RFSCs. To the best of our knowledge, this is the first organized effort in conducting a systematic literature review on RFSC logistics. This review can serve as a source guide and starting point for RFSC practitioners to gain insights on potential solutions to logistics challenges, which are often the biggest barriers to their growth and success. The recommendations and implementation examples for the 16 best practices cited in this paper will also give RFSC practitioners an opportunity to connect with fellow practitioners and RFSC researchers who have experienced similar challenges and have identified workable solutions. Most importantly, this review has identified several gaps in the existing RFSC literature, which opens up potential research avenues and provides research directions for the academic community. As demand for regionally produced food continues to grow, the knowledge gained from this research will be increasingly necessary to support efficient and effective connections between consumers and producers and overall regional food system success.
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CHAPTER 3. A HYBRID SIMULATION MODELING FRAMEWORK FOR REGIONAL FOOD HUBS

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3.1 Abstract

As demand for regionally produced food has increased, regional food hubs have helped to facilitate connections between consumers and small-scale food producers. However, food hubs often struggle to achieve the logistical and operational efficiencies that characterize conventional large-scale food distribution. In many cases, implementation of innovations adopted by conventional food distributors has proved to be challenging and even counterproductive for food hubs, due to their distinct business structure and mission. To address this problem, an empirical agent-based and discrete-event hybrid simulation model was developed to determine the effects of incorporating various efficiency-enhancing practices into food hub warehousing operations. The model was validated using data from a food hub in central Iowa. Experimental results demonstrate the potential usefulness of this model in supporting food hub managers’ operational planning decisions, as well as the effectiveness of incorporating agent-based and discrete-event simulation modeling paradigms to study warehousing operations.

3.2 Introduction

Modern industrial food supply chains (FSCs) have enabled the production and distribution of food at an enormous scale, providing consumers with inexpensive food from producers across
the globe, irrespective of season. Despite these benefits, consumers are increasingly seeking food that is produced regionally and at a smaller scale. In fact, surveys indicate that consumers are willing to pay a premium for this regionally produced food [1]. By purchasing regionally produced food, many consumers believe that they are contributing to the welfare of their community by promoting a system that is more socially and environmentally sustainable than conventional FSCs. Regional food systems can revitalize rural economies by supporting small and midsize food producers, and they provide consumers with an opportunity to connect with these producers, visit their farms, and learn about their farm stories [2]. Regional food systems can also support environmental sustainability through reduced transportation distances between producers and consumers, thereby reducing fossil fuel consumption and greenhouse gas production [3].

Over the past 10 years, regional food hubs have begun to play a pivotal role in strengthening regional food systems. The United States Department of Agriculture defines a food hub as “a business or organization that actively manages the aggregation, distribution, and marketing of source-identified food products primarily from local and regional producers to strengthen its ability to satisfy wholesale, retail, and institutional demand” [2]. Unlike conventional large-scale food distributors, food hubs strive to provide fair pricing and increased market access to small and midsize producers [4]. However, food hubs are not profitable on average [5]. In fact, the highest performing (i.e., top 25%) food hubs earn only a 4% profit margin, and the average across all food hubs is -2% [6]. Many food hubs fail because they lack systematic supply chain management structures [7]. Therefore, to achieve long-term economic, environmental, and social sustainability, food hubs should consider implementing the kinds of efficiency-enhancing supply chain management techniques that have been adopted by conventional FSCs [8]. Unlike
conventional distributors, however, most food hubs have a strong social mission that guides their strategic, tactical, and operational decision making. For some food hubs, this mission involves supporting small and midsize food producers; others focus on providing consumers with affordable access to healthy food. Unfortunately, reconciling socially motivated and financial objectives has proved to be very difficult for them.

This tension between social and financial considerations is evident in the unstructured approach that many food hubs take with respect to their inbound warehousing operations. Conventional distributors typically have many suppliers that deliver enormous volumes of products to their warehouses in rapid succession, which requires that suppliers strictly adhere to delivery schedules [9]. By contrast, regional food hubs, which have comparatively smaller operations, do not typically assign fixed delivery times to their producers [10]. Interviews with a food hub manager in central Iowa suggest that food hubs view producer delivery schedules as an unnecessary burden on the producers, who tend to highly value their autonomy and prefer flexible delivery schedules [11], [12]. However, unscheduled deliveries have negatively impacted this food hub’s inbound operations. In particular, many of the food hub’s producers arrive for delivery simultaneously, typically at the end of the day, rather than spreading delivery times uniformly throughout the delivery period [10]. As a result, long queues form at the warehouse, and producers must wait to receive service from food hub personnel. This is inconvenient for the producers and results in problems for the food hub’s customers. As the number of producers in the queue increases, food hub personnel tend to rush through service in an effort to reduce queue time. As a result, quality inspections and proper inventory put-away procedures are often curtailed, and poor-quality and incorrect products often reach customers, which has had severe consequences for their satisfaction and long-term retention.
In general, few models exist that address the management of shipping and receiving operations of a warehouse [13], and very few simulation models have been developed to study sustainable food logistics management [14]. In particular, there is a need for more research in the area of regional FSC modeling [15]. In this chapter, an empirically informed and validated hybrid simulation model of the inbound warehouse operations of a regional food hub in central Iowa is described. The purpose of this model is to give the food hub manager a better understanding of his warehouse operations, such that he is better able to make informed decisions to improve operational efficiency and effectiveness. Three different versions of the model are described in this chapter: (1) a baseline model that represents the status quo conditions at the food hub warehouse, (2) a version in which producers are incentivized to preschedule their deliveries, and (3) a version that incorporates a heuristic approach to generate work schedules for the food hub personnel.

3.3 ABM and DES Paradigms

Two of the most widely used simulation paradigms for modeling supply chain operations are discrete-event simulation (DES) and agent-based modeling (ABM) [16]. DES and ABM share some similarities (e.g., they both support discrete-time simulation), and in some cases, it may be feasible to use either ABM or DES to represent a particular system or subsystem, depending upon the modeler’s preference. However, their capabilities and intended uses differ significantly. Therefore, while ABM and DES can sometimes be used interchangeably (given enough memory and computational time), it is important to consider the comparative flexibility and efficiency of each methodology in modeling the particular system under study [17].

In an ABM, autonomous agents make decisions and take action to achieve their objectives, with behavioral complexity that can range from simple binary decisions to the complexity of human intelligence. Agents are proactive, autonomous, and intelligent, and they can perceive,
reason, memorize, and take initiative based on their knowledge, their past experiences, and pre-defined rules determined by the modeler [17]. Agents also interact with each other and with their environment directly or indirectly per their behavioral rules. These interactions often involve information and/or resource sharing. By contrast, the behavior of entities in a DES is governed by system-level rules—the individual entities do not have rules embedded within them that alter their behavior based on entity-entity or entity-environment interactions [18]. While it is possible to model agent actions as arrival, service, and exiting events using DES, doing so will exponentially increase the number of events in the DES, making the model inefficient and difficult to analyze [17]. Therefore, if active and autonomous entities are required to achieve an accurate representation of the modeled system, ABM may be more appropriate than DES [19].

Conversely, there are many systems that can be readily modeled using DES, whereas modeling the same system using ABM would be less efficient, harder to develop, or would not match with the nature of the system [20]. One reason for this is that simulated time in an ABM progresses in uniform steps that is defined by the modeler, whereas in a DES, it leaps between events. For many systems (particularly queuing systems), having event-triggered advances in simulated time can facilitate model creation, enable greater precision, and reduce simulation run times [21]. Modeling a queuing system with ABM is possible—entities and resources can be represented by agents that update their states (e.g., waiting in queue, receiving service, busy, idle) at the time of each event occurrence to reflect the current state of the system [20], [21]. However, achieving sufficient precision would require that the modeler uses a very small time-step, which can potentially result in long simulation run times [21]. For example, modeling an M/M/1 queuing system with inter-arrival times and service times that are defined in fractions of minutes would require that the modeler defines the ABM time-step in fractions of minutes to
ensure full precision. Because simulated time would then progress in fractions of minutes, if the
times between events are long, running the ABM would likely require significantly more time
than would a DES version of the model. Therefore, it is generally easier and more
computationally efficient to use DES to model queuing behavior, rather than ABM. Majid et al
2009 [22] demonstrated this by comparing the performance of DES and ABM when modeling an
M/M/1 queuing system. They developed ABM and DES versions of a model of a retail fitting
room operation in parallel using AnyLogic and found that both models performed equally well.
However, the DES model was easier to build and validate than the equivalent ABM.

The different strengths of DES and ABM suggest that combining the two techniques could
be advantageous for modeling queuing systems in which the autonomous and adaptive decisions
and behaviors of the constituent entities play a defining role. Although DES and ABM have
historically been used in isolation [23], the development of hybrid simulation models, in which
multiple simulation techniques are employed to leverage the advantages of each, is a growing
trend. Hybrid simulation enables the analysis of systems that could not be realistically modeled
using a single approach [24]. For example, a hybrid DES - ABM model of patients in a
healthcare clinic in the United Kingdom incorporated patient interactions into the clinic’s
queuing process [25], [26]. The authors argue that the integration of patient interactions with the
queuing process could not have been easily accomplished using a single simulation technique
and therefore required the use of a hybrid methodology, which enabled them to realistically
reflect the key elements of the real-life system.

However, the integration of multiple techniques necessarily increases a model’s
complicatedness, particularly when different modeling platforms are used. In particular, hybrid
simulation models are difficult to validate due to increased complexity [27]. To determine
whether hybrid simulation is a worthwhile approach, a modeler should first determine whether accomplishing his/her objectives is feasible using a single simulation technique. Even if this is the case, it is still possible that hybridism can be beneficial—for example, a hybrid structure might improve computational efficiency and/or make the model easier to develop and explain to others. Therefore, a modeler should carefully assess the value of the additional capabilities that hybrid simulation will provide, and then compare this value with the extra effort that is required to develop and run a hybrid model.

In modeling the inbound warehouse operations of the central Iowa food hub, it was determined that a hybrid ABM - DES approach would be necessary to realistically represent the system. The resulting model utilizes ABM to model intelligent and adaptive autonomous agents (i.e., a food hub manager agent and multiple producer agents) and DES to model the queueing process at the warehouse. In each simulated time-step, the producer agents decide, based on their experiences in previous time-steps, whether to preschedule their deliveries before arriving at the food hub warehouse, and the food hub manager agent uses an adaptive heuristic approach to schedule the warehouse personnel to best meet the producers’ needs. The agents’ adaptive decision making would have been difficult to realistically incorporate and analyze using a DES model alone, particularly because adaptations among many agents within the same system can result in overall system-wide behavior that emerges over time [28]. Such emergent system behavior can be difficult to predict without the use of ABM. The DES model captures the FIFO queuing mechanism by which the producer agents receive service from personnel at the food hub warehouse, and it enables the evaluation of service quality and food hub personnel utilization, which would be cumbersome (if not impossible) to model using ABM alone.
3.4 Hybrid Simulation Model

In this section, the empirical hybrid simulation model of the inbound warehouse operations of an Iowa food hub is described. The food hub manager has given the food hub’s producers the option of prescheduling their deliveries online, but very few producers actually participate. The manager is certain that mandating producer scheduling is infeasible; producers would simply refuse to show up at their scheduled times and might cease using the food hub’s services altogether. The manager has struggled to find ways of improving the food hub’s inbound operations without impinging upon its producers’ autonomy. Therefore, it would be valuable for the manager to have a better understanding of the conditions that would encourage producers to schedule their deliveries to the food hub and to be able to evaluate the impacts of scheduling on the food hub’s performance. The hybrid simulation model employs an ABM to capture producers’ delivery scheduling decisions and behaviors and a DES model to represent the food hub’s receiving process, which includes quality inspections and product put-away.

Agent-based model

The ABM (developed using NetLogo 5.1.0) will be described using the ODD (Overview, Design concepts, and Details) protocol [29]. First, an overview of the ABM is provided:

*Purpose* - The purpose of this model is to assess the effects of food hub producers’ delivery scheduling decisions on the efficiency and effectiveness of the food hub warehouse’s inbound operations. The model is also used to test the effects of different management policies on producers’ scheduling decisions and warehouse operational performance.

*Agents* - This model contains two types of agents: producer agents and a food hub manager agent. In each timestep, the 72 producer agents make decisions regarding whether or not they will schedule their deliveries to the food hub warehouse and in which time slots they will make their deliveries. The food hub manager agent periodically assesses the performance of
warehouse’s inbound operations (in terms of service level and worker utilization) and uses this information to make operational improvements. The agents are characterized by static and dynamic state variables, which are summarized in Tables 3.1 and 3.2.

Table 3.1 Producer agent state variables in the ABM

<table>
<thead>
<tr>
<th>State variables</th>
<th>Description</th>
<th>Possible values</th>
<th>Static/dynamic</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>i</td>
<td>Unique number assigned to each producer agent in ABM</td>
<td>1 - 72</td>
<td>Static</td>
<td>–</td>
</tr>
<tr>
<td>PHi</td>
<td>Probability that harvesting schedule impact ith producer agent decision making</td>
<td>0 - 0.8</td>
<td>Static</td>
<td>Survey</td>
</tr>
<tr>
<td>PCI</td>
<td>Probability that other deliveries in the route impact ith producer agent decision making</td>
<td>0 - 0.8</td>
<td>Static</td>
<td>Survey</td>
</tr>
<tr>
<td>QSi</td>
<td>1 x 7 row vector indicating satisfaction level of the ith producer agent in seven different wait time ranges (from 0 to 30+ minutes, in 5-min increments)</td>
<td>Range of each element is 1 - 5 (1 - least and 5 - most preferred)</td>
<td>Static</td>
<td>Survey</td>
</tr>
<tr>
<td>Si</td>
<td>1 x 11 row vector where the elements represent the preference level of the ith producer agent for each of the 11 time slots</td>
<td>Range of each element is 1 - 5 (1 - least and 5 - most preferred)</td>
<td>Static</td>
<td>Survey</td>
</tr>
<tr>
<td>Qin</td>
<td>Queue time of the ith producer agent at the food hub</td>
<td>–</td>
<td>Dynamic</td>
<td>DES output</td>
</tr>
<tr>
<td>UCI</td>
<td>Utility gain from queue time by the ith producer agent</td>
<td>0.2 - 1</td>
<td>Dynamic</td>
<td>ABM</td>
</tr>
<tr>
<td>UAI</td>
<td>Utility gain from autonomy by the ith producer agent</td>
<td>0.8, 1</td>
<td>Dynamic</td>
<td>ABM</td>
</tr>
<tr>
<td>Ui</td>
<td>Overall utility of the ith producer agent</td>
<td>0.56 - 1</td>
<td>Dynamic</td>
<td>ABM</td>
</tr>
<tr>
<td>WA</td>
<td>Weight on autonomy</td>
<td>0.6</td>
<td>Static</td>
<td>Experimental</td>
</tr>
<tr>
<td>WC</td>
<td>Weight on queue time</td>
<td>0.4</td>
<td>Static</td>
<td>Experimental</td>
</tr>
<tr>
<td>si</td>
<td>Time slot number in which the ith producer agent delivers the products in an order cycle</td>
<td>1 - 8 (day 1) 9 -11 (day 2)</td>
<td>Dynamic</td>
<td>ABM</td>
</tr>
<tr>
<td>ti</td>
<td>Arrival time of the ith producer agent at the food hub in an order cycle</td>
<td>0 - 480 min (day 1) 0 - 180 min (day 2)</td>
<td>Dynamic</td>
<td>ABM</td>
</tr>
<tr>
<td>UT</td>
<td>Threshold utility</td>
<td>0.8</td>
<td>Static</td>
<td>Experimental</td>
</tr>
<tr>
<td>Mki</td>
<td>Probability that the ith producer agent will schedule the delivery at kth level of monetary incentive (k varies from 1 to 4 with incentive levels &lt;1%, between 1 and 3%, between 3 and 5%, and &gt; 5%)</td>
<td>Range of each element is 1 - 5 (1 - least and 5 - most preferred)</td>
<td>Static</td>
<td>Survey</td>
</tr>
</tbody>
</table>
**Process overview and scheduling** - The Iowa food hub that serves as the basis for this model operates as an online grocery store. In each bimonthly order cycle, producers deliver their products to the food hub warehouse over the course of 2 days, after which the products are sorted by food hub personnel and are then distributed to customers. There are eight 1-h time slots available for producer deliveries on the first delivery day and three slots available on the second day. Each time-step in the ABM represents a single order cycle. In each time-step, the producer agents decide whether to schedule their deliveries and in which time slot they will make their deliveries. Based on the producer agents’ decisions and the performance of the warehouse in the previous time-step(s), the food hub manager agent may decide to increase/decrease the number of warehouse receiving personnel assigned to work in each time slot.

<table>
<thead>
<tr>
<th>State variables</th>
<th>Description</th>
<th>Possible values</th>
<th>Static/dynamic</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>ULj</td>
<td>Percentage of total man hours spent on receiving process to total available man hours in jth time slot (j varies from 1 to 11)</td>
<td>0–100%</td>
<td>Dynamic</td>
<td>DES output</td>
</tr>
<tr>
<td>SLj</td>
<td>Service level of jth time slot (j varies from 1 to 11)</td>
<td>0–100%</td>
<td>Dynamic</td>
<td>DES output</td>
</tr>
</tbody>
</table>

In the second element of the ODD protocol, the model design concepts are described:

**Basic principles** - Multi-attribute utility theory is used to represent the producer agents’ decision process [30]. The values of the agents’ utility function parameters are based on
empirical data that was collected via a survey of the Iowa food hub’s producers. By contrast, the food hub manager agent uses a heuristic approach for scheduling the warehouse receiving personnel.

**Emergence** - The collective behavior of the producer agents and the food hub warehouse’s overall performance are emergent properties of the ABM. The scheduling decisions of the producer agents and corrective actions of the food hub manager agent in each time-step impact warehouse performance, which determines the quality of the producer agents’ experience at the warehouse (i.e., their queue times). Their experiences in turn affect their future scheduling decisions. This feedback loop yields system-wide behavior that emerges over time.

**Adaptation** - The producer agents adapt their scheduling decisions and time slot selections based on how satisfied they are with the outcomes of past decisions. The food hub manager agent’s decision strategy adapts over time in response to changes in the warehouse’s performance.

**Objectives** - Each producer agent’s objective is to maximize its level of satisfaction (i.e., its utility) with respect to its experiences at the food hub warehouse. The objective of the food hub manager agent is to maximize the performance of the warehouse’s inbound operations.

**Prediction** - Each producer agent that decides to schedule its delivery will select the time slot that it believes will yield the shortest queue time at the food hub warehouse. This prediction is based on its experiences at the food hub in previous order cycles. The food hub manager agent determines the number of personnel to be scheduled in each time slot by predicting the resulting improvements in utilization rates and service levels.
Stochasticity - The values of several parameters that influence producer agent decision making are drawn from probability distributions, which were derived from survey data. These variables are summarized in Table 3.1.

Observation - Each time the ABM is executed, its outputs producer agent scheduling decision outcomes and arrival times, as well as warehouse personnel time slot assignments. These output data serve as input data to the DES model.

Initialization - The time slot preference vectors and stochastic decision parameters of each of the 72 producer agents in the ABM are initialized in the first time-step.

Input data - For an ABM to be capable of making accurate and reliable predictions, the modeling logic must be based on highly realistic assumptions that are supported by empirical data [31], [32]. To this end, there has been an increasing trend of combining ABM with empirical data [33]. Providing input values to ABM variables and parameters through social survey data is one strategy for providing a strong empirical foundation for ABM development [34]. To gather the necessary empirical data to describe the different factors that affect food hub producers’ scheduling decisions, a survey of 25 Iowa food hub producers was conducted. Due to missing values from one of the respondents, the responses of 24 of these producers were used. The survey contained demographic questions, as well as 15 valued questions with ratings on a Likert scale from 1 to 5. Questions 1 through 4 sought to understand the degree to which the producers’ delivery routes and harvesting schedules affected their scheduling decisions. Questions 5 to 11 asked the producers about the degree to which queueing at the food hub affected their level of satisfaction. Questions 12 to 15 captured the likelihood that producers would schedule their deliveries, given different levels of monetary incentives.
Next, hierarchical cluster analysis (Ward’s Method) was performed on the participants’ responses to the 15 valued questions to develop categories of producers with distinct behavioral patterns [35]. This analysis yielded four producer clusters, which are shown in Figure 3.1.

![Figure 3.1 Results of cluster analysis, based on responses to 15 valued questions. The width of the colored bar in each cell indicates the Likert-scaled response (1 to 5).](image)

The behavioral attributes derived from the cluster analysis (summarized in Table 3.3) were then used to inform the design of the producer agents’ decision-making process in the ABM for four distinct agent types. According to its sales records, the food hub works with an average of 70 producers in each order cycle. In order to up-scale the data from 24 producers to a model population of 72 agents, the proportional cloning strategy of Schreinemachers et al
2009 [36] was adopted, such that 18, 15, 27, and 12 agents were created with the attributes of Clusters 1, 2, 3, and 4, respectively.

Based on the cluster to which it belongs, each producer agent $i$ is assigned two different probabilities that it will decide not to preschedule its delivery due to operational factors: a probability based on its harvesting schedule ($P_{Hi}$) and a probability based on its delivery route ($P_{Ci}$). These factors were assessed in Questions 1–4 of the survey. These probability values correspond to the average value of the responses (on a scale of 1–5) within each cluster, where larger values correspond to higher probabilities of not scheduling. It is assumed that the relationship between the 5-point Likert scale used in the survey and the corresponding probabilities (0–0.8) is piecewise linear.

Table 3.3 Description of four distinct clusters from the producer survey data

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Product types</th>
<th>Delivery routes</th>
<th>Harvesting schedule</th>
<th>Queue time</th>
<th>Monetary incentives</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster 1 (n = 6, 25%)</td>
<td>Primarily frozen meat and/or shelf-stable goods</td>
<td>Located relatively far from food hub (avg. 41.6 miles); thus, often incorporate other deliveries in their routes</td>
<td>Harvesting schedule has limited effect on scheduling decision because products are not perishable</td>
<td>Queue time moderately impacts scheduling decision</td>
<td>Strongly consider scheduling if provided with monetary incentives</td>
</tr>
<tr>
<td>Cluster 2 (n = 5, 21%)</td>
<td>Primarily meat and/or dairy products</td>
<td>Located far from food hub (avg. 68.1 miles); thus, often incorporate other deliveries in their routes</td>
<td>Harvesting schedule has limited effect on scheduling decision because products are not perishable</td>
<td>Queue time moderately impacts scheduling decision</td>
<td>Monetary incentives are unlikely to influence their scheduling decision</td>
</tr>
<tr>
<td>Cluster 3 (n = 9, 37%)</td>
<td>Primarily fresh fruits and/or vegetables</td>
<td>Located relatively near food hub (avg. 24.1 miles); thus, other deliveries do not impact their scheduling decisions much</td>
<td>Harvesting schedule highly impacts scheduling decision because products are perishable</td>
<td>Queue time moderately impacts scheduling decision</td>
<td>Monetary incentives moderately influence their scheduling decision</td>
</tr>
<tr>
<td>Cluster 4 (n = 4, 17%)</td>
<td>A mix of fresh produce and/or shelf-stable goods</td>
<td>Located near the food hub (avg. 18.3 miles); thus, other deliveries do not impact their scheduling decisions</td>
<td>Harvesting schedule has no effect on scheduling decision</td>
<td>Queue time strongly impacts scheduling decision</td>
<td>Monetary incentives are unlikely to influence their scheduling decision</td>
</tr>
</tbody>
</table>
In Questions 5–11 in the survey, producers were asked to rate their satisfaction level on a scale of 1–5 (where 1 is least satisfied and 5 is most satisfied) if they must wait in a queue at the food hub warehouse to receive service. Seven different possible time ranges (from 0 to 30+ min, in 5-min increments) were presented in the survey. The average values of each producer cluster’s responses were used to define a queue time satisfaction vector ($Q_{Si}$) for each of the four agent types. Each of the seven elements of this vector represents the satisfaction level of a producer agent in each of the seven different queue time ranges.

Based on the survey data, each of the agents was also level of a producer agent in each of the seven different queues assigned a delivery time preference. The Iowa food hub’s time ranges. online schedule currently offers eleven 1-h time slots from which the producers can choose to deliver their products: eight slots between 9:00 a.m. and 5:00 p.m. on Day 1 and three slots between 8:00 a.m. and 11:00 a.m. on Day 2. Each of the 24 surveyed producers was asked to rate his/her preference for each of the eleven time slots, on a scale of 1–5 (where 5 is most preferred and 1 is least preferred). These data were translated into 24 distinct scheduling preference vectors ($Si$). The 11 elements of this vector were used to represent a producer agent’s preference for each of the 11 time slots. The 24 preference vectors were assigned to the producer agents proportionally within each producer cluster.

Input data to the ABM from the DES model include the queue times of each producer agent from the previous order cycle ($Qi$), as well as the food hub personnel utilization ($UL_j$) and producer service levels ($SL_j$) in each time slot $j$.

**Sub-models** - The ABM contains three sub-models: Producer Agent Utility Assessment, Producer Agent Scheduling Decision, and Food Hub Agent Management Decision. All three sub-models are executed in each time-step.
Sub-model 1 - producer agent utility assessment - A producer agent’s scheduling decision is influenced by the degree of satisfaction (i.e., utility) that it experiences in its interactions with the food hub. Agent utility is a function of two components: convenience and autonomy. An agent’s utility from convenience ($U_{Ci}$) is a function of its queue time at the food hub warehouse ($Q_i$). Each producer agent’s queue time preference vector ($QS_i$) is normalized to yield a piecewise linear utility function, which ranges from 0 (least satisfied) to 1 (most satisfied). To determine its value of $U_{Ci}$ in the current time-step, an agent will map its queue time from the previous time-step ($Q_i$) to this piecewise linear function. An agent’s utility from autonomy ($U_{Ai}$) is represented by the flexibility that it has in scheduling its deliveries. Thus, the value of $U_{Ai}$ depends upon the agent’s decision to preschedule its delivery in the previous time-step. $U_{Ai}$ is assigned a value of 1 (i.e., highest satisfaction) if the agent does not schedule its delivery. If the agent does decide to schedule, it is assumed that the value of $U_{Ai}$ decreases to 0.8. A producer agent’s overall utility ($U_i$) is a weighted combination of $U_{Ai}$ and $U_{Ci}$, given by

$$U_i = W_C U_{Ci} + W_A U_{Ai}$$

where $W_A$ and $W_C$ are measures of the producer’s relative preferences for autonomy and convenience, respectively. Each producer agent memorizes its overall utility value ($U_i$) from the latest time-step when operational factors do not prevent the agent from scheduling the delivery.

Sub-Model 2 - producer agent scheduling decision - Each producer agent decides in each time-step whether or not it will preschedule its delivery to the food hub warehouse. This decision is driven by the probability that operational factors (i.e., harvesting schedule ($P_{Hi}$) and/or delivery routes ($P_{Ci}$)) will prevent the agent from scheduling, as well as the agent’s current overall utility value ($U_i$). In the first time-step, a number between zero and one is
randomly generated for each producer agent \( i \), and if this value is less than \( P_{Hi} \) and/or \( P_{Ci} \), the agent will decide not to preschedule because of operational factors. If the agent decides not to preschedule, it is assumed that the agent will arrive in one of its most-preferred time slots \( (s_i) \). Otherwise, the agent is initialized to schedule its delivery for one of its most preferred time slots. If an agent has multiple most-preferred time slots, it will initially select one of these at random and memorize it. In subsequent time-steps if the agent decides to schedule and was satisfied with its previous selection of time slot (i.e., its queue time was less than 5 min), it will select the same time slot again. Otherwise, it will randomly select a different time slot from its list of most-preferred time slots and update its memory. It is assumed that if a producer agent schedules its delivery in a given time slot, it is guaranteed to arrive at the food hub in that time slot. The specific producer arrival times to the food hub \( (t_i) \) are assumed to be uniformly distributed within the chosen 1-h time slots \( (s_i) \).

In subsequent time-steps, each producer agent will reevaluate its decision to schedule its delivery. If operational factors do not prevent the agent from scheduling, it will compare its overall utility value \( U_i \) to the threshold utility value \( (U_T) \) of 0.8. If \( U_i \) is greater than \( U_T \), the agent will maintain its previous scheduling decision strategy (irrespective of operational factors); otherwise, it will reverse its decision. Figure 3.2 shows the agent decision-making process in the ABM. This adaptive decision-making process, in which each individual producer agent evaluates the impact of its decisions in each time-step, memorizes this information, and then utilizes it to make future decisions, is readily captured using ABM and would have been difficult to realistically incorporate into a DES model.

**Sub-Model 3 - food hub agent management decision** - In the baseline version of the model, the food hub manager agent is assumed to be inactive, which represents the status quo
conditions of the Iowa food hub. In the second and third versions of the model (i.e., Experimental Scenarios 1 and 2), the food hub manager agent makes decisions regarding producer incentives and personnel scheduling, in an effort to improve the food hub warehouse’s performance. These decision processes of the food hub manager agent are described in detail in Sects. 4.2 and 4.3.

![Flowchart](image)

Figure 3.2 Producer agent decision-making process.
Discrete-event simulation model

This section describes the DES model (developed using Arena 14.7), which represents the inbound operations of the food hub warehouse.

Model overview - Each entity $i$ in the DES model corresponds to a producer agent $i$ in the ABM. The four stages in the DES model represent the four stages of operations at the Iowa food hub. The producer entities arrive at the warehouse and then wait in a queue to receive service (i.e., quality inspections and product put-away) from food hub personnel. After receiving service, each producer entity exits the system. Figure 3.3 shows the flow of each producer entity through the DES model.

Model details - In this section, each of the four stages in the DES model is described in detail. A summary of all of the input parameters and variables used in the DES model is provided in Table 3.4.

Producer arrival - The arrival times of the producer entities were previously determined in the ABM, in which the producer agents selected their preferred time slots, and their specific arrival times within these time slots were drawn from a uniform distribution. These arrival times ($t_i$) were written to a text file, which served as an input file to the producer arrival process in the DES model.

Queueing - Each producer entity joins a single FIFO queue to wait for an available server.
Receiving process - The modeling of the receiving process was based on multiple observations of the actual receiving process at the Iowa food hub, as well as operational data that were provided by the food hub manager. Two entity attributes define the receiving process for the entity: the types of products that it is delivering (i.e., frozen, refrigerated, shelf-stable, or live plants) and the number of products of each type. The time required for quality inspection and product put-away is a function of these two attributes. For example, the time required for the inspection of fresh vegetables (i.e., a detailed visual inspection) is different from milk container inspection (i.e., counting by quantity/type and determining expiry dates). Because the food hub has adopted different storage strategies for each of the four product types, the put-away times also vary by type. For example, shelf-stable goods (e.g., flour, potatoes) are stored according to distribution site location and are further sorted by each customer’s identification number, while frozen goods are stored in designated freezers as per the distribution site location and are then sorted by producer name and customer identification number. Table 3.5 shows the relationships between product types and food hub storage policies.
Table 3.4 Input variables and parameters used in the DES model

<table>
<thead>
<tr>
<th>Input variables</th>
<th>Description</th>
<th>Possible values</th>
<th>Static/dynamic</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>i</td>
<td>Unique number assigned to each producer entity in DES (correspond to the agent in ABM)</td>
<td>1–72</td>
<td>Static</td>
<td>ABM output</td>
</tr>
<tr>
<td>t&lt;sub&gt;i&lt;/sub&gt;</td>
<td>Arrival time of the ith producer entity at the food hub</td>
<td>0–480 min (day 1) 0–180 min (day 2)</td>
<td>Dynamic</td>
<td>ABM output</td>
</tr>
<tr>
<td>r&lt;sub&gt;1&lt;/sub&gt;</td>
<td>Time required to receive per unit volume of products in “frozen” category</td>
<td>TRIA (0.89,1.02,1.18)</td>
<td>Dynamic</td>
<td>Time study at the food hub</td>
</tr>
<tr>
<td>r&lt;sub&gt;2&lt;/sub&gt;</td>
<td>Time required to receive per unit volume of products in “refrigerated” category</td>
<td>TRIA (0.2,0.25,0.3)</td>
<td>Dynamic</td>
<td>Time study at the food hub</td>
</tr>
<tr>
<td>r&lt;sub&gt;3&lt;/sub&gt;</td>
<td>Time required to receive per unit volume of products in “shelf-stable” category</td>
<td>TRIA (0.44,0.72,1)</td>
<td>Dynamic</td>
<td>Time study at the food hub</td>
</tr>
<tr>
<td>r&lt;sub&gt;4&lt;/sub&gt;</td>
<td>Time required to receive per unit volume of products in “plants” category</td>
<td>TRIA (0.89,1.02,1.18)</td>
<td>Dynamic</td>
<td>Time study at the food hub</td>
</tr>
<tr>
<td>V&lt;sub&gt;i1&lt;/sub&gt;</td>
<td>Average sales volume of products brought by the ith producer entity per order cycle in the “frozen” category</td>
<td>–</td>
<td>Static</td>
<td>Food hub historical sales data</td>
</tr>
<tr>
<td>V&lt;sub&gt;i2&lt;/sub&gt;</td>
<td>Average sales volume of products brought by the ith producer entity per order cycle in the “refrigerated” category</td>
<td>–</td>
<td>Static</td>
<td>Food hub historical sales data</td>
</tr>
<tr>
<td>V&lt;sub&gt;i3&lt;/sub&gt;</td>
<td>Average sales volume of products brought by the ith producer entity per order cycle in the “shelf-stable” category</td>
<td>–</td>
<td>Static</td>
<td>Food hub historical sales data</td>
</tr>
<tr>
<td>V&lt;sub&gt;i4&lt;/sub&gt;</td>
<td>Average sales volume of products brought by the ith producer entity per order cycle in the “plants” category</td>
<td>–</td>
<td>Static</td>
<td>Food hub historical sales data</td>
</tr>
<tr>
<td>FP&lt;sub&gt;j&lt;/sub&gt;</td>
<td>Number of food hub personnel in jth time slot (j varies from 1 to 11)</td>
<td>Baseline model: 2 for j [1,8]; 6 for j [9,11] Adaptive scheduling model: [1, n]</td>
<td>Baseline model: static Adaptive scheduling model: dynamic Baseline model: food hub database Adaptive scheduling model: food hub agent decides</td>
<td></td>
</tr>
</tbody>
</table>
Table 3.5 Storage policies for each product type

<table>
<thead>
<tr>
<th>Product type</th>
<th>Customer ID number</th>
<th>Distribution location</th>
<th>Producer name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frozen goods</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Refrigerated goods</td>
<td></td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Shelf-stable goods</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Plants</td>
<td>✓</td>
<td></td>
<td>✓</td>
</tr>
</tbody>
</table>

A time study was conducted at the Iowa food hub warehouse to determine the receiving time distributions ($r_1$ to $r_4$) for each product type. Table 3.6 summarizes the probability distributions that were derived from the time study data. These distributions were used to generate receiving times (per unit of food) in the DES model. Using data from the Iowa food hub’s sales records, the average sales volume per order cycle for each of the four product types ($V_{1i}$ to $V_{4i}$) was identified for the 24 surveyed producers, and these values were assigned to the producer entities proportionally within each producer cluster. The unit receiving times drawn from the distributions in Table 3.6 were then multiplied by the entity’s sales volume values to determine that entity’s total required service time in a given order cycle.

Table 3.6 Receiving time distributions for each product type

<table>
<thead>
<tr>
<th>Product type</th>
<th>Time distribution (minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frozen goods</td>
<td>TRIA (0.89,1.02,1.18)</td>
</tr>
<tr>
<td>Refrigerated goods</td>
<td>TRIA (0.20,0.25,0.30)</td>
</tr>
<tr>
<td>Shelf-stable goods</td>
<td>TRIA (0.44,0.72,1.00)</td>
</tr>
<tr>
<td>Plants</td>
<td>TRIA (0.89,1.02,1.18)</td>
</tr>
</tbody>
</table>
The number of servers (i.e., food hub personnel) allotted to each time slot \( j \) for the receiving process in the DES model \( (FP_j) \) is based on the actual number of personnel that are typically available at the food hub for the receiving process. On Day 1, two personnel were typically available during each of the eight 1-h time slots, and on Day 2, six personnel were available in each of the three 1-h time slots. It was assumed that these are parallel and identical servers.

*Producer exit* - After receiving service from the food hub personnel, each producer entity exits the system.

*Model outputs* - As each producer entity moves through the system, the DES model captures its queue time \( (Q_i) \) and then writes this value to a file. Once all of the producer entities have exited the system, the utilization levels of the food hub personnel \( (UL_j) \) as well as the service level \( (SL_j) \) for all 11 time slots are also written to the output file. A summary of the outputs from the DES model is provided in Table 3.7 below.

<table>
<thead>
<tr>
<th>Output variables</th>
<th>Description</th>
<th>Possible values</th>
<th>Static/Dynamic</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Q_i )</td>
<td>Queuing time of the ( i )th producer entity at the food hub</td>
<td>–</td>
<td>Dynamic</td>
</tr>
<tr>
<td>( UL_j )</td>
<td>Percentage of total man hours spent on receiving process to total available man hours in ( j )th time slot (( j ) varies from 1 to 11)</td>
<td>0–100%</td>
<td>Dynamic</td>
</tr>
<tr>
<td>( SL_j )</td>
<td>Service level of ( j )th time slot (( j ) varies from 1 to 11)</td>
<td>0–100%</td>
<td>Dynamic</td>
</tr>
<tr>
<td>Qavg1</td>
<td>Average queue time on day 1</td>
<td>–</td>
<td>Dynamic</td>
</tr>
<tr>
<td>Qavg2</td>
<td>Average queue time on day 2</td>
<td>–</td>
<td>Dynamic</td>
</tr>
</tbody>
</table>

*Hybrid ABM—DES model*

The hybrid simulation begins with the ABM. The producer agent arrival times are determined and are then written to an output file to become inputs for the DES model. At this point, the simulation switches to the DES model of the food hub warehouse’s inbound operations. In the DES model, each producer entity receives service from the food hub
personnel, and its queue time \( (Q_i) \) is written to an output file. These queue times become inputs to the ABM that will inform the producer agents’ scheduling decisions. The model then advances one time-step and returns to the ABM. Figure 3.4 shows the hybrid simulation framework.

![Figure 3.4 Hybrid simulation (ABM-DES) framework.](image)

3.5 Experimentation and Results

This section describes the experiments that were performed using three different versions of the hybrid simulation model: a baseline status quo model for validation, a version in which producer agents are incentivized to schedule their deliveries (Experimental Scenario 1), and a version in which food hub personnel are adaptively scheduled by the food hub manager agent (Experimental Scenario 2). The required number of replications for each experimental condition was determined using the iterative procedure described by Law and Kelton 1991 [37], in which the output metric used for evaluation was the average number of producers scheduling in each time-step. Initially, 5 replications of 120 time-steps each were run. The minimum number of replications required to achieve an absolute error of 1.0 at a confidence level of 95% was 9. Therefore, for each of the three model versions, 10 replications of 120 timesteps each were run. The initial 20 time-steps were used as a warm-up period to allow the system to stabilize, and the average values over the final 100 time-steps from each iteration were captured for further analysis. Key output metrics of interest were the number of producer agents that decided to preschedule their deliveries (from the ABM), the average producer entity queue times (from the
DES model), service level and the average utilization of the food hub personnel (from the DES model).

**Baseline model**

The baseline version of the model, which represents the status quo conditions at the Iowa food hub, was validated using the historical data validation technique, in which the model outputs are compared with historical data from the real system that is completely independent of the simulation input variables and parameters [38]. An iterative process of parameter variability sensitivity analysis was used to validate key parameter values [38]. For example, the values assigned to the weights on autonomy ($W_A$) and convenience ($W_C$) in the producers’ utility function were iteratively tuned to assess validity. The producer survey data indicated that nearly all of the producers considered scheduling flexibility (i.e., autonomy) to be more influential than queue time (i.e., convenience) in their decisions to preschedule deliveries. Therefore, throughout the sensitivity analysis, values of $W_A$ were always assigned to be greater than values of $W_C$. Figure 3.5 shows the number of producer agents that decided to schedule their deliveries in each time-step over the course of the simulation run for three different values of $W_A$ and $W_C$. The simulation results show that the average number of producers scheduling their deliveries increases as the weight on convenience increases. In reality, approximately 25% of the food hub’s producers (i.e., 18 of 70 producers) schedule their deliveries in each order cycle. When the values of $W_A$ and $W_C$ are set to 0.6 and 0.4, respectively, the simulated number of scheduling producers is closest to that of the actual system (15.1 producers (21%), SD = 1.0). Therefore, it was concluded that these values would serve as a valid representation of the weights in the producer decision process.
The model yielded average queue times ($Q_{avg1}$ and $Q_{avg2}$) on Days 1 and 2 of 10.5 min (SD = 2.1) and 0.4 min (SD = 0.1), respectively. The long average queue time on Day 1 is a result of highly variable producer arrival times throughout the day, with many arrivals concentrated in time slots 2 and 6, and insufficient receiving capacity. Because the food hub manager has not placed any capacity limits on the time slots, many producers arrive in the same time slot (as per their preferences), whether they scheduled their deliveries or not. The model also yielded an average of 37 producer deliveries on Day 1 and 35 on Day 2. In the real system, 40 producers typically deliver their products on Day 1, and 30 deliveries occur on Day 2. Thus, the simulation results closely approximate those of the real system.

Figure 3.5 Number of producers scheduling their deliveries in each time-step for status quo conditions with different weights on autonomy and convenience.

**Experimental Scenario 1: producer incentives**

To encourage producers to preschedule their deliveries using the food hub’s online scheduling tool, the manager could consider offering monetary incentives. In conventional supply chains, high-performing suppliers are often motivated by incentives in which the buyer shares cost savings or profits [39], [40], [41]. The surveyed producers were asked in Questions
12-15 of the survey how likely they would be to preschedule their deliveries in exchange for receiving four different levels (k) of monetary incentives as a percentage of their sales (i.e., less than 1%, between 1 and 3%, between 3 and 5%, and greater than 5%). The average responses within each of the four producer clusters were used to define a vector (\(M_{ki}\)). Each element k of the vector represents the likelihood (on a five-point Likert scale) that a producer agent would schedule its delivery if provided with kth level of monetary incentive. This vector was used in the ABM to assign scheduling probabilities to the producer agents belonging to that cluster, given a certain incentive level. The probability value was defined on a linear scale, decreasing from 0.8 to 0 as the average Likert-scaled response values decreased from 5 to 1.

The ABM was modified to test the effects of the four different incentive levels on producer delivery scheduling. As in the baseline model, the probability values (\(P_{Ci}\) and \(P_{Hi}\)) for each agent were first used to determine whether operational factors would prevent agent i from prescheduling. If not, the agent first decides whether or not to preschedule based on the incentive level promised by the food hub and its associated probability value. If the incentive does not convince the agent to schedule, its final decision is based on its overall utility (\(U_i\)), as in the baseline model.

Results indicated that providing monetary incentives did not substantially change the producer agents’ scheduling behaviors. Even when the maximum incentive level was applied (i.e., greater than 5% of the producer’s sales), on average only 21.5 producers (29.9%, SD = 1.2) decided to preschedule their deliveries. While this is a modest increase over the baseline model, in which an average of 15.1 producers decided to preschedule, interestingly, it did not yield meaningful reductions in average queue times. The average queue time on Day 1 decreased from an average of 10.5 min (SD = 2.1) in the baseline model to 10.1 min (SD = 2.1) in the modified
version of the model. On Day 2, the average queue time actually increased slightly, from 0.4 min (SD = 0.1) to 0.5 min (SD = 0.2). This is because the incentive did not influence the producers to change their arrival patterns. Although more producer agents prescheduled, they continued to arrive in their most preferred time slots, resulting in long queues during the most desirable time slots.

The results of this experiment indicated that even if incentives somehow encouraged every producer to preschedule, queue times would not decrease unless the food hub manager placed a capacity constraint on the time slots. After discussing these results with the Iowa food hub manager, it became apparent that he would be unwilling to do this, because he believes that it would unduly constrain the producers’ autonomy. Based on this feedback, the modeling focus changed. Rather than focusing on finding ways to motivate the producers to preschedule their deliveries, it was decided that reallocating the food hub’s receiving personnel would be a more effective intervention, because the food hub manager has more control over personnel scheduling than producer behavior.

**Experimental Scenario 2: adaptive personnel scheduling**

The baseline model was developed further to help the food hub manager determine the appropriate number of receiving personnel (FP$_j$) to assign to each of the 11 time slots. In this new scenario, the food hub manager agent in the ABM employed an adaptive personnel scheduling heuristic that was informed by the producers’ arrival patterns, as well as outputs from the DES (i.e., the food hub’s service level and receiving personnel utilization). Although optimality is not guaranteed, embedding a heuristic within the ABM provided an efficient means of generating workforce schedules that balanced cost, service level, and individual workers’ preferences and utilizations, as well as enabling the consideration of stochastic producer arrivals.
[42]. A heuristic approach is also a realistic representation of a scheduling process that the real-life food hub manager could use.

In alternating time-steps in the ABM, the food hub manager agent generates a schedule that sets the capacity of the receiving personnel (i.e., servers) in the DES for each of the 11 time slots. After the delivery cycle is completed, the manager agent then uses DES outputs to evaluate the schedule’s effectiveness and determine whether it requires modification. Specifically, the manager agent seeks to allocate personnel to achieve a target service level \( (SL_j) \) and server utilization level \( (UL_j) \) in each time slot. The target service level was set to 80%, such that the producer queue times do not exceed 5 min at least 80% of the time. If the average service level for a particular time slot over the previous two time-steps is less than 80%, the manager agent allocates one additional server to that time slot. If the target service level is achieved, the manager agent assesses the average server utilization in each time slot. Target server utilization levels were set to minimum and maximum values of 0.50 and 0.85, respectively, in an effort to prevent both overutilization and underutilization of food hub personnel, since overutilization can lead to frustration and burnout, and underutilization can lead to boredom. If server utilization is greater than 0.85 in a particular time slot, the manager agent assigns one additional resource to that time slot. If average utilization is less than 0.50 in a particular time slot and more than one server is currently scheduled, the manager agent removes one server from that time slot. It was assumed that there was no upper limit on the number of personnel available to assign to each 1-h time slot.

For the first two time-steps of the simulation run, the Iowa food hub’s existing personnel schedule was used. With the manager agent adaptively managing the server schedule, an average of 34.0 (SD = 0.6) total servers were used to cover all 11 time slots, which is slightly fewer than
the baseline model (36 servers). Moreover, as Figure 3.6 shows, the average queue time on Day 1 was substantially reduced, from 10.5 min in the baseline model to 3.4 min (SD = 1.0) with adaptive server scheduling. These results suggest that adaptive personnel scheduling could help the food hub improve both its operational efficiency and its effectiveness.

![Figure 3.6 Comparison of average queue times in the baseline model and Experimental Scenario 2.](image)

Interestingly, the average number of producer agents that scheduled their deliveries under Experimental Scenario 2 was reduced from 15.1 in the baseline model to 9.3 (SD = 1.4). This was likely because adaptive personnel scheduling reduced the queue times, irrespective of producer agent scheduling behaviors. As a result, there was no motivation for them to attempt to improve their convenience utility by choosing to schedule.

### 3.6 Conclusion

By effectively managing its inbound operations, a regional food hub can allocate its resources more efficiently and provide better service to its customers. This will likely increase customer loyalty and business for the food hub, thereby improving the economic growth
opportunities and quality of life for participating small and midsize producers. However, producers greatly value their autonomy, and they tend to resist having constraints placed on their ability to set their own schedules. As a result, predicting the effects of specific management policies on producer scheduling behavior and subsequent system-wide outcomes is very difficult.

To address this problem, an empirical hybrid simulation model of the inbound logistics operations at a regional food hub in central Iowa was developed and validated. Upon validation, the baseline model was modified to incorporate producer scheduling incentives and adaptive personnel scheduling. The results of Experimental Scenario 1 suggest that providing financial incentives will not guarantee improved system efficiency. This result reflects a core difference between regional and conventional FSCs and reflects the fact that not every conventional supply chain innovation will be appropriate for a regional FSC. By contrast, the results of Experimental Scenario 2 suggest that adaptive personnel scheduling has the potential to increase efficiencies without eroding the food hub’s commitment to its social mission of supporting producers. These results demonstrate the potential usefulness of this model in supporting food hub managers’ operational planning decisions.

The model also demonstrates the utility of integrating ABM and DES modeling paradigms to study warehousing operations. The ability of ABM to represent heterogeneous producer preferences and attributes via autonomous agents, combined with the ability of DES to capture the queuing behavior of the producers at the warehouse, yielded more realistic model behavior than either method could have accomplished alone. Additionally, the feedback loop between the food hub manager’s adaptive scheduling decisions and the receiving capacity of the food hub warehouse would have been extremely cumbersome (if not impossible) to model and analyze using a single simulation technique. The hybrid approach also yielded some unexpected and
useful results. In particular, fewer producer agents scheduled their deliveries under the adaptive personnel scheduling scenario, but food hub queue times reduced substantially. It is unlikely that these kinds of interesting results would have been observed using DES or ABM alone.

In future research, it would be interesting to observe how the agents belonging to different behavioral clusters respond to different food hub policies. Additionally, the food hub might consider modifying the monetary incentive by informing the producers that they will receive the benefit only if they arrive in the less desirable time slots. Another possible future development of the model presented in this chapter is the inclusion of multiple Iowa food hubs, enabling the collection of information from a wider variety of producers and food hub managers. This would improve the generalizability of the model and would allow implications from experimental results to be extended to other food hubs, thereby increasing the model’s usefulness as a decision support tool for food hub managers.

References


CHAPTER 4. AN AGENT BASED APPROACH TO MODELING ZERO ENERGY COMMUNITIES

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4.1 Abstract

As zero energy buildings take on an increasingly prominent role in overall efforts to reduce energy consumption, it is necessary to identify effective policies for their design and implementation. However, current zero energy building (ZEB) policies focus mainly on new buildings, primarily through on-site renewable energy generation, such as rooftop photovoltaic (PV) systems. Having a few high performing buildings will have limited impact if the community as a whole is not net zero. A more practical approach to achieve zero energy goals is to extend the zero energy boundaries beyond an individual building and have a group of buildings evaluated together as a community, such that the community in itself becomes a zero-energy community (ZEC). Successful ZEC implementation requires that community members actively participate in renewable energy and energy efficiency programs and collectively support the goal of zero energy. Hence, a consumer-oriented analysis is needed to support effective ZEC design decisions and promotion efforts. This paper describes a conceptual agent-based model for an urban neighborhood in Des Moines, Iowa, to predict household level renewable energy adoption behaviors in presence of multiple options. Specifically, the level of consumer participation before and after introducing a community solar option for the neighborhood is
evaluated via experimentation with the model. Simulation results demonstrate that introducing a community solar program increases household level adoption as well as the proportion of community level electricity consumption met through renewable sources. The amount of increase in adoption, however, depends on the choice of design parameters, such as premium that households must pay to participate. The results also show that timeliness of achieving ZEC goals depends upon the frequency of social interactions in the neighborhood, indicating the importance of community events in the successful creation of a ZEC.

**Keywords:** Zero energy building; zero energy community; agent-based model; community solar; rooftop PV; sociotechnical system

### 4.2 Introduction and Background

#### 4.2.1 Research Objective

The objective of this paper is to conduct a consumer level analysis to identify how zero energy goals can be achieved at the community level through consumer adoption of different renewable energy options.

#### 4.2.2 Zero Energy Buildings – Motivation, Implementation, and Challenges

Residential and commercial buildings consume significant amounts of energy, accounting for 40% of the total U.S. energy consumption over the last decade [1]. Concern for environmental issues and the impact of climate change has resulted in an increased interest among policymakers and the scientific community to reduce building energy consumption and fulfill energy requirements using renewable sources of energy. The goal of minimizing building energy consumption has led to the concept of zero energy buildings. A zero energy building (ZEB) strives to produce as much renewable energy as it consumes over a defined time period, thereby reducing the building’s carbon footprint [2].
In this paper, we adopt the U.S. Department of Energy (DOE) definition of a ZEB as “An energy-efficient building where, on a source energy basis, the actual annual delivered energy is less than or equal to the on-site renewable exported energy” [3]. Source energy includes the energy consumed in the process of power generation, starting from extracting fuel and transporting it, the losses occurring in the process of power generation, and transmission and distribution losses, in addition to the energy consumed at consumers’ premise. Energy consumed at consumers’ premises, referred to as site energy, includes indoor and outdoor lighting within a given boundary, heating, ventilation, domestic hot water, and transportation systems within the building. On-site renewable energy refers to the energy generated within the premises of consumption, while excess generation is exported outside the boundary. A rooftop photovoltaic (PV) system is one type of on-site renewable energy source for a building. In addition to offsetting energy consumption by renewables, a ZEB must implement energy efficiency practices to reduce overall energy demand. Thus, adopting an over-sized PV system to offset the energy consumption of an energy inefficient building is insufficient for ZEB classification [4].

ZEBs have become integral to energy policy in many countries. Current policies and government mandates focus mainly on new buildings, primarily through on-site renewable energy generation via rooftop PV [5]. For example, the European Union requires all new buildings and existing buildings undergoing major retrofitting to be “nearly net-zero” energy buildings by 2020 [6]. In the U.S., the California Public Utilities Commission has an energy action plan to achieve net zero energy for all new residential construction by 2020 and net zero for all new commercial construction by 2030. They plan to achieve this goal by mandating highly energy efficient construction and offsetting the remaining energy consumption through renewable sources such as rooftop PV [7]. However, new buildings represent a small portion of
the built environment. Also, the annual replacement rate of buildings in the U.S. is only about 2% [8]. Therefore, to create a larger impact from ZEBs, the carbon footprint of existing buildings must also be reduced.

Achieving ZEB status for existing buildings can be challenging, as implementing renewable energy projects on these buildings depends on their type, location, and operating requirements. Therefore, some buildings will be able to achieve more cost-effective results than others [9]. In particular, many buildings cannot meet the ZEB renewable energy requirements only through on-site renewables. Installing rooftop PV may be infeasible due to inadequate roof size/orientation and issues related to shading [10]. In fact, the likelihood of a commercial building attaining ZEB status through rooftop PV decreases as number of floors in the building increases and is highly unlikely if it has more than four floors [11]. Furthermore, only 57% of all residential buildings in the U.S. are suitable for rooftop PV installation [12], and 36% of U.S. households are renters [13], who are typically unable to adopt on-site renewables due to ownership issues.

For buildings that are suitable for rooftop PV, net metering can offset energy costs through the electricity generated by their PV systems. However, in many states in the U.S., net metering is capped based on a building’s electrical loads. In other words, consumers with rooftop PV are paid retail rates for the electricity they generate to offset their building’s electrical load, but any excess generated energy sent to the grid will only be paid at a much lower wholesale electricity rate. Since the source energy used to evaluate a building’s ZEB status consists of more than just the building’s electrical load [3], it might not be cost effective for buildings to become ZEB by offsetting other forms of energy consumption through excess rooftop PV production beyond the electrical load.
Such buildings can complement their on-site renewables by buying renewable energy certificates (REC) or enrolling in utility green pricing programs [3], [14]. In this case, the building can be certified as an REC-ZEB, which is defined as “an energy-efficient building where, on a source energy basis, the actual annual delivered energy is less than or equal to the on-site renewable exported energy plus acquired Renewable Energy Certificates” [3].

To achieve REC-ZEB status, individual consumers can procure RECs through multiple options [15]. For example, residential consumers can buy unbundled RECs from an open market and through utility green pricing programs. In a green pricing program, the utility adds an additional fee each month to a consumer’s electric bill, depending on the percentage of electricity consumption a consumer wants to meet through renewable energy sources. However, consumer decisions to adopt a renewable energy option are highly motivated by its associated financial benefits [16]. Utility green pricing programs do not offer financial benefits and is primarily an outgrowth of social motivations of consumers.

Current zero energy efforts are thus very narrowly focused, as many buildings either cannot be classified as ZEB due to an inability to adopt on-site renewables, or because consumers are not sufficiently motivated to buy enough RECs to become REC-ZEB due to a lack of associated financial benefits. Achieving the goal of net zero energy at the building level, therefore, becomes challenging and poses difficulties for policymakers in their efforts to encourage ZEB. While the number of zero energy projects in the U.S. has increased significantly over the last few years (from 60 buildings/projects in 2012 to 482 in 2018), it is still a small fraction compared to the existing infrastructure [17]. In order to have a significant impact, this number must grow at a much faster pace. In other words, having a few high-performing buildings will have limited impact if the community as a whole is not net zero.
4.2.3 Adopting a Community Level Zero Energy Approach

A more realistic and feasible approach to achieve zero energy goals is by extending the zero energy boundaries beyond an individual building and having a group of buildings evaluated together as a community, such that the community in itself becomes a zero-energy community (ZEC). The U.S. DOE defines a ZEC as an “energy-efficient community where, on a source energy basis, the actual annual delivered energy is less than or equal to the on-site renewable exported energy” [3]. Achieving community level zero energy goals has relied primarily on on-site renewables (i.e., rooftop PV) [5]. But the community level approach allows for flexibility to incorporate other options, as well. For example, community choice aggregation (CCA) programs establish a contract with an energy generator for a group of consumers, allowing them to reduce their energy bills and retain control of their energy mix, mainly green energy through local utilities. However, the gap between the renewable energy supplied by the utility and that needed by a community to become net-zero is so large that renewable energy installed at the community level is needed to bridge this gap [9].

To address this gap, some utilities have developed community scale renewable facilities for their customers. One emerging option for community scale renewables is community solar. Under a community solar program, the actual generation of solar energy does not occur at the consumer’s home. Instead, the consumer subscribes to a portion of a shared PV facility located elsewhere in the community, much like a resident investing in a community garden, and each subscriber benefits in proportion to his or her investment [18]. For example, if a consumer subscribes to 1 kW of PV panels in a 100-kW system, he/she would receive 1 percent of the net metering credits generated by the entire system in his/her monthly utility bill. Community solar systems can be developed and administered by utilities, businesses, local governments, groups of consumers, nonprofit organizations, or a combination, and may be located on public buildings,
private land, brownfields, or any location with suitable solar resources. By definition, CCA and community solar programs cannot be practically implemented for individual buildings and require a community level approach [15], [19].

A community level approach can take advantage of load diversity, avoid oversizing of energy systems, and leverage shared heating requirements, infrastructure cost, and resources [19]. In particular, community solar programs can improve grid efficiencies and save utilities money by reducing the additional infrastructure required to maintain individual rooftop PV systems [20]. Such projects also generate more electricity, as large solar arrays can be adjusted throughout the day to catch more sunlight, which is often not possible for individual buildings [10]. Further, building energy requirements can be viewed collectively, thereby eliminating the need to account for individual performance and evaluate standalone consumption [19]. Therefore, instead of focusing on achieving ZEB/REC-ZEB status for each building, it may be more appropriate to consider a multi-building framework for evaluating zero-energy efforts.

A community level approach can encourage renewable energy adoption by households that are less motivated at an individual level or are financially limited. Specifically, consumers who might not adopt measures to become ZEB or REC-ZEB as individuals, might participate in making their community a ZEC. At a community level, individuals tend to view themselves as “citizens” rather than “consumers”, which can encourage collective action to transform the energy infrastructure on the local level, yielding a healthier environment and new employment opportunities for the community [21], [22]. Further, consumers who perceive high financial risk in adopting rooftop PV systems may view joint investment in programs such as community solar as less risky [23]. Community solar programs can also enable lower-income households to participate in the zero energy mission and reap the financial benefits of cheaper solar electricity
due to economies of scale [10]. Community solar programs also allow renters and households that cannot adopt rooftop PV due to structural constraints to adopt renewables and contribute to the achievement of a ZEC.

4.2.4 Current Challenges in Achieving Zero Energy Communities and Research Gaps

Despite their advantages, to be successful, ZECs require that community members are collectively aligned with the net-zero goal [24]. It is not always easy to predict the level of buy-in for a given community. For example, many community solar programs in Wisconsin having the same rate and plan structure have different subscription rates at different geographic locations [25]. This suggests that ZEC success depends on the degree to which the available renewable energy options meet the specific needs and requirements of that community’s members. Individual consumer willingness to participate in a ZEC is influenced by external factors, such as cost, availability of alternative renewable energy models, interactions with peers, and government policies, as well as internal factors, such as financial and social beliefs/preferences. The relative importance of these factors depends on demographics (e.g., income, age, location). For example, consumers tend to adopt rooftop PV systems later in life [26].

Hence, ZEC design decisions, which include selecting community solar program parameters, designing financial rebate schemes for low income households, and influencing consumers through social media campaigns, should be informed through a consumer-oriented analysis. A consumer-oriented analysis incorporates not just the technical aspects of the ZEC, but also the social and financial motivations and external influences that drive individual renewable energy adoption decisions in the community [10]. This type of analysis can provide a greater understanding of how well a community’s zero energy objectives will be met, given a portfolio of competing renewable energy options, at both household and community levels.
Currently, however, there is a lack of quantitative methodological approaches to consumer-oriented analysis for community level energy planning [27], [28], and there are few tools available to support the design decisions of community solar programs, such as required size or payment structure [29].

4.2.5 Research Approach

A ZEC can be considered as a sociotechnical system, since achieving a ZEC is driven by technical, financial, and social factors [28], [30]. It is important to analyze and design such systems holistically to capture stakeholder heterogeneity. Such sociotechnical systems are well-suited to analysis using agent-based modeling (ABM).

ABM is a powerful computational tool that can be used to examine sociotechnical system performance over time, wherein system behavior is subject to complex and dynamic individual human behaviors and social interactions. In an ABM, autonomous agents, modeled as software entities, make decisions and take action to achieve their objectives, with behavioral complexities that can range from simple binary decisions to the complexity of human intelligence [31]. Agents are proactive, autonomous, and intelligent, and can perceive, reason, memorize, and take initiative based on their knowledge, past experiences, and pre-defined rules determined by the modeler. Given that the collective success of a ZEC is driven by heterogeneous consumer motivations, social interactions, and individual adoption decisions over time, ABM is useful in predicting consumer adoption of renewable energy options for different design parameter values.

4.2.6 Contribution

This paper describes an ABM that can be used to predict the effectiveness of different renewable energy options in creating a successful ZEC. The purpose of this study is to extend the perspective of zero energy from individual buildings to communities, thereby furthering the overall objective of net zero energy consumption and reduced building carbon footprints.
Specifically, this study seeks to evaluate design trade-offs for community scale renewables and determine how to maximize renewable energy generation through consumer participation. As the concurrent presence of multiple different renewable energy options (e.g., rooftop PV and green pricing programs) can affect participation, it is important to model these options simultaneously.

4.3 Related Work

4.3.1 Zero Energy Communities

A commonly used approach to achieve zero energy goals is to look at standalone buildings for their energy requirements and meet the targets for them individually. There are only a few studies in literature that take this approach to a broader level and discuss zero energy communities [32], [33]. The first mention of zero energy communities came out not even a decade ago, in 2009 [9], [19]. Existing literature on zero energy communities is concentrated in two aspects: evaluating financial benefits of community scale renewables such as community solar and identifying design parameters of large-scale PV systems for communities to optimally meet their energy needs from power system efficiency and grid stability perspective. For example, a simulation optimization model using Monte Carlo method was developed to evaluate the uncertainty involved in the community solar projects investment based on physical, environmental and financial factors [29]. The authors also compared the uncertainty in investment in community solar with the equal size of PV systems on individual houses and concluded that investment return is less volatile in a community solar project over individual rooftop PV systems. Another study was conducted to determine the battery economics for a community while adopting a community-level and individual household level energy storage system [34]. The results highlight numerous advantages of community level storage over household storage like reduced storage requirements and high internal rate of return. Similarly, a technical report compared economic benefits of powering a residential community of 200 homes
in Minnesota and New Mexico through two separate configurations: zero energy homes with individual rooftop PV systems and ZEC with a community solar project [10]. The report concluded that the community solar project could lead to total cost savings of 30 to 35 percent as compared to individually powering residential homes through rooftop PV systems. Similarly, for a net zero solar community in West Village in Davis, California, financial benefits were evaluated based on the community’s effective scheduling of their appliance usage, given solar generation and electricity charges are time-dependent [35].

From the power system efficiency perspective, a simulation-based framework was developed to identify optimum community solar system size and layout for a community of 42 households in Edmonton, Canada to achieve zero energy objectives [36]. A similar study includes designing effective centralized PV plants for communities with an objective of becoming a ZEC. The study considers buildings’ electrical load, electricity generation from PV panels as well as PV panels interface with the grid to effectively design large-scale PV systems [37]. Another calculation-based framework was developed to identify feasibility of communities to become net zero based on energy needs of a community, its location with respect to transportation energy consumption and on-site renewable energy generation potential [2].

4.3.2 Agent-based Modeling and Zero Energy

An empirical ABM was developed to consider a multi-stakeholder approach to study the growth of ZEBs in Netherlands [38]. These stakeholders involved building contractors, financial institutions, project managers and national government and building owners. The simulation results from the model suggest that buyers’ high price consciousness and large price difference between normal and ZEB buildings leads to a slower diffusion of ZEBs. Several ABMs have been developed to study the effect of consumer behavior on the adoption of renewable energy. For example, an ABM was developed to gain an understanding of the discrepancy between
consumers’ opinions, as measured by market surveys, and their actual participation in dynamic
electricity tariffs programs [39]. Another ABM was developed to investigate the adoption of
green electricity tariffs by households in Germany [40]. The model results helped to determine
the impact of different factors, such as geographic location and lifestyle, on green tariff adoption
decisions.

To the best of our knowledge, there are no bottom-up simulation approaches described in the
scholarly literature that have been designed to study how the motivations among consumers vary,
at an individual level and a community level, towards adoption of renewable energy with the
objective of making their community a ZEC. It is also important to understand how these
motivations change over time and what the driving factors are. The community-level approach
adds to the complexity of the analysis, since in this case, the consumers are motivated as
responsible citizens beyond their individual motivations to adopt energy efficiency and
renewable energy measures, to achieve the objective of a ZEC. Moreover, existing models do not
consider multiple competing renewable energy options, such as rooftop PV, community solar,
and green pricing programs simultaneously, which is important to gather a true picture of
adoption within a system.

4.4 Agent-based Model

The ABM was developed using NetLogo 6.0.4. The purpose of this model is to predict
consumers’ adoption behaviors in the presence of different renewable energy options.
Specifically, the level of consumer participation is assessed before and after introducing a
community solar option for households in a neighborhood. It has been recommended in the
literature to consider a phase-wise approach for community level studies by setting intermediate
milestones [9]. Hence, household adoption of renewable energy to meet their electrical load will
help the neighborhood to achieve a milestone in its journey to become a ZEC. The model does not account for the energy mix of the utility company that provides electricity to the neighborhood; only household level participation in different renewable energy options is considered.

4.4.1 Description of Household Agents

The ABM contains 270 household agents that represent the Chesterfield residential neighborhood in the City of Des Moines, Iowa as shown in Figure 4.1 [41] - [43]. Based on demographic data for the Chesterfield neighborhood, each household agent $i$ is assigned to one of 15 levels (1-15) of income ($I_i$) and 10 levels (1-10) of education ($E_i$), where higher levels correspond to higher income brackets and educational attainment [43]. Of the 270 households in the Chesterfield neighborhood, 154 (57%) are homeowners and 116 (43%) are renters [42], so the household agents are categorized according to this distribution. This assignment remains constant throughout each simulation run. It is assumed that only home-owner agents can install rooftop PV, while both homeowner and renter agents can adopt a community solar or green pricing program offered by the utility company. However, not all homeowners can adopt rooftop solar: a study by NREL suggests that in the U.S. only 57% of residential buildings’ roofs are suitable for PV panel installation [12]. Therefore, it is assumed that 57% of the home-owner agents have no structural constraints preventing them from adopting rooftop PV.
Figure 4.1 Map of the City of Des Moines and boundary of the Chesterfield neighborhood.

The distribution of home sizes (in terms of number of bedrooms) for the City of Des Moines was used to assign home size values to the 270 household agents [44]. The average monthly electricity consumption of a residential household in Iowa of 831 kWh [45] was then used to assign each household agent a monthly electricity consumption value ($Q_i$), which is proportional to its home size. The model does not take into account the adoption of energy efficiency measures; therefore, each household agent’s electricity consumption is assumed to be constant throughout each simulation run.

4.4.2 Model Overview

In each time-step of the simulation (where one time-step represents one month), each household agent assesses whether it wants to participate in one of three different renewable energy options: install rooftop PV, participate in a community solar project, or enroll in a green pricing program. It is assumed that a household agent’s adoption decision is influenced by both financial and attitudinal factors, which are the two broad drivers of consumer behavior related to renewable energy adoption decisions [46], [47]. A household agent’s adoption decision may influence other household agents’ decisions via interactions that occur between them. At the end of each time-step, the number of households that adopt a particular renewable energy option and
the percentage of total electrical consumption of the neighborhood met through consumer-adopted renewable energy options are captured.

4.4.3 Sub-models

The ABM contains three sub-models: Household Agent Financial Assessment, Household Agent Attitude Assessment, and Household Agent Decision. All three sub-models are executed sequentially in each time-step.

4.4.3.1 Sub-model 1 - Household Agent Financial Assessment

To incorporate the financial component of decision making, household agents are classified into four agent types ($T_x$) based on their optimism toward renewable energy [48], where larger values of the index $x$ correspond to greater optimism toward solar power’s financial prospects. An agent’s type ($T_x$) determines its expectation of both the future annual growth rate of the cost of electricity provided by the utility company ($PG_i$) and the annual rooftop PV maintenance costs associated with adopting rooftop PV ($PM_i$), as a percentage of the up-front system cost. The values for $PG_i$ and $PM_i$ for each agent type are given in Table 4.1. These values were adapted from Sigrin (2013) [48].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>$T_1$</th>
<th>$T_2$</th>
<th>$T_3$</th>
<th>$T_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$PG_i$</td>
<td>Expectation of future annual growth rate of electricity cost (%)</td>
<td>0.00</td>
<td>2.60</td>
<td>3.30</td>
<td>5.00</td>
</tr>
<tr>
<td>$PM_i$</td>
<td>Expectation of annual rooftop PV maintenance cost as a percentage of up-front system cost (%)</td>
<td>0.50</td>
<td>0.25</td>
<td>0.15</td>
<td>0.00</td>
</tr>
</tbody>
</table>

A household’s propensity to invest in green technology is directly correlated to its income [49]. Specifically, the high up-front cost of purchasing and installing rooftop PV deters lower-income households from installing solar. Similarly, higher-income households tend to enroll in green pricing program more frequently than low and middle-income households, because they
can afford to pay an additional cost beyond their regular energy bills [50]. By contrast, solar loans and community solar programs, which do not require up-front payments, tend to attract low and middle-income household participants, who typically invest in these options to hedge against future energy cost increases [51].

To incorporate the influence of household income on adoption behavior, each agent is assigned an affordability factor \( (AF_i) \) on a scale of 0-1, which determines an agent’s relative ability to adopt rooftop PV via up-front purchase or pay green pricing premiums. The value of \( AF_i \) for each agent depends on its income level \( (I_i) \): \( AF_i = z(I_i) \), where \( z \) is a random number \((z)\) between 0 and 1, normalized to 1, such that \( AF_i = \frac{z(I_i)}{15} \). A larger value of \( AF_i \) represents a greater probability that agent \( i \) can afford to pay the high up-front cost of purchasing solar panels or pay green pricing premiums. In each time-step, a random number between 0 and 1 is generated, and if the number is less than the agent’s \( AF_i \) value, it is assumed that the agent can afford to buy rooftop PV or pay green pricing premiums.

If an agent can afford to adopt a renewable energy option, the adoption decision is influenced by the option’s expected future financial returns. Therefore, each household agent also evaluates the financial viability of options with anticipated future returns, including paying out-of-pocket for a rooftop PV system, paying for rooftop PV with a solar loan, and participating in a community solar project, by calculating their net present value (NPV) in each time-step. Because participation in green pricing programs is primarily driven by social motivations (i.e., there are no anticipated future financial returns), it is assumed that affordability is the only financial barrier for agent adoption of green pricing.

If a home-owner agent has the ability to adopt rooftop PV (i.e., it does not face any structural constraints) and can afford the up-front installation cost, it will calculate the NPV of
paying out-of-pocket for a rooftop PV system, paying for rooftop PV with a solar loan, and participating in a community solar project. If a home-owner agent can adopt rooftop PV (i.e., no structural constraints) but cannot afford the high up-front cost of purchasing a PV system, it will evaluate the NPV of using solar loans to pay for installation, as well as the NPV of participating in a community solar project. If a household agent cannot adopt rooftop PV due to structural constraints or roof ownership issues (i.e., it is a renter), then it only calculates the NPV of the community solar program.

Based on hourly solar PV insolation and temperature data for the City of Des Moines from 1999 to 2010, it is assumed that 109 kWh of energy is generated each month by each kW (DC) of a PV system [52]. Further, it is assumed that if a household agent decides to adopt rooftop PV or participate in a community solar project, it will choose a PV module of size $S_i$ (in kW, DC) or subscribe to a portion of a solar array that will be capable of meeting 100% of its monthly electric energy needs. Similarly, if a household agent adopts green pricing, its contribution toward the program will contribute RECs equivalent to its total electricity consumption. Also, based on Iowa’s current net metering policy, it is assumed that households will be able to offset 100% of the energy generated by their PV systems through net metering.

**NPV evaluation for rooftop PV buy option**

The present value of the installation cost of rooftop PV ($P_{b\text{\{install\},i}}$) for a house-owner agent $i$ at time $t$ is given by (1), where $S_i$ is the size of the solar panel array (in kW, DC) required by the home-owner agent to meet 100% of its energy needs (AC), $W_i$ is the installation cost ($/kW (DC)$), and $ITC_i$ is the percentage of income tax credit (federal and state). It is assumed that a household agent’s minimum federal and state tax liability in the year of purchasing rooftop PV is greater than or equal to the corresponding tax rebates it receives from purchasing rooftop PV.
Therefore, reduced cost of PV system through ITC is not discounted when evaluating the present value of $P_{b(\text{install}),i}$.

$$P_{b(\text{install}),i} = S_i W_t (1 - ITC_t) \quad (1)$$

The present value of agent $i$’s future monthly utility bill savings ($P_{b(\text{mbs}),i}$) from buying rooftop PV is given by (2). $P_{b(\text{mbs}),i}$ is calculated by discounting (by annual discount rate $d$, assumed to be 5%) the amount that the household agent would have paid to the utility company annually if it had not installed rooftop PV, over 25 years (the average life of solar panels). An agent’s annual electricity bill is evaluated by multiplying the number of months in a year by the agent’s monthly consumption value ($Q_i$, in kWh) and the current electricity rate ($C_t$, in $$/kWh), where $C_t$ increases each year based on the agent’s expectation ($PG_i$).

$$P_{b(\text{mbs}),i} = \sum_{t=1}^{25} 12Q_iC_t \left( \frac{1 + PG_i}{1 + d} \right)^{t-1} \quad (2)$$

The present value of agent $i$’s future rooftop PV maintenance cost ($P_{b(\text{maint}),i}$) is given by (3), in which the present value of installation cost ($P_{b(\text{install}),i}$) is multiplied by the agent’s expected annual maintenance cost ($PM_i$) and the expected life of the solar panel array (i.e., 25 years).

$$P_{b(\text{maint}),i} = 25PM_iP_{b(\text{install}),i} \quad (3)$$

The NPV of buying rooftop PV for agent $i$ ($NPV_{b,i}$) is given by (4), which is the difference in the present value of total cash inflow and total cash outflow.

$$NPV_{b,i} = P_{b(\text{mbs}),i} - (P_{b(\text{install}),i} + P_{b(\text{maint}),i}) \quad (4)$$

*NPV evaluation for rooftop PV loan option*

It is assumed that a household agent will borrow an amount equal to the cost of the PV system after deducting income tax credits. Thus, calculating the present value of the principal amount for house-owner agent $i$ at time $t$ ($P_{l,i}$) is equivalent to calculating the initial investment
cost \( (P_{b\text{\{install\}},i}) \) of the rooftop PV buying option, which is given by (1). Similarly, calculating the present value of future total monthly bill savings \( (P_{l\{mbs\}},i) \) and maintenance costs \( (P_{l\{maint\}},i) \) associated with the rooftop PV loan option is the same as the buying option for rooftop PV, given in (2) and (3), respectively.

It is assumed that a household agent will be able to borrow the principal amount \( (P_{l,i}) \) through a solar loan at a monthly interest rate of \( r\% \), which is assumed to be 0.5%. Each equal monthly installment \( (M_{emi,i}) \) for an agent \( i \) is given by (5), where \( n \) is the total number of installments a household agent must pay toward the loan. A 10-year loan period is assumed, such that \( n \) is equal to 120.

\[
M_{emi,i} = P_{l,i} \left( \frac{r(i + r)^n}{(1 + r)^n - 1} \right) \tag{5}
\]

The present value of the monthly installments \( (P_{l\{emi\},i}) \) is given by (6), where the total value of installments each year is discounted by an annual discount rate of \( d\% \) (assumed to be 5%).

\[
P_{l\{emi\},i} = \sum_{t=1}^{10} \frac{(12M_{emi,i})}{(1 + d)^{t-1}} \tag{6}
\]

The NPV of the rooftop PV loan option \( (NPV_{l,i}) \) is given by (7):

\[
NPV_{l,i} = P_{l\{mbs\},i} - (P_{l\{emi\},i} + P_{l\{maint\},i}) \tag{7}
\]

NPV evaluation for community solar option

In a typical community solar engagement, a customer pays a fixed premium \( (C_p) \) per unit of energy in addition to the conventional electricity rate at the time of adoption \( (C_{t*}) \), such that the total unit price that the agent pays \( (C_p + C_{t*}) \) remains constant for the life of the community solar program [53] (Barry, 2017). A similar pricing structure has been assumed in this model. The
present value at time $t$ of the total amount agent $i$ will pay if it chooses to participate in the community solar program ($P_{CS,i}$) is given by (8), in which the discounted monthly energy bills (annual discount rate $d\%$) are summed over 25 years:

$$P_{CS,i} = \sum_{t=1}^{25} \left( \frac{12Q_i(C_{t^r} + C_p)}{(1 + d)^{t-1}} \right)$$

(8)

If a household agent continues to buy electricity from the utility company, then calculating the present value of its future monthly bills ($P_{o,i}$) is equivalent to (2), which is the present value of monthly bill savings over 25 years if the agent installs rooftop PV. The NPV of investing in community solar ($NPV_{CS,i}$) for an agent $i$ is the difference between these two values:

$$NPV_{CS,i} = P_{o,i} - P_{CS,i}$$

(9)

4.4.3.2 Sub-model 2 - Household Agent Attitude Assessment

A national survey of energy consumers provides insights on attitudinal factors that influence consumer decisions to adopt renewable energy [47]. These factors include a desire to become independent from the utility company, concern for the environment and future generations, and the influence of recommendations from people in their social and spatial networks. In this model, the attitudinal factors for each agent $i$ are broadly characterized as energy ownership ($EO_i$) and overall concern ($OC_i$). Both factors are defined on a scale of 0-1, such that each household agent can be assigned values from the following ranges: very low [0 – 0.2], low (0.2, 0.4], neutral (0.4, 0.6], high (0.6, 0.8], and very high (0.8, 1]. Higher values of $EO_i$ represent a greater affinity for the rooftop PV option than the community solar project. Similarly, higher values of $OC_i$ correspond to a greater probability that a household agent will choose to adopt a renewable energy option.
Community-level energy goals help in creating social cohesion among community members, an important aspect for their increased participation. Therefore, successful community-level zero energy projects demonstrate social benefits to the community members alongside the economic benefits [22]. Community-level goals also instill a sense of being responsible community citizens. Therefore, individual household social motivations to support renewable energy will likely be bolstered by a community level approach. To capture this, the overall concern ($OC_i$) of a household agent is influenced by interactions with other adopter households in the neighborhood over time.

Results from a national survey indicate that, on average, a person knows approximately 13 people in his/her neighborhood [54]. To model the interactions between household agents in each simulation run, the 270 household agents are randomly grouped into 18 equally-sized agent-sets (i.e., 15 agents in each). It is assumed that in each time-step a household agent will interact with each agent in its agent-set with a probability of 0.3, which is based on empirical survey data on the frequency of interactions of households within a neighborhood [55]. If a renewable energy adopter agent interacts with a non-adopter agent, it is assumed that the overall concern ($OC_i$) of the non-adopter will increase by 1% of its maximum value. However, if two non-adopters interact, it is assumed that there is no effect.

4.4.3.3 Sub-model 3 - Household Agent Decision

In each monthly time-step, it is assumed that a household agent will either adopt one of the available renewable energy options or continue to buy electricity from the utility company. Both attitudinal and financial factors influence the agent’s adoption decision. An agent’s current overall concern ($OC_i$) serves as a proxy for its attitude toward adoption. For the agent to adopt rooftop PV or participate in the community solar program, $OC_i$ of the household agent should be
at least in the high range (0.6, 1]. By contrast, since green pricing does not provide financial returns, it is assumed that the $OC_i$ of the household agent must be in the very high range (0.8, 1] for it to adopt green pricing.

If an agent’s $OC_i$ value supports the adoption of a renewable energy option, then its final decision to adopt a particular option is driven by its associated financial benefits (evaluated in Sub-model 1) and the agent’s attitude towards energy ownership ($EO_i$). If the NPV is greater than zero for both rooftop PV (buy and/or loan option) and community solar options, the agent’s decision is driven by its current $EO_i$ value. If $EO_i$ is less than neutral (0.4, 0.6], the agent will adopt the model that has the highest NPV. If $EO_i$ is in neutral range (0.4, 0.6], then the agent will equally prefer rooftop PV and community solar. If $EO_i$ is high (0.6, 0.8] or very high (0.8, 1], the agent will prefer rooftop PV over community solar. In any of the above cases, if the NPV is greater than zero for both buying and loan option of rooftop PV, then the household agent will adopt the option which has greater NPV. Finally, a household agent will participate in a green pricing program only if it does not have a positive NPV for any other option and it can afford to pay the premium prices as determined by $AF_j$.

Once a household agent has adopted a renewable energy option, it cannot simultaneously adopt another renewable energy option in a later time-step. However, it can reevaluate its decision and potentially switch to another option, but this is only allowed from green pricing to either rooftop PV or community solar. Upon reevaluating its decision, the agent will calculate the NPV of both the rooftop PV buy and loan options (based on its ability to adopt and afford rooftop PV), as well as the NPV of participating in the community solar project. The agent’s final decision to switch will be governed as per the decision-making rules defined in Sub-model 3. The flowchart in Figure 4.2 summarizes the decision-making process of a household agent.
when NPV is greater than zero and the agent’s overall concern \((OC_i)\) supports adoption for multiple renewable energy options, and the agent can afford to pay high up-front cost of purchasing solar panels or pay green pricing premiums.

Figure 4.2 Household agent decision-making process in each time-step (Y: yes, N: no).
4.4.4 ABM Initialization

At the beginning of each simulation run, each household agent is initialized to be a non-adopter that buys electricity from the utility company. Because individuals with higher levels of education are more likely to adopt renewable energy [49], the value of \( OC_i \) for each agent is initialized as the normalized product of its education level \( E_i \) and a random number \( q \) between 0 and 1, such that \( OC_i = \frac{q(E_i)}{10} \). The initial value of energy ownership \( EO_i \) for each household agent is assigned randomly (Uniform (0,1)) and remains constant throughout the simulation run. The initial unit electricity cost \( C_t \) for residential customers is set to 9 ¢/kWh, which is the current weighted average of winter and summer residential electricity rates for MidAmerican Energy, the utility that serves the Chesterfield neighborhood [56]. This cost is assumed to increase by 1.67% annually, which is the average annual increase in residential electricity prices in Iowa from 1990 to 2016 [57]. Installation cost per kW of a PV system \( W_t \) is initialized to $3430/kW, which is the current average residential installation cost of a PV system in Iowa [58]. The installation cost is assumed to decrease by 6% annually, based on the average decline in residential sector installation prices in the U.S. between 2000 and 2016 [59]. The federal and Iowa state income tax credit \( ITC_t \) associated with buying rooftop PV was initialized to be 45% and was reduced to 39% after 12 monthly time-steps, to 33% after 24 time-steps, and to 0% after 36 time-steps. This reduction in income tax credit \( ITC_t \) reflects the current federal and State of Iowa rebate policies for rooftop PV consumers [60].

4.5 Experiments

4.5.1 Experiments

The ABM was used to test consumer adoption behaviors over time in the presence of different renewable energy options. Table 4.2 summarizes the four experimental scenarios that
were tested. In Scenario 1, a household agent has the options to adopt rooftop PV by paying out of pocket, adopt rooftop PV through a loan, or participate in a utility-sponsored green pricing program. This scenario represents the current conditions of the neighborhood under study. In Scenarios 2 through 4, household agents have the option to participate in a community solar program at different premium prices ($C_p, \text{¢/kWh}$), in addition to rooftop PV and green pricing.

Table 4.2 Experimental Scenarios

<table>
<thead>
<tr>
<th>Experimental scenario</th>
<th>Rooftop PV (buy and loan)</th>
<th>Green pricing program</th>
<th>Community solar</th>
<th>Community solar premium ($C_p, \text{¢/kWh}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>NA</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>2</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>3</td>
</tr>
<tr>
<td>Scenario 4</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>4</td>
</tr>
</tbody>
</table>

Two versions of the model were created. In the ‘baseline version’ of the model, the household agents interact only with other households in their agent-sets. In the second version, subsequently referred to as the ‘enhanced interaction version’, the household agents can interact both within and outside of their agent-sets, with an assigned probability. These versions were created to test the effect of increased interaction beyond an agent’s immediate circle of regular interaction on consumers’ adoption decisions.

4.5.2 Output Metrics of Interest

While moving toward the overall objective of becoming a ZEC, the agent neighborhood’s intermediate milestone is to generate sufficient energy from renewable sources to meet all households’ demand for electricity within the next 10 years. Three key output metrics measure the neighborhood’s progress toward this intermediate milestone:

- **Number of renewable energy adopters**—This metric captures the cumulative number of renewable energy adopters after each monthly time-step.
Number of renewable energy adopters by PV-restricted households - The total number of renter agents and home-owner agents that cannot adopt rooftop PV due to structural constraints but choose to participate in green pricing or community solar is captured separately to evaluate the ability of these programs to increase the participation of these agents.

Percentage of household renewable energy – At the end of each simulated year, the percentage of total neighborhood electrical load met through renewable energy sources is captured. This metric reflects the degree to which different renewable energy options support the community in achieving its intermediate milestone.

4.6 Results and Discussion

In all four experimental scenarios under each model version, the output metric values were captured at the end of every 12 time-steps (i.e., each simulated year). The output metrics reported throughout this section of the paper are average values over 50 replications for each experimental scenario. Error bars in the figures below represent 95% confidence intervals. Statistical analysis was carried out to test the effects of renewable energy option availability and personal interactions on the output metrics of interest. Unpaired two-sample two-tailed t-test with Welch’s correction of unequal variances was used to calculate p-values. p-value of less than 0.05 was considered statistically significant. JMP Pro (version 14.2.0) was used to conduct the statistical analysis.

4.6.1 Baseline Model

Figure 4.3 shows the total number of adopters for each experimental scenario at the end of 120-time steps. The total number of adopters increased when community solar was introduced as an option (Scenarios 2, 3, and 4) versus when only rooftop PV and green pricing program options were available (Scenario 1). Further, the total number of adopters was greatest in Scenario 2 ($M = 68.7, SD = 20.6$) with significant difference from Scenario 1 ($M = 16.7, SD =$
13.6; \( t(85.0) = 14.84, p < .001 \), Scenario 3 \( (M = 57.5, SD = 25.0; t(94.6) = 2.43, p = .02) \), and Scenario 4 \( (M = 36.4, SD = 16.0; t(92.2) = 8.75, p < .001) \). Figure 4.4 shows the percentage of total adoption captured by each renewable energy option in these scenarios. The increase in adoption in Scenario 2 was primarily driven by households’ participation in the community solar program \( (M = 46.6, SD = 15.6) \).

There was no significant difference in the total number of rooftop PV adopters between Scenario 1 \( (M = 7.1, SD = 5.5) \) and Scenario 2 \( (M = 7.8, SD = 3.5) \), \( t(82.4) = -0.76, p = .45 \). However, Scenario 2 saw increased participation by potential rooftop PV adopter agents, from either adoption of community solar \( (M = 10.6, SD = 4.2) \) or the green pricing program \( (M = 5.1, SD = 2.2) \). This is likely a consequence of the overall increase in number of adopters in the presence of community solar option in Scenario 2 and an increase in the number of agents achieving a higher overall concern \( (OC_i) \) value. The average \( OC_i \) value of the neighborhood increased significantly from 0.28 \( (SD = 0.04) \) in Scenario 1 to 0.34 \( (SD = 0.04) \) in Scenario 2, \( t(97.9) = 8.41, p < .001 \).
Figure 4.3 Total number of renewable energy adopters at the end of 120 time-steps in Scenarios 1–4 of the baseline model (error bars represent 95% confidence interval).

Figures 4.5 and 4.6 show the renewable energy adoption among PV-restricted agents that are renters or house-owners but cannot adopt rooftop PV due to structural constraints. These agents, however, can participate in green pricing and community solar programs. Figure 4.5 indicates that there was a significant increase in renewable energy adoption among these agents as they were introduced to the community solar option (Scenarios 2, 3 and 4). Figure 4.6 shows the percentage of these adopters that chose community solar and green pricing for each of the four scenarios. Scenario 2 yielded the greatest participation (\(M = 45.2, SD = 14.7\)), with significant difference from Scenario 1 (\(M = 8.5, SD = 7.5; t(73.0) = 15.73, p < .001\)), Scenario 3 (\(M = 37.5, SD = 16.6; t(96.6) = 2.46, p = .02\)) and Scenario 4 (\(M = 22.7, SD = 10.2; t(87.4) = 8.89, p < .001\)).
The percentage of the neighborhood’s total electricity consumption met using renewable energy sources at the end of each simulated year was evaluated under the four scenarios. Figure 4.7(a) shows that Scenario 2, which had the greatest number of total adopters, yielded the highest percentage, with 25.3% ($SD = 7.8$) of total electricity consumption provided by renewable sources. This is significantly greater than Scenario 1’s result of 6.1% ($SD = 4.9$; $t(83.0) = 14.74$, $p < .001$), Scenario 3 of 20.9% ($SD = 9.1$; $t(95.8) = 2.59$, $p = .01$) and Scenario 4 of 13.2% ($SD = 5.8$; $t(90.3) = 8.85$, $p < .001$). Scenario 2, which had the lowest community solar premium ($C_p$), yielded faster progress toward meeting the neighborhood’s renewable energy milestone in the early years, as compared to Scenarios 3 and 4, which had higher premiums. These results demonstrate that premium pricing for community solar is an important design consideration with respect to the timeline for achieving the ZEC objective.

Introducing a community solar program generated positive results in terms of percentage of total adoption, as well as the proportion of neighborhood electricity consumption met through
renewable sources. However, the results of this analysis indicate that the intermediate ZEC milestone (i.e., 100% of consumption met by renewables) is not guaranteed to be successfully achieved by just introducing community scale renewable energy options, even at attractive premiums. In the baseline model, which incorporates social interactions that are limited to an agent’s agent-set, less than 30% of the neighborhood energy requirement is met with renewable energy sources over ten years. One of the main reasons for slow diffusion of renewable energy among consumers is a lack of awareness and knowledge [61]. Simulation results also show that barrier for adoption is insufficient overall concern \((OC_i)\) among household agents in their attitude toward achieving a ZEC.

4.6.2 Enhanced Interaction Model

Personal interactions are a key driver for consumer participation in renewable energy. Household level interactions that are generated through community level events are known to highly influence consumer participation in renewable energy, even more so than more traditional mass-media outreach via print, radio, or direct mail [62]. Therefore, the enhanced interaction model was developed to determine the effect of increased interactions from community level events, which was represented by allowing interactions to occur between households of different agent-sets.

The probability of an interaction between agents within agent-sets in each monthly time-step is assumed to be 0.30 (as in the baseline model), and the probability of an interaction between agents belonging to different agent-sets is assumed to be 0.01. The effect of interactions between two agents of different agent-sets is assumed to be the same as interactions within an agent-set. Community events occur at experimentally varied intervals: once every six months (semi-annually), once every three months (quarterly), and monthly. Figure 4.7(b) shows that semi-annual household community events led the neighborhood to achieve 31.8% \((SD = 11.5)\) of its
intermediate goal in Scenario 2, which is significantly greater than the percentage yielded by Scenario 2 of the baseline model ($t(86.2) = 3.30, p = .001$). Figure 4.7(c) shows the results for quarterly community events. The neighborhood was able to meet 47.1% ($SD = 21.1$) of its total electricity consumption through renewable sources in Scenario 2 by the end of the tenth year. Figure 4.7(d) shows that monthly community events in Scenario 2 led to the fulfillment of 94.2% ($SD = 14.3$) of the neighborhood’s total electricity consumption using renewable energy sources, which was significantly greater than the best results achieved via semi-annual ($t(93.6) = 24.03, p < .001$) and quarterly interactions ($t(86.2) = 13.05, p < .001$).

Figure 4.8 compares the percentage of electricity consumption met using renewable energy sources at the end of ten years for each of the four experimental scenarios for each level of community event frequency of the enhanced interaction model and the baseline model. Scenario 2 with community-level interactions happening at a monthly frequency shows the potential for the community to meet the desired renewable energy milestone.

The increased levels of adoption when agents were allowed to interact outside of their agent-sets (enhanced interaction version of the model) is a consequence of the increased number of household agents that were able to overcome the threshold of overall concern ($OC_i$). To analyze the effect of overall concern on agent adoption decisions, the average $OC_i$ of the neighborhood was plotted as a function of time for Scenario 2 (see Figure 4.7).

Figure 4.9 indicates that with monthly community events, the overall concern ($OC_i$) among households with respect to achieving a ZEC increases at a much faster pace compared to quarterly or semi-annual events. However, toward the end of the ten-year period, the concern level appears to approach a threshold. Further, the level of concern increases in the middle years in the model. This indicates that there needs to be a persistent effort towards influencing
communities and members before their concern level increases and they start adopting renewable energy sources at a bigger scale.

Figure 4.7 Percentage of total neighborhood electricity consumption met using renewable energy sources at the end of each simulated year in Scenarios 1-4 in (a) baseline model (b) enhanced interaction model with semi-annual frequency of community events (c) enhanced interaction model with quarterly frequency of community events (d) enhanced interaction model with monthly frequency of community events (error bars in the figures represent 95% confidence interval).
Figure 4.8 Percentage of total neighborhood electrical consumption met using renewable energy sources for all four scenarios for baseline model and for each level of agent-set interaction frequency of the enhanced interaction (EI) model (error bars represent 95% confidence interval).

Figure 4.9 Average overall concern ($OC_i$) of the neighborhood in each time-step in Scenario 2 for baseline model and for each level of agent-set interaction frequency of the enhanced interaction (EI) model.
4.7 Conclusion

Achieving the objective of net zero energy will require moving beyond the building level to the community level. In particular, a community level approach will be necessary to achieve zero energy goals in a timely and impactful manner. Community solar programs are an attractive option for consumers, enabling the participation of a broader community, including renters and lower-income households, to participate in the ZEC objective. For a ZEC to be successful, households with widely heterogeneous preferences and abilities must be encouraged to participate. To accomplish this, the power of social interactions among community members should be leveraged to motivate renewable energy adoption. Furthermore, households should be encouraged to think of themselves as a community member and citizen, rather than autonomous individuals.

Achieving a community level zero energy objective will also require the involvement and support of different multiple stakeholders, such as utilities, solar installers, and policymakers. For example, many state policies in the U.S. do not allow net metering through community solar projects. However, as this paper demonstrated, community solar can be integral to ZEC success. Thus, policymakers should make community solar an easy option for solar project developers and utilities to provide to consumers. Further, coordination between policymakers and utilities will likely be required for seamlessly achieving objectives of zero energy communities. The results of the experiments in this paper showed that significant renewable energy targets could be met when a community solar program was provided to consumers at premiums of both 2 and 3 $/kWh. However, renewable energy targets were achieved more quickly in the case of 2 $/kWh. Therefore, policies and business strategies should weigh the tradeoffs involved when balancing timeliness of achieving objectives and achieving business targets.
The conceptual model described in this paper serves as a starting point for the development of an empirically validated model. Empirical survey data on consumer motivations to adopt different renewable energy options, and household level demographic data can be mapped to calibrate the financial, attitudinal, and demographic state variables of consumer agents in the ABM. Outputs from the empirically based model, such as the number of consumer agents adopting different renewable energy options, could be compared with the actual consumer adoption data for a neighborhood. Agent-level validation includes a comparison of the demographic characteristics of consumer agents from the ABM and the demographics of actual adopters.

References


CHAPTER 5. AN AGENT BASED APPROACH TO DESIGNING RESIDENTIAL RENEWABLE ENERGY SYSTEMS

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5.1 Abstract

Residential consumers in the U.S. have demonstrated a growing interest in rooftop photovoltaic (PV) systems, resulting in increased adoption over the last decade. However, this has diminished utility revenues, and policymakers have expressed concerns about inequitable consumer access to publically-funded rooftop PV adoption incentives. In response to these concerns, policymakers and utility companies are changing their policies to discourage rooftop PV adoption. Alternative renewable energy models, such as utility-provided community solar programs, offer a potential solution. However, when designing such programs, it is important to consider the potential impacts on different system stakeholders, including utilities, policymakers, and solar installers. This paper describes an agent-based model that predicts the performance of different residential distributed solar models with respect to these stakeholders’ objectives. In this model, consumer agents residing in an urban utility territory decide in each time-step whether they will adopt a particular renewable energy model, and the impacts of their adoption decisions on stakeholder performance metrics are captured over time. Simulation results suggest that if community solar program premium prices are set appropriately, all stakeholders can benefit: the utility can recover part of its revenue losses even as rooftop PV adoption increases, solar installers’ businesses can thrive, and increased renewable energy adoption can be achieved.
equitably. The proposed modeling methodology can help to inform design decisions of distributed solar energy models that avoid benefiting some stakeholders at the unnecessary expense of others.

5.2 Introduction

Over the last decade, there has been tremendous growth in distributed generation in the U.S. residential energy sector. Recent advances in renewable energy technology, coupled with increased consumer awareness and interest, are yielding a shift in the electricity market from a centralized generation system to a distributed and consumer-driven model [1]. Specifically, solar photovoltaic (PV) technology has become increasingly popular among U.S. residential energy consumers as PV panels have become more reliable and less expensive [2]. PV systems on owner-occupied houses (known as rooftop PV) allow consumers to generate their own electricity, thereby enabling them to lower their energy bills, gain ownership and control of the energy infrastructure, and reduce their environmental impact.

However, as more consumers are generating their own energy using rooftop PV systems, utility companies’ revenues have declined [3]. Furthermore, not all residential buildings are suitable for rooftop PV installation, many U.S. households are renters, and high installation cost limits access to higher-income households [4]–[6]. This has caused concern among policymakers about inequitable access to rooftop PV and its associated benefits, which include publically-funded incentives [7]. In response to these concerns, many policymakers and utility companies are changing their policies to discourage rooftop PV adoption [8]. With fewer government rebates available and waning utility support for grid interconnection, fewer consumers are adopting rooftop PV. As a result, despite several years of positive growth, the installed capacity of residential solar in the U.S. fell by 14 percent in 2017 [9].
Alternative renewable energy models, such as utility-provided community solar programs, offer a potential solution. Under a community solar program, the generation of solar energy does not occur at the consumer’s home. Instead, the consumer subscribes to a portion of a shared PV facility located elsewhere in the community. Such programs allow renters and homeowners who cannot install PV systems due to structural or shading issues to access renewable energy, while allowing utilities to retain their customers and revenues. However, community solar could fail to address policymaker concerns about equitable access if the program is priced inappropriately, and it could also have a negative impact on solar installers’ revenues if consumers substitute community solar for rooftop PV.

This paper proposes an agent-based approach to modeling consumer adoption behavior in the presence of competing renewable energy models (i.e., rooftop PV and community solar), such that the impacts on multiple stakeholder objectives can be understood. Agent-based modeling is a powerful computational tool that can be used to examine sociotechnical system performance over time, wherein system behavior is subject to complex and dynamic individual human behaviors and social interactions. The conceptual agent-based model (ABM) described in this paper is a novel approach to designing urban residential renewable energy systems that equitably satisfy consumer demand while maintaining solar installers and utility revenues. Fulfilling the conflicting and competing objectives of these key stakeholders will support the overarching goal of greater renewable energy deployment in the energy sector.

The paper is structured as follows: Section 2 provides a review of the relevant literature, Section 3 describes the ABM, Section 4 describes the experiments performed using the model, Section 5 summarizes the experimental results, Section 6 discusses the results and their practical implications, and Section 7 concludes the paper.
5.3 Background and Literature Review

Approximately 60% of the current residential rooftop PV installations in the U.S. are grid-connected systems [10], which allow consumers to net meter their energy bills. In a net metering program, consumers’ meters are allowed to run backwards if the electricity generated by their PV systems is more than they consume. The net metered solar power from rooftop PV systems helps utility companies to meet their required renewable portfolio standard (RPS), under which they are mandated to provide a percentage of their electricity supply from renewable energy technologies [11]. Overall, however, utility companies view their customers’ rooftop PV installations as a source of lost revenue [12]. Rooftop PV adoption also increases utilities’ operational costs. Because the electricity grids were not originally designed for the dual-flow of electricity, increased rooftop PV adoption has required utilities to make significant upgrades to the transmission and distribution infrastructure to ensure safe PV systems operation and maintain grid reliability [13]. Additionally, utilities retain responsibility for providing solar-powered consumers with energy if their systems fail or if their energy needs increase.

In response, utilities have increased electricity tariffs. These increased tariffs create an unfair financial burden on consumers who do not have the ability to install rooftop PV, and they can result in a feedback loop in which PV adoption accelerates, yielding further tariff increases [14]. Utilities are also discouraging rooftop PV adoption by changing their net metering policies, which has had a negative impact on utility-customer relationships [8]. For example, the Indiana Regulatory Public Commission is considering replacing its current net metering policy with a “buy-all, sell-all” option, in which consumers are charged for their consumption as per the utility’s current electricity rate structure and are paid for the electricity generated by their PV systems at the much lower wholesale electricity rates [15].
Increased rooftop PV adoption has also led to equity concerns among policymakers. Publically-funded incentives have been created that encourage residential rooftop PV adoption, including federal and state income tax credits and property and sales tax exemptions. However, the high up-front cost of purchasing and installing rooftop PV has limited access to higher income households: the median income of U.S. rooftop PV adopters is $32,000 higher than the average U.S. household income [4]. Although leasing and solar power purchase agreement (PPA) options attempt to address this issue by eliminating the need for high up-front investment, most U.S. house-owners are still unable to install rooftop PV systems because of structural, shading, or roof ownership issues. In the U.S., only 57% of all residential buildings are suitable for rooftop PV installation [6], and 36% of the U.S. households are renters [5] who do not own the roof space needed to install PV panels.

Community solar programs have the potential to address both utility and policymaker concerns. In a utility-sponsored community solar model, the utility owns and/or operates a project that is open to voluntary ratepayers [16]. The geographic proximity of community solar subscribers to the solar installation varies by program; for example, the utility can require subscribers to be in the same utility territory, county, or neighborhood as the solar installation [17]. Offering customers the opportunity to invest in a community solar program can help utility companies to stabilize their revenues, increase the renewable sources in their energy portfolios, increase customer satisfaction and engagement, address customer demand for renewable energy, make a transition toward clean energy, and enhance overall grid power quality via a small number of large-sized distributed generating units, as opposed to numerous small rooftop PV systems [18], [19]. In addition, as consumers become investors in the creation of new energy
infrastructure and utilities maintain control over it, utility-customer relationships can improve [20].

Community solar also expands the availability of distributed solar power to a broader range of consumers. For example, lower-income energy consumers who may not be able to afford rooftop PV can invest in a shared PV system according to their financial ability [21]. Renters and homeowners who are unable to install rooftop PV because they do not own the roof, or because the roof is ill-suited for panels, can also access solar electricity through community solar programs, with the flexibility of selling their subscription when they move or having their solar credits follow them [21]. Community solar is also a viable alternative for consumers who are interested in supporting renewable energy but do not wish to install rooftop PV on their houses because of the perceived complexity of installation procedures and required paperwork, the possibility of moving residences in the future, risk of roof damage, and high investment uncertainty associated with installation [22], [23].

However, the success of a community solar program depends on the degree to which its design meets consumer needs and requirements. It is important for the provider (e.g., the utility company) to be able to predict its customers’ response to program design parameters, including capacity and duration, household participation limits, payment terms and conditions, site selection, and subscription transfers [20]. Predicting consumer participation requires consideration of consumers’ heterogeneous preferences and objectives, which include reducing energy costs, protecting the environment, gaining independence from utility companies, and investing in their homes [24]. Consumer demographics are also known to influence renewable energy adoption decisions. For example, many consumers install rooftop PV just before retirement, coinciding with decisions about whether to stay in their homes [25]. Adoption
decisions are also often socially motivated, influenced through peer interactions, online media, and seeing solar panels on neighbors’ rooftops [26], [27]. Social networks play a crucial role in providing consumers with relevant information to inform their decisions, including the available options, which supplier to choose, and financial incentives [28]. Therefore, consumers’ preferences may also evolve over time as they learn more about different renewable energy models from their friends, family and neighbors.

Agent-based modeling is a method that is well-suited to studying the system-wide effects of individual energy consumers’ heterogeneous behaviors, boundedly rational decision processes, and social interactions on energy technology adoption over space and time [29]. ABMs consist of individual software entities, generally referred to as “agents”, that are situated in a virtual environment [30]. An agent may represent an individual entity (i.e., single consumer) or an aggregate of individuals (e.g., household). Agents may be assigned heterogeneous attributes, preferences, objectives, and behavioral rules in the form of mathematical and/or logical statements, which inform their decisions about the most appropriate action to take in a given situation. Agents can also be programmed to interact with each other and their environment, which can in turn influence future decisions and behaviors through a process of dynamic adaptation. The interactions of decisions, actions, and adaptations among many agents within the same system are non-linear and can result in an overall system-wide behavior that emerges over time [31]. Such emergent system behavior can be difficult to predict without the use of ABM.

ABM has been used to study the effect of consumer behavior on sustainable energy technology adoption [32]. For example, an ABM was developed to understanding the discrepancy between consumers’ opinions and their actual participation in dynamic electricity tariffs programs [33]. Rai and Robinson [34] developed an ABM to predict the effects of
different rebate programs on residential rooftop PV adoption rates in Austin, Texas, wherein household agent adoption decisions depend on their demographic, attitudinal, and economic characteristics. ABM was also used to study the impact of factors such as geographic location and lifestyle on households’ green tariff adoption decisions [35].

While existing models account for heterogeneous consumer behavior, they do not examine the effects of consumer adoption on the conflicting and competing objectives of other key energy system stakeholders, nor do they consider multiple competing renewable energy models, such as rooftop PV and community solar [36], [37].

Also, these existing models are specific to a particular geographic location, such that it is difficult to generalize the findings (Hansen et al. 2019). Thus there is a need to develop conceptual models to demonstrate the capacity of ABM for energy transition studies [38]. A conceptual model is a structured representation of a system that has the purpose of understanding the system’s behavior through a consecutive description of all relevant entities [39]. A conceptual ABM can serve as the basis for the future development of more sophisticated and geographic-centric models via interdisciplinary collaboration (e.g., between social scientists, engineers, and policymakers) for the purpose of studying the implications of introducing new policy, planning, and/or technology. This paper describes a conceptual agent-based model for designing a residential renewable energy system, allowing for consumer adoption of multiple models and taking into account the objectives of utilities, solar installers, and policymakers to enable conflict-free energy system decentralization. The City of Des Moines, Iowa, is used as an example to develop the model.

5.4 Agent-based Model

The ABM was developed using NetLogo 6.0.4 and is described using the Overview, Design concepts and Details (ODD) protocol [40].
5.4.1 Purpose – The purpose of this model is to predict consumer adoption of different renewable energy models and to determine the resulting impacts on energy system performance, in terms of key stakeholders’ metrics. Examples of stakeholder metrics include present value of utility and solar installer revenues, total green power added to the grid, and total consumer participation in renewable energy models in each simulated time-step. A complete list of stakeholder metrics captured from the ABM is provided in Section 4.2. Model outputs can be used to inform energy system design decisions in support of individual stakeholder objectives and the overarching objective of increasing renewable energy deployment.

5.4.2 Entities, state variables, and scales – This conceptual model contains 300 residential consumer agents that reside in the territory of a single hypothetical utility company. The description of state variables associated with the consumer agents, their possible values and data sources are summarized in Table A.1 of Appendix A. Each agent has a unique identification number (\(i\)), as well as a community identification number (\(C_i\)) that corresponds to the community in which the agent resides. Communities 1 through 7 consist of 70, 30, 20, 70, 40, 30, and 40 agents, respectively. These values were chosen as a proof of concept in using the model to design a renewable energy system at an urban scale.

Each consumer agent is characterized by four demographic factors: age (\(A_i\)), income (\(I_i\)), education (\(E_i\)), and race (\(R_i\)), with values assigned using probabilities derived from publicly available demographic data for the City of Des Moines, Iowa [41]. The values of \(I_i\), \(E_i\), and \(R_i\) remain constant throughout each simulation run, while \(A_i\) increases as simulated time progresses. Each agent is also categorized as being either a house-owner, a renter, or an apartment-owner, and this assignment remains constant throughout each simulation run. Of the 300 consumer agents, 174 (58%) are house-owners and 126 (42%) are either renters or apartment-owners,
based on the City of Des Moines demographic data. It is assumed that only house-owner agents buy/lease rooftop PV panels, while house-owner, renter, and apartment-owner agents can all adopt community solar. However, only 57% of the house-owner agents’ homes are modeled to be structurally capable of accommodating rooftop PV, based on data from [6].

The distribution of home sizes (in terms of number of bedrooms) for the City of Des Moines was used to assign agent home size values [42]. The average monthly residential electricity consumption in Iowa of 831 kWh [43], was then used to assign each agent a monthly electricity consumption value ($Q_i$), which is proportional to its home size. The model does not take into account the adoption of energy efficiency measures; therefore, each consumer agent’s electricity consumption is assumed to be constant throughout each simulation run.

5.4.3 Model Overview – In each monthly time-step, each consumer agent decides between two courses of action: buy electricity from the utility or adopt one of four different renewable energy models (buy rooftop PV through up-front cash payment, buy rooftop PV through solar loan option, lease rooftop PV from a solar installer, or enroll in a utility-sponsored community solar program). This decision is driven by the agent’s financial position, its attitude toward solar electricity, its demographic attributes, influence from other agents in its social network and geographic vicinity, and information received from the utility company and solar installers.

5.4.4 Basic Principles – The various financial, attitudinal, and demographic factors that drive the consumer agents’ decisions to adopt a renewable energy model were shortlisted through a review of existing empirical studies that have identified consumers’ motivations for adopting renewable energy [23], [25], [44], [45]. These are described in detail in the sub-models’ descriptions below.
5.4.5 Emergence – Consumer agents’ decisions to adopt a particular renewable energy model influence other agents’ decision via their interactions, yielding emergent system performance [26], [34], in terms of stakeholder metrics (e.g., utility/solar installers revenue and equitable consumer access to renewable energy).

5.4.6 Adaptation – As the attributes of a consumer agent and its environment change over time, its position on adopting a renewable energy model adapts accordingly. For example, changes in electricity prices, PV installation cost, and available tax credits all influence an agent’s adoption likelihood. Further, as agents interact and learn from one another about renewable energy options (e.g., community solar), environmental benefits of solar, and PV installation procedures, their adoption decisions may change. In addition, as agents near retirement, they become increasingly likely to adopt rooftop PV.

Utility companies and policymakers are not represented as agents in this model. Therefore, it is assumed that their respective pricing/tax credit policy parameters do not adapt over the course of a simulation run.

5.4.7 Objectives – Each consumer agent’s fundamental objectives are to lower its energy bills and to contribute to a social cause by adopting renewable energy. The achievement of these objectives is informed by the agent’s financial position and attitudinal and demographic factors.

5.4.8 Interactions – Agents interact via visual interactions and information exchange. Research on consumer rooftop PV adoption shows that regions with more rooftop PVs have a greater likelihood of adoption [26]. To capture this, visual interactions (i.e., seeing PV panels on a neighbor’s roof) between agents can occur as follows: if a house-owner agent adopts rooftop PV, in the next time-step every other agent within its community becomes aware, and their
likelihood of participating in a renewable energy model (rooftop PV or community solar program) in future time-steps increases.

The second type of interaction involves the exchange of information (e.g., about the availability of a community solar program) between agents within their social networks, which can occur between agents of the same as well as different communities. To create the agents’ social network, a small-world network was generated using the Watts-Strogatz algorithm [46]. A small-world network structure is considered appropriate for representing consumer social behavior with respect to renewable energy adoption [34], [47]. A small-world network is characterized by the number of nodes in the network \( n \), the number of neighbors a node has \( K \), and rewiring probability \( p \), with which the right end of an arc connected to a node is rewired uniformly randomly to any of the other nodes [48]. In this model, the number of nodes is equal to the number of consumer agents \( n = 300 \), each node is assumed to be connected to its immediate neighbors \( k = 2 \), and the rewiring probability \( p \) is varied experimentally. Each of the links connecting two consumer agents \( j \) and \( k \) is assigned a similarity index \( \text{Sim}_{jk} \) using (1).

Because consumer similarity (i.e., homophily) is a predictor of the strength of interactions within a social network [49], it is assumed that higher \( \text{Sim}_{jk} \) values will yield more influential interactions. It is assumed that \( \text{Sim}_{jk} \) is indirectly proportional to the differences in the agents’ age \( A_i \), income \( I_i \), education \( E_i \), and race \( R_i \). The maximum possible value of similarity contributed by each demographic factor is 0.25, which occurs when two agents are at the same level for that factor. The minimum possible value of similarity contributed by each demographic factor is 0, which occurs when the two agents are at opposite ends of the factor’s range (e.g., age levels 0 and 6). One exception is the race factor: \( R_{jk} \) is 0 if the race of agents \( j \) and \( k \) are the same; otherwise, it is assigned a value of 1.
\[ Sim_{jk} = \left( 0.25 - \frac{|A_j - A_k|}{24} \right) + \left( 0.25 - \frac{|I_j - I_k|}{60} \right) + \left( 0.25 - \frac{|E_j - E_k|}{20} \right) + \left( 0.25 - \frac{R_{jk}}{4} \right) \]  \hspace{1cm} (1)

5.4.9 Observations – Consumer agents’ decisions to adopt rooftop PV and community solar are captured in each monthly time-step. The present value of utility company and solar installers revenues are also recorded, as well as system-wide green power addition (kW).

5.4.10 Initialization – At the beginning of the simulation run, each consumer agent is initialized to be a non-adopter that buys electricity from the utility company. The electricity cost is set to the current average electricity rate for Iowa, i.e. 13.23 ¢/kWh [50]. This cost is assumed to increase by 1.67% annually [51]. The income tax credit (ITC) associated with buying rooftop PV is initialized to 45% and reduces to 39% after 12 time-steps, to 33% after 24 time-steps, and to 0% after 36 time-steps, which reflects current federal and State of Iowa rebate policies [52].

5.4.11 Sub-models – The ABM contains three sub-models and all three are executed in each monthly time-step for each consumer agent.

5.4.11.1 Sub-model 1 – Consumer Agent Attitude Assessment – Each consumer agent is assigned an initial awareness index (AW) on a 0-1 scale, which represents the agent’s overall awareness of renewable energy and its environmental benefits. Because individuals with more education are more likely to adopt renewable energy [44], the initial value of AW is assigned as the normalized product of an agent’s education level (E) and a random number (p) between 0 and 1, such that \[ AW_i = \frac{p(E_i + 1)}{6} \]. Larger values of AW correspond to a greater probability that an agent will adopt a renewable energy model. If a house-owner agent adopts rooftop PV, the value of AW for each non-adopter in its community increases by one percent of its maximum value (a consequence of visual interactions). The value of AW for a non-adopter also increases if it interacts with an adopter in its social network. The amount of increase is determined by (2), where \[ AW_{j(before)} \] and \[ AW_{j(after)} \] are non-adopter agent j’s awareness index values before and after
the interaction, $AW_k$ is the adopter agent $k$’s awareness index, and $Sim_{jk}$ is the similarity index value of the link between agents $j$ and $k$.

$$AW_{j(after)} = AW_{j(before)} + \frac{AW_k Sim_{jk}}{100}$$  \hspace{1cm} (2)

The awareness index of an agent also increases if it attends a solar installer’s renewable energy fair (focused on rooftop PV) and/or a utility-sponsored renewable energy seminar (focused on community solar) [25]. Only house-owner agents that can adopt rooftop PV can attend a renewable energy fair, but any agent can attend a seminar. In each time-step the likelihood that an agent will attend a fair/seminar depends on $AW_i$, where a higher value corresponds to a greater probability of attending. If an agent attends a fair/seminar, $AW_i$ increases by 0.1. An agent that attends a seminar becomes aware of community solar, such that its value of $CS_i$, updates from 0 (unaware) to 1 (aware). If agent $j$ is aware of community solar and interacts with agent $k$ via its social network, agent $k$ also becomes aware of community solar, irrespective of attending a seminar. An agent can attend a fair/seminar only once during a simulation run.

Consumers tend to consider rooftop PV purchase to be a complex issue, because of the effort required to learn about installation procedures, incentive policies, net metering policies, house-owners’ association regulations, and the required paperwork [23]. However, when a consumer leases solar panels or adopts community solar, a project developer assumes these responsibilities. Each house-owner agent is initially assigned a random perceived complexity index ($PC_i$) value on a 0-1 scale. Lower values of $PC_i$ correspond to greater probabilities that an agent will buy rooftop PV. If a non-adopter attends renewable energy fair, $PC_i$ decreases by 0.1. This value also decreases if non-adopter $j$ interacts with a rooftop PV buyer $k$ via its social network, based on (3). $PC_{j(before)}$ and $PC_{j(after)}$ are agent $j$’s perceived complexity index values
before and after the interaction, $PC_k$ is the perceived complexity index of agent $k$, and $Simi_{jk}$ is the agents’ similarity index.

$$PC_j(\text{after}) = PC_j(\text{before}) - \frac{Simi_{jk}(1 - PC_k)}{100}$$

(3)

Each house-owner agent is also randomly assigned an ownership index ($O_i$) on a 0-1 scale, where higher values of $O_i$ correspond to stronger agent preference for rooftop PV over community solar. This value remains constant throughout the simulation run. Lastly, each house-owner agent is assigned an age-based index ($AB_i$) on a 0-1 scale, based on its current age level ($A_i$). $AB_i$ is evaluated by normalizing to 1 the product of $A_i$ and a random number $q$, such that $AB_i = \frac{q(A_i+1)}{7}$. Higher values of $AB_i$ correspond to greater probabilities that the agent will buy/lease rooftop PV, because consumers tend to adopt rooftop PV as they approach retirement [25].

5.4.11.2 Sub-model 2 – Consumer Agent Financial Assessment – Agents are classified into four agent types ($T_x$) based on their optimism towards solar electricity [45], where larger values of the index $x$ correspond to greater optimism toward solar power’s financial prospects. $T_x$ represents an agent’s expectation of future electricity cost growth ($PG_i$) and annual rooftop PV maintenance costs ($PM_i$), as a percentage of up-front investment. Table 5.1 provides values for $PG_i$ and $PM_i$ for each agent type, adapted from [45]. An affordability factor ($AF_i$) on a 0-1 scale is also assigned to each house-owner consumer agent by normalizing to 1 the product of its income level ($I_i$) and a random number $r$, such that $AF_i = \frac{r(I_i+1)}{16}$. A higher $AF_i$ corresponds to a greater probability that the agent can afford to pay the high up-front cost of purchasing solar panels.
Table 5.1 Financial parameters assigned to each agent type

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>$T_1$</th>
<th>$T_2$</th>
<th>$T_3$</th>
<th>$T_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$PG_i$</td>
<td>Expectation of future annual growth rate of electricity cost (%)</td>
<td>0.00</td>
<td>2.60</td>
<td>3.30</td>
<td>5.00</td>
</tr>
<tr>
<td>$PM_i$</td>
<td>Expectation of annual rooftop PV maintenance cost as a percentage of up-front system cost (%)</td>
<td>0.50</td>
<td>0.25</td>
<td>0.15</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Each consumer agent evaluates the financial viability of a renewable energy model by calculating its net present value (NPV) in each time-step. An agent will only evaluate NPV of models that are feasible for it to adopt (as summarized in Table 5.2), and it is assumed that a consumer agent will evaluate the NPV of participating in a community solar program only if it is aware of it ($CS_i = 1$). Based on hourly solar PV insolation and temperature data for the City of Des Moines from 1999 to 2010, it is assumed that 109 kWh of energy is generated each month by each kW (DC) of solar panel installed through either rooftop PV or a community solar program [53]. Further, it is assumed that if an agent decides to buy/lease rooftop PV or subscribe to community solar, it will choose a PV module of size $S_i$ that meets 100% of its monthly energy requirements ($Q_i$).

Table 5.2 Logic determining consumer agent evaluation of renewable energy models NPV
(Y: yes, N: no, NA: not applicable)

<table>
<thead>
<tr>
<th>Agent Description</th>
<th>Buy Rooftop PV (up-front cash payment)</th>
<th>Buy Rooftop PV (solar loan)</th>
<th>Lease Rooftop PV</th>
<th>Community Solar</th>
</tr>
</thead>
<tbody>
<tr>
<td>House-owner agents who are structurally capable of accommodating rooftop PV and can afford to pay the up-front-cost to install PV systems</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y ($CS_i = 1$)</td>
</tr>
<tr>
<td>House-owner agents who are structurally capable of accommodating rooftop PV but cannot afford to pay the up-front-cost to install PV systems</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N ($CS_i = 0$)</td>
</tr>
<tr>
<td>House-owner agents who are not structurally capable of accommodating rooftop PV</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>Y ($CS_i = 1$)</td>
</tr>
<tr>
<td>Renters and apartment-owner agents</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>Y ($CS_i = 1$)</td>
</tr>
</tbody>
</table>
**NPV (buying rooftop PV through up-front cash payment)** – The present value of rooftop PV installation cost \( P_{b\text{(install),i}} \) for a house-owner agent \( i \) at time \( t \) is given by (4), where \( S_i \) is the size of the solar panel array (in kW, DC) required by the agent to meet 100% of its energy needs \( Q_i \) (AC), \( W_i \) is the installation cost ($/kW (DC)) and \( ITC_t \) is the income tax credit percentage (federal and state) at time \( t \). It is assumed that an agent’s minimum tax liability in the year of purchasing rooftop PV is greater than or equal to the corresponding tax rebates it gets from purchasing rooftop PV. Therefore, the income tax credit is not discounted to evaluate the present value of the installation cost. \( W_i \) is initialized to be $3430/kW [54], and this value decreases by 6% annually, based on the average decline in residential sector installation prices in the U.S. between 2000 and 2016. It is assumed that the utility allows customers to offset 100% of the energy generated by their rooftop PV systems, as per the current net metering policy in Iowa.

An agent’s present value of future monthly bill savings \( P_{b\text{(mbs),i}} \) from buying rooftop PV, evaluated over 25 years (the average life of solar panels), is given by (5). \( P_{b\text{(mbs),i}} \) is calculated by discounting (by annual discount rate \( d \), assumed to be 5%) the annual electricity costs for 25 years that the agent would have paid to the utility if it had not installed rooftop PV. An agent’s annual electricity cost is evaluated by multiplying the number of months in a year by its monthly consumption \( Q_i \) and the current electricity rate \( C_i \), where \( C_i \) increases annually based on the agent’s expected growth rate \( PG_i \). The present value of an agent’s future rooftop PV maintenance costs \( P_{b\text{(maint),i}} \) is given by (6), in which the present value of installation cost \( P_{b\text{(install),i}} \) is multiplied by the agent’s expected annual maintenance cost \( PM_i \) and the expected life of the solar panel array (i.e., 25 years). The NPV of buying rooftop PV \( NPV_{b,i} \) for agent \( i \) is given by (7), which is the difference in the present value of total cash inflow and total cash outflow.
\[ P_{b\text{(install)},i} = S_i W_t \left( 1 - ITC_t \right) \quad (4) \]

\[ P_{b\text{(mbs)},i} = \sum_{t=1}^{25} 12 Q_i C_t \left( \frac{1 + PG_i}{1 + d} \right)^{t-1} \quad (5) \]

\[ P_{b\text{(maint)},i} = 25 PM_i P_{b\text{(install)},i} \quad (6) \]

\[ NPV_{b,i} = P_{b\text{(mbs)},i} - (P_{b\text{(install)},i} + P_{b\text{(maint)},i}) \quad (7) \]

**NPV (buying rooftop PV through solar loan)** – It is assumed that an agent will borrow an amount equal to the cost of the PV system after deducting income tax credits. Thus, calculating the present value of the principal for agent \( i \) at time \( t \) \( (P_{s,i}) \) is equivalent to calculating the installation cost of paying cash \( (P_{b\text{(install)},i}) \), given in (4). Similarly, calculating the present value of future total monthly bill savings \( (P_{s\text{(mbs)},i}) \) and maintenance costs \( (P_{s\text{(maint)},i}) \) associated with solar loans is the same as cash payment, given in (5) and (6), respectively. The agent borrows the principal \( (P_{s,i}) \) through a solar loan at a monthly interest rate of \( r\% \) (assumed to be 0.5\%). Each equal monthly installment \( (M_{emi,i}) \) is given by (8), where \( N \) is the total number of installments the agent must pay toward the loan. A 10-year loan is assumed, such that \( N \) equals 120. The present value of the monthly installments \( (P_{s\text{(emi)},i}) \) is given by (9), where the total value of installments each year is discounted by an annual discount rate of \( d\% \) (assumed to be 5\%). The NPV of the rooftop PV loan option \( (NPV_{s,i}) \) is given by (10).

\[ M_{emi,i} = P_{s,i} \left( \frac{r(i + r)^N}{(1 + r)^N - 1} \right) \quad (8) \]

\[ P_{s\text{(emi)},i} = \sum_{t=1}^{10} 12 M_{emi,i} \left( \frac{1}{1 + d} \right)^{t-1} \quad (9) \]

\[ NPV_{s,i} = P_{s\text{(mbs)},i} - (P_{s\text{(emi)},i} + P_{s\text{(maint)},i}) \quad (10) \]

**NPV (leasing rooftop PV)** – If an agent decides to lease solar panels at time \( t \), its monthly leasing cost is determined by the solar installer and depends on the size of the solar panel array \( (S_i) \), the income tax credit rate \( (ITC_t) \) at time \( t \), the installation cost \( (I_i) \), the solar installer’s
expected rate of return ($PD_s$, assumed to be 5%), and the leasing period (assumed to be 25 years). The solar installer’s total cost ($I_i$) to install solar panels for agent $i$ is equivalent to the installation cost of paying cash ($P_{b(\text{install}),i}$), given by (4), but the solar installer reaps the benefit of income tax credits on behalf of the customer. $I_i$ is recovered from the consumer agent via the fixed monthly leasing cost ($M_i$) over 25 years. The present value of the total maintenance cost ($P_{l(\text{maint}),i}$) for an agent $i$ over the next 25 years is given by (11). $P_{l(\text{maint}),i}$ is evaluated by discounting by $PD_s$ (the solar installer’s expected return) the annual maintenance cost ($m_s$, assumed to be 3%) as a percentage of $I_i$ over the 25-year leasing period. This total maintenance cost is also recovered by the solar installer as a part of the monthly leasing cost ($M_i$).

$M_i$ is evaluated using (12), which equates the sum of $I_i$ and $P_{l(\text{maint}),i}$ to the then present value of the total future leasing cost that the consumer agent will pay over the next 25 years. The NPV of the leasing option ($NPV_{li}$) for agent $i$ is the difference between the present value of the total savings in monthly energy bills over the next 25 years (evaluated using (5)) and the present value of the total monthly leasing cost that the consumer pays over 25 years, as shown in (13).

$$P_{l(\text{maint}),i} = m_s I_i \sum_{t=1}^{25} \left( \frac{1}{1 + PD_s} \right)^{t-1}$$

$$I_i + P_{l(\text{maint}),i} = \sum_{t=1}^{25} \left( \frac{12M_i}{(1 + PD_s)^{t-1}} \right)$$

$$NPV_{li} = \sum_{t=1}^{25} 12Q_i C_t \left( \frac{1 + PG_i}{1 + d} \right)^{t-1} - \sum_{t=1}^{25} \left( \frac{12M_i}{(1 + d)^{t-1}} \right)$$

**NPV (community solar)** – In a typical community solar engagement, a customer pays a fixed premium ($C_p$) per unit of energy in addition to the conventional electricity rate at the time of adoption ($C_t^*$), such that the total unit price that the customer pays ($C_p + C_t^*$) remains constant for the life of the community solar program [55]. A similar pricing structure is assumed in the
model. The present value of an agent’s total monthly energy bills if it chooses to participate in a community solar program ($P_{cs,i}$) at time $t$ is given by (14), in which the discounted energy bills are summed over 25 years. An agent’s NPV of investing in community solar ($NPV_{cs,i}$) is the difference between the present value of its future monthly bills if it continues buying electricity from the utility company ($P_{b(mbs),i}$ – evaluated using (5)) and $P_{cs,i}$, given by (15).

$$P_{cs,i} = \sum_{t=1}^{25} \frac{12Q_i(C_t + C_p)}{(1 + d)^{t-1}}$$  \hspace{1cm} (14)

$$NPV_{cs,i} = P_{b(mbs),i} - P_{cs,i}$$  \hspace{1cm} (15)

5.4.11.3 Sub-model 3 – Consumer Agent Decision – For consumer agent $i$ to adopt a particular renewable energy model, its awareness index ($AW_i$) must be greater than the threshold ($AW_h$) value, and the NPV of the renewable energy model must be greater than 0. Thus renters, apartment owners, and house-owners that cannot adopt rooftop PV due to structural constraints will adopt community solar if $NPV_{cs,i}$ is greater than 0 and $AW_i$ is greater than the $AW_h$.

However, if a house-owner agent that can adopt rooftop PV has $AW_i$ greater than the $AW_h$ and its NPV is greater than 0 for multiple renewable energy models, its final selection depends on the values of its perceived complexity ($PC_i$), ownership index ($O_i$), and age-based index ($AB_i$). A random number is generated, and if the number is less than $O_i$, the agent will prefer rooftop PV (either buy, loan, or lease) over community solar. Otherwise, the agent will prefer the option with the highest expected NPV. This randomness is introduced to represent heterogeneity in consumer behaviors that is not explicitly represented by the state variables in the model. If a house-owner agent favors rooftop PV over community solar, a random number is again generated. If the number is less than $AB_i$, the agent will adopt rooftop PV; otherwise, it will participate in a community solar program. The choice of paying cash, taking a solar loan, or leasing rooftop PV depends on $PC_i$: a random number is generated, and if it is greater than $PC_i$, 

the agent will favor the option with the highest expected financial returns (NPV value); otherwise, it will lease rooftop PV. Figure 5.1 summarizes the consumer agent decision process in each time-step.

5.5 Experiments

The ABM was used to examine the impact of residential consumers’ renewable energy adoption decisions on critical performance metrics for utility companies, policymakers, and solar installers, given different combinations of renewable energy models for the consumers to choose from. For each experiment, the output metric values were analyzed over 120 monthly time-steps (i.e., 10 years), averaged over 50 replications. A simulation run length of 10 years was chosen such that potential future disruptions (e.g., the introduction of a new renewable energy technology) could be reasonably ignored.

5.5.1 Experimental Factors and Levels

Model parameter settings were varied in six experiments, which are summarized in Table 5.3. In each experiment, different renewable energy models are available. For example, in experiment BLC(4), consumer agents have three options: buy rooftop PV through up-front cash payment or solar loans, lease rooftop PV from solar installers, or participate in a utility-sponsored community solar program at a premium ($C_p$) of 4 ¢/kWh.
Figure 5.1 Flowchart of the consumer agent decision process in each time-step (*\textsuperscript{**} - consumer agent’s NPV should be greater than zero for at least one of the renewable energy models). As indicated by the superscripts, the gray decision blocks are specific to the following agents: 1) house-owner agents that can adopt rooftop PV and are aware of the community solar option, 2) house-owner agents that can adopt rooftop PV but are unaware of the community solar option, and 3) renters, apartment owners, or house-owner agents that cannot adopt rooftop PV due to structural constraints, but are aware of the community solar option.
Table 5.3 Six experiments with different combinations of renewable energy models (Y: available, N: not available)

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Buy rooftop PV (up-front cash payment)</th>
<th>Buy rooftop PV (solar loan)</th>
<th>Lease rooftop PV</th>
<th>Community solar ($C_p$, $$/kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>BL</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>BLC(2)</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y ($C_p = 2 $/kWh)</td>
</tr>
<tr>
<td>BLC(3)</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y ($C_p = 3 $/kWh)</td>
</tr>
<tr>
<td>BLC(4)</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y ($C_p = 4 $/kWh)</td>
</tr>
<tr>
<td>BLC(5)</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y ($C_p = 5 $/kWh)</td>
</tr>
</tbody>
</table>

For all experiments, the rewiring probability ($p$) of the small-world network is assumed to be 0.5, and the probability of interaction between two connected agents is assumed to be 0.5. All agents’ awareness threshold values ($AW_h$) are initialized to 0.6. The sensitivity of model outputs to varying the values of these parameters was tested. The results (summarized in Appendix B) indicate that the model’s behavior is robust, i.e., it is not predicated on a specific set of input parameter values.

5.5.2 Model Outputs

The outputs of interest include performance metrics that are aligned with the objectives of key system stakeholders. These metrics are summarized in Table 5.4 and are described in detail below:
Table 5.4 Outputs metrics of interest

<table>
<thead>
<tr>
<th>Stakeholder</th>
<th>Metric (unit)</th>
<th>Time of capture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utility company</td>
<td>Present value of revenue ($1000)</td>
<td>End of each monthly time-step</td>
</tr>
<tr>
<td></td>
<td>Total green power added to the grid (kW)</td>
<td>End of 120 time-steps</td>
</tr>
<tr>
<td></td>
<td>Incremental community solar capacity increase (kW)</td>
<td>End of each monthly time-step</td>
</tr>
<tr>
<td>Policymakers</td>
<td>Total adopters (rooftop PV and community solar)</td>
<td>End of each monthly time-step</td>
</tr>
<tr>
<td></td>
<td>Percentage of restricted population participating in renewable energy (%)</td>
<td>End of 120 time-steps</td>
</tr>
<tr>
<td>Solar installers</td>
<td>Present value of revenue ($1000)</td>
<td>End of each monthly time-step</td>
</tr>
</tbody>
</table>

5.5.2.1 Utility company: One key performance metric of interest to the utility company is the present value of its revenues. In particular, utility companies are interested in determining which renewable energy model(s) are best able to help them recover the revenue losses resulting from increased consumer rooftop PV adoption. Revenue is considered as a performance metric for the utility company, rather than profit or gross margin, as it is assumed that the utility buys electricity at the same cost either through wholesale electricity market or via a PPA signed through a community solar program [56]. The utility earns revenues from non-adopters who buy their electricity from the utility at the market rate \(C_t\) and from community solar adopters who pay the utility a fixed electricity price \(C_p + C_t^*\), where \(C_t^*\) is the price of electricity at the time of adoption, and \(C_p\) is the community solar premium. Present value of the utility revenue is evaluated by summing the discounted total revenue each year from non-adopters and community solar adopters assuming an annual discount rate of 5%. Other key performance metrics for the utility are total green power added to the grid through consumer adoption of community solar and rooftop PV and the incremental community solar capacity increases that are needed to satisfy the growing consumer demand for renewable energy. This metric is important for the utility to understand the relative effectiveness of different renewable energy models in meeting the RPS.
5.5.2.2 Policymakers: Key performance metrics of interest to policymakers are the total number of renewable energy adopters as well as percentage of ‘restricted’ population (renters, apartment owners, and house-owners that cannot adopt rooftop PV due to structural constraints) participating in renewable energy. These metrics allow policymakers to determine the degree to which rebate programs for different renewable energy models (e.g., rooftop PV and community solar) lead to their increased adoptions equitably.

5.5.2.3 Solar installers: The key performance metric for solar installers is the present value of their revenues. This metric will help solar installers understand the financial impact of offering consumers a rooftop PV leasing option, as well as the impact of a utility-sponsored community solar program on their own business. Because the model does not consider solar installers as individual agents, the present value of revenue represents the total revenue for all installers offering similar pricing for PV buying and leasing. The present value of revenue for the solar installers is evaluated as the sum of present value of revenues from consumers buying and leasing rooftop PV. Present value from the PV buying option is evaluated by summing the discounted (annual rate of 5%) up-front cost of each purchased rooftop PV system over 120 time-steps (10 years). The present value of revenue from the PV leasing option is evaluated by summing the discounted value of the annual leasing costs for each adopter over 25 years from the year of adoption.

5.5.3 Data Analysis

As not all of the output data was normally distributed, the Steel-Dwass test (nonparametric version of the Tukey’s HSD) was conducted on each pairwise combination of experiments. Error bars in the figures below represent 95% confidence intervals. The results are reported as significant for a significance level alpha <0.05. When two conditions do not share a letter in the figures, they are significantly different from one another.
5.6 Results

Figure 5.2 compares the present value of the utility company’s revenue (in $1000s) over 10 years for each experiment. Present value of utility company’s revenue is evaluated using the method described in Section 4.2.1. Utility revenues are the greatest when community solar is available and $C_p$ is 3 and 4 ¢/kWh, with no significant difference in revenues between BLC(3) ($M = 3278.3$, $SD = 55.0$) and BLC(4) ($M = 3271.1$, $SD = 59.9$), ($p = .99$). However, the utility’s revenue in all six cases is less than the maximum revenue (represented by a horizontal line in Figure 5.2) it would have earned if no renewable energy options were available and all agents were forced to purchase wholesale market electricity.

![Figure 5.2 Present value of utility company’s revenue over 10 simulated years (lower-case letters are used to indicate significant pairwise differences between present value of utility company revenue across the six experiments; means that do not share a letter are significantly different).](image)

The simulation results were further analyzed to determine the total amount of green power added to the grid by the rooftop PV and community solar adopters combined. Figure 5.3 shows that offering a community solar program at premiums ($C_p$) of 2, 3 or 4 ¢/kWh yielded the maximum total green power addition, with no significant difference in the addition of green power between BLC(2), BLC(3), and BLC(4).
Figure 5.3 Total green power (kW) added to the grid in each experiment (lower-case letters are used to indicate significant pairwise differences between total green power added across the six experiments; means that do not share a letter are significantly different).

Figure 5.4 shows the incremental community solar capacity increases needed each year (kW) to satisfy consumer demand for renewable energy. The capacity increase is high in the first year for the BLC(2) and BLC(3) scenarios but then drops and remains relatively low for the remaining 9 years. In the BLC(4) scenario, this initial spike in required capacity is more evenly distributed between years 1 and 2 but then also drops off from the third year onward.

Figure 5.4 Incremental community solar (CS) capacity (kW) required to be added by the utility company to meet consumer demand in each experiment.
Figure 5.5 shows the number of adopters of rooftop PV and community solar at the end of 120 monthly time-steps for all six experiments. Introducing a community solar program, in addition to offering rooftop PV buying and leasing options (i.e., the four BLC experiments), increased the total number of adopters, compared with offering rooftop PV buying (B) or buying/leasing (BL) only. Figure 5.5 also shows that offering community solar increased the number of rooftop PV adopters. This somewhat counterintuitive result is a consequence of an overall increase in the agents’ awareness values ($AW_i$) with the inclusion of an additional renewable energy option. Furthermore, although there were fewer total adopters in BLC(5) than BLC(4), the number of rooftop PV adopters significantly increased (BLC (4): $M = 52.5$, $SD = 6.2$, BLC(5): $M = 57.5$, $SD = 6.9$), ($p < .01$), as some consumers preferred rooftop PV over a community solar program with a high premium ($C_p$).

![Figure 5.5](image)

Figure 5.5 Total number of rooftop PV and community solar (CS) adopters at the end of 10 simulated years (lower-case and upper-case letters are used to indicate significant pairwise differences between number of rooftop PV and community solar adopters across the six experiments, respectively; means that do not share a letter are significantly different).

The cumulative number of adopters (rooftop PV and community solar) each year for all six experiments is shown in Figure 5.6. The rate of solar adoption was much higher in BLC(2),
BLC(3), BLC(4), and BLC(5) than in the B and BL experiments. The rate of adoption remains fairly constant until the eighth year, after which it begins to decrease in BLC(2), BLC(3), BLC(4) and BLC(5) (also observable in Figure 5.4). For example, in the BLC(3) experiment, the percentage of consumer agents adopting solar (rooftop PV and community solar) was 78.3% and 81.6% at the end of 15 and 20 years, respectively.

Figure 5.6 Cumulative number of rooftop PV and community solar (CS) adopters over 10 simulated years for each experiment.

Figure 5.7 shows the percentage of the restricted population (renters, apartment owners, and house-owners that cannot adopt rooftop PV due to structural constraints) participating in renewable energy for all four experiments in which consumers have the option to participate in a community solar program. Offering community solar at premiums ($C_p$) of 2, 3 or 4 ¢/kWh results in maximum participation by the restricted population, with no significant difference in the output between BLC(2), BLC(3), and BLC(4).
Figure 5.7 Percentage of restricted population participating in community solar for the four BLC experiments (lower-case letters are used to represent significant differences in percentage of restricted population participating in community solar across the four experiments; means that do not share a letter are significantly different).

Finally, the present value of solar installers revenue (in $1000s) over 120 time-steps was captured for all six experiments (Figure 5.8). Present value of solar installer revenue is evaluated using the method described in Section 4.2.3. Offering consumers, a rooftop PV leasing option in addition to the buying option (BL) did not significantly increase solar installers revenue (B: $M = 783.4, SD = 129.4$, BL: $M = 789.6, SD = 160.5$), ($p = .99$). Furthermore, if the utility company offers a community solar program at $C_p$ values of 2 and 3 ¢/kWh (BLC(2) and BLC(3), solar installers revenues do not change significantly. However, when community solar is available at $C_p$ values of 4 and 5 ¢/kWh (BLC(4) and BLC(5)), solar installers revenue increases significantly, as more agents adopt rooftop PV.
Figure 5.8 Present value of solar installers revenue (lower-case letters are used to indicate significant pairwise differences between present value of solar installers revenue across the six experiments; means that do not share a letter are significantly different).

5.7 Discussion

5.7.1 Discussion of Simulation Results

The output from the six experiments provides insight into the degree to which different renewable energy models support the objectives of multiple energy system stakeholders (utility companies, policymakers, and solar installers), while also meeting consumers’ demand for renewable energy. The BLC(4) experiment yields the highest utility revenue of all six experiments, which was earned through premiums paid by community solar adopters among the restricted population who otherwise would have been forced to purchase electricity from the utility company at market rates. This enabled the utility company to recover 46% of the revenue losses it experienced due to consumer rooftop PV adoption in the B and BL scenario. The BLC(4) experiment also results in one of the highest amounts of green power added to the grid, which supports the utility’s efforts to meet its renewable energy portfolio requirements. Furthermore, the results of the BLC(4) experiment address policymakers’ equity concerns, yielding the largest number of residential solar power adopters as well as greatest participation
from the restricted population. Remarkably, high rates of community solar adoption in the BLC(4) experiment did not translate into revenue losses for solar installers; in fact, both BLC(4) and BLC(5) experiments yielded the highest present value of solar installers revenue among the six experiments. This result is a consequence of the increased number of social interactions that occurred between potential rooftop PV adopters and the large number of early-adopting community solar participants, such that the awareness of many potential adopters increased in the early time-steps of the simulation.

Alternatively, the utility company could introduce a community solar program at a premium of 3¢/kWh (experiment BLC(3)) and achieve the same revenues and green power addition as BLC(4). Experiments BLC(3) and BLC(4) have the same impact on overall solar power adoption and are therefore equivalent in terms of addressing policymakers’ equity concerns and satisfying consumer demand for renewable energy. However, over a 10 year period, introducing community solar at 3¢/kWh instead of 4¢/kWh did not provide any added benefits to the utility company with respect to their objectives but restricted the potential of higher revenues for the solar installers (solar installers revenues were significantly higher in BLC(4) over BLC(3) experiment).

These results demonstrate that, through experimentation, the model enables an exploration of the degree to which different renewable energy offerings could yield mutually beneficial outcomes for all stakeholders. This is a particularly important consideration when certain actions by one stakeholder can negatively impact the others. For example, policymakers predict that increased availability of community solar for residential consumers could rival the rooftop PV market within a decade [57]. Therefore, an important contribution of the system-based modeling
approach proposed in this paper is its ability to inform renewable energy model design decisions that avoid benefitting some stakeholders at the unnecessary expense of others.

5.7.2 Practical Significance of the Model Outputs

Simulation results indicate a consumer agent adoption rate as high as 65%-70% for community solar and rooftop PV after 10 years in scenarios BLC(2), BLC(3), and BLC(4). For these scenarios, the presence of a community solar program provided increased access to solar for the restricted population and for consumer agents that chose not to adopt rooftop PV because of perceived installation complexity and/or risk of moving. Such high adoption rates have been observed in utility territories that have introduced community solar programs for their consumers. For example, within one year of introducing a community solar program, the Cedar Falls Utility in Iowa gained 1200 (around 10% of households) consumer adopters [58], [59]. Likewise, a community solar project introduced in Fremont, Nebraska, had 200 adopters (demanding a total capacity of 1.55 MW) within 7 weeks [60]. As utilities transition from centralized generation to more consumer-centric distributed models [61], their ability to achieve high adoption rates can be enhanced by having consumers participate as stakeholders in the energy infrastructure. This is particularly important for cities like Chicago, which has committed to 100% renewable energy by 2035 [62].

The results of experimentation with the conceptual ABM presented in this paper help demonstrate the phenomenon of interdependencies in consumer adoption trends in the presence of different renewable energy models. For example, model outputs indicated that rooftop PV adoption rates may actually increase in the presence of a utility-sponsored community solar option. This phenomenon was observed in the utility territory of Cedar Falls Utilities (CFU), a municipally owned public utility in northeast Iowa. In an effort to meet consumer demand for
solar energy, in 2016 CFU introduced a 1.5 MW community solar program called ‘Simple Solar’. CFU initially introduced a 0.5 MW project with each share (i.e., each 170 W panel) priced at $390. However, as a result of strong customer demand, CFU increased the capacity of the project to 1.5 MW, which reduced the cost per share to $270, due to economies of scale. This rate is competitive with that of an equivalent rooftop PV system. As a consequence, the number of new residential rooftop PV installations in CFU’s territory initially reduced from five in 2015 to only one in 2016 (the year when the community solar program was introduced). However, the number of customer enquiries on interconnecting rooftop PV with the CFU grid were higher in 2017 than in previous years, with four new residential installations that year [58], likely due to increased awareness among the CFU territory residents about renewable energy.

A mutually beneficial arrangement between energy stakeholders has been observed in practice, as well. Xcel Energy, an investment-owned utility based in Minneapolis, has introduced 169 community solar programs throughout Minnesota to enable consumers become stakeholders in the new energy infrastructure and add capacity to the grid [63]. All of these community solar programs are owned and operated by solar developers or investment companies and are connected to Xcel Energy’s system, which provides bill credits to subscribers. Another example of a mutually beneficial partnership between utilities and solar companies is located in New York, which has an aggressive target of meeting 50% of its energy needs from renewable sources by 2030 [64]. The state government has encouraged utilities and solar companies to jointly develop a proposal that would establish distributed energy resources on the grid [65]. The partnership aims to reduce solar installers’ risk through increased solar adoption while at the same time ensuring that utilities have sufficient financial resources to manage the grid. Several utilities, including Consolidated Edison Company of New York, New York State Electric & Gas
Corporation, and Rochester Gas and Electric have partnered with solar developers like SolarCity and SunEdison to become alternative energy stakeholders [65]. Framing renewable energy policies such that key energy system stakeholders’ objectives are aligned can lead to partnerships that increase solar development and consumer participation, as well as improving the electric distribution system.

5.7.3 Limitations and Future Research

This conceptual model has several limitations. The model does not consider the potential for future disruptions in the energy sector, such as the introduction of a new renewable energy technology or a sudden drop/rise in electricity prices due to changing fuel prices, which can significantly affect renewable energy adoption trends. The model also has not yet been validated with empirical human behavior data. Finally, as the model was intended as proof-of-concept, some of the assumptions with respect to the agents’ decision-making process were implemented rather simplistically. For example, an agent’s visual interactions were modeled within a single community, which will be extended in the future version of the model based on the actual locations of the consumer agents.

Future model developments will focus on empirical validation. To develop an empirically informed and validated ABM, an urban area in southern California will serve as a case study in which consumers have multiple renewable energy options. Geospatial and household-level demographic data will be used to inform the model, as well as survey data on consumer adoption behavior and preferences [66]. Model outputs, such as the number of consumer agents adopting distributed solar in a census block group (the smallest entity for which the U.S. Census Bureau publishes the demographic data of its residents) will be compared with historical adoption data for both spatial and numerical validation. Agent-level validation will include a comparison of the
demographic characteristics of consumer agents from the ABM and the demographics of actual adopters.

Upon validation, the ABM can be applied to other geographic regions to study consumer adoption of different renewable energy models, given consumer household-level characteristics (e.g., demographics), the serving utility’s tariff structure, and available financial incentives. It is important to account for differences in demographics and other factors influencing consumer decision-making across different geographies. For example, community solar projects in different regions of Wisconsin have different subscription rates, despite having similar pricing and payment structures, due to differences in local demographics [67]. The validated model can also be further extended to incorporate other variations specific to certain geographic regions, such as the effect of competition among utilities on their tariff structures in a deregulated electricity market (e.g. the State of Texas in the U.S.).

5.8 Conclusion

This paper describes an ABM that was developed to predict consumers’ renewable energy adoption decisions in the presence of multiple competing models, as well as the effects of these decisions on multiple energy system stakeholders’ objectives. Experimental results suggest that, for a renewable energy system to be successful and sustainable in the long term, design decisions should be made with consideration given to the objectives of all key system stakeholders, including utilities, solar installers, and policymakers, as well as the heterogeneous preferences and objectives of consumers. The results also demonstrate how mutually beneficial partnerships between stakeholders (e.g., utility companies and solar installers) and alternative renewable energy models (e.g., community solar program) can help to sustain equitable renewable energy systems.
The conceptual agent-based model described in this paper serves as a starting point for the development of an empirically validated model. Once validated, the model can be used by different stakeholders to help them determine appropriate values for their respective business model parameters. In particular, it could serve as a decision support tool for utility companies and enable them to assess the ability of different alternative renewable energy model structures to satisfy customer demand for solar-based electricity and maintain their renewable energy portfolios and revenues. Similarly, the model can be used to test the effect of varying policy incentives, such as tax benefits, on adoption patterns. The validated model can be used as a tool by solar installers to find their next customer, given behavioral and decision-making attributes. Finally, the model can help policymakers to gauge the likely effects of different policies on improving equitable adoption of renewable energy among consumers.

References


CHAPTER 6. BEHAVIORAL FACTOR SELECTION IN AGENT-BASED MODELS OF SOLAR DIFFUSION: A REVIEW

This chapter describes a structured approach to identifying the key behavioral and social factors that should be drawn from a set of empirical data in order to parameterize an ABM. This approach will be used to develop an empirically validated ABM of residential consumer solar adoption in the City of Livermore in California. The motivation for selecting the City of Livermore for the case study came from a collaborative research partnership with Sunrun, a leading solar installer in the U.S. To better understand the consumer decision making process in the presence of various renewable energy options, Sunrun is interested in developing a validated consumer adoption model to identify their potential customers. As part of this collaboration, Sunrun has provided household level demographic data for the City of Livermore, as well as demographic data for the households that have adopted distributed solar. This data will enable model validation, via statistical comparison of model outputs with actual adoption data.

Behavioral and social factors are critical in accurately predicting demographic and spatial patterns of residential solar diffusion [1]. Therefore, it is necessary to identify the salient behavioral and social factors that should be included in a validated ABM of solar adoption in the City of Livermore. However, the most appropriate method for deciding which factors should be included in the model, and which were unnecessary and could be ignored, was unclear. To determine best practices for behavioral and social factor selection, a systematic review of state-of-the-art literature on ABMs that study solar diffusion among residential households was conducted. The outline of this chapter is as follows: Section 6.1 describes the standard review method that was adopted. Section 6.2 summarizes and analyzes the review with respect to methods of selecting behavioral and social factors. Finally, Section 6.3 discusses potential future directions for a structured approach towards factor selection.
6.1 Review Process

A standard three-step process was followed to conduct the systematic literature review, including planning the review, conducting the review, and reporting and dissemination [2]. Peer-reviewed journal articles published between 2009 and 2018 were considered for the review. The Scopus and Web of Science database was used to search for journal articles using a specific set of keywords (listed in Table 6.1). Articles were shortlisted based on combinations of keywords, a technique that is widely practiced in literature reviews that are published in reputed journals [3-5]. Every possible combination of keywords was used, resulting in an exhaustive search process. Table 6.1 provides the logic that was used to generate these combinations.

Table 6.1 Keyword set used for shortlisting journal articles in the Scopus and Web of Science database

<table>
<thead>
<tr>
<th>Keyword 1</th>
<th>Boolean</th>
<th>Keyword 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>agent-based</td>
<td>AND</td>
<td>solar</td>
</tr>
<tr>
<td>multi-agent</td>
<td></td>
<td>photovoltaic</td>
</tr>
</tbody>
</table>

In total, 60 journal articles were reviewed. Out of these, 14 journal articles were determined to be the most relevant and were included in this chapter. The flowchart in Figure 6.1 shows the literature search and screening process adopted in this study as per PRISMA guidelines.
The models described in the existing literature can be classified into two broad categories: abstract and applied ABMs. The abstract models focus on gaining insight into the influence of a particular factor or group of factors on diffusion trends. The number of agents included in all of these models is determined by the modeler. For example, a total of 1000 agents were included in the ABM developed by Zeng et al. 2018 [6] to simulate consumers deciding between adopting either conventional or renewable energy technology. The model studied the effect of time of entrance of a technology in the market, price, and reliability of renewable energy technology on diffusion trends of both conventional and renewable energy technology over time.
The applied models focus on studying energy technology adoption by residential households for a particular geographic region, with the aim of assessing policies that could result in increased adoption. The number of agents in the applied models depends on the actual number of residential households in the geographic region of study. For example, Rai and Robinson [7] developed an ABM with 173,466 household agents in Austin, Texas, to predict the effect of different rebate programs on residential rooftop PV adoption rates. Household agent adoption decisions depend on their demographic, attitudinal, and economic characteristics. Many of the existing applied models have been first calibrated with historical adoption data and then used to predict future adoption trends [7 – 12]. For example, the ABM developed by Rai and Robinson 2015 [7] was first calibrated with the historical data on residential solar adopters between 2008 and 2014 in Austin and was then used to make future predictions for support policy evaluations.

The creators of many of the existing ABMs have also conducted empirical surveys to understand consumers’ motivations to adopt solar [7, 8, 13, 14]. However, some of the surveys were not designed to elicit a comprehensive understanding of consumers’ preferences [14]. Also, the validated ABMs are parameterized using a subset of potential social and behavioral factors that appear to have been selected on an ad-hoc basis. Therefore, these models do not include certain factors that have been identified as highly important in consumers’ decisions to adopt solar.

National Renewable Energy Laboratory (NREL) has recently conducted a survey of three different types of household populations: households that have installed solar PV or have signed a contract to do so (adopters), households that have seriously considered solar PV adoption but have not yet installed it (considerers), and the general population that has not adopted solar PV (generals) [15]. The data was collected from households in four U.S. states: New Jersey, New
York, Arizona, and California. The purpose of the survey was to determine why people do or do not adopt rooftop PV, the motivating factors for adoption, and differences in demographic characteristics (e.g., education and income) of adopters and non-adopters. One of the outcomes of the analysis of this survey data shows that residential households are more likely to adopt if they perceived less risk in investing in solar PV [16].

Investment risk can be categorized into two types: financial and physical. Although many of the existing ABMs have considered the effect of financial gains, in terms of payback period or net present value, on consumer adoption decisions, they do not explicitly consider the effect of financial risk. The survey data by NREL shows that 57% of households that have not considered adopting solar are discouraged by the perceived financial investment risk, based on the belief that they are unlikely to stay in their current home long enough for the PV investment to pay off [15, 16]. This is also a major concern for households that have not adopted solar but have at least considered it (45%). Other empirical studies on solar adoption have found that many consumers install rooftop PV just before retirement, coinciding with decisions regarding staying in their homes [17].

Physical risk associated with investment in solar involves considerations such as damaging the roof upon installation. Around 40% of households that considered solar for their home responded that the risk of damage to their roofs was an important factor in their decision to no longer consider adopting solar [15, 16]. However, adopters seem to perceive leasing as a way to reduce risk. For example, 68% of the adopter respondents mentioned that they spoke with one or two solar companies, with leasers talking to fewer companies than buyers. These results suggest that consideration of multiple renewable energy options (e.g. buying vs leasing solar PV) is
important when developing empirical ABMs, in order to establish a valid representation of adoption behavior among residential households.

Another important behavioral factor that has been excluded from existing ABMs involves the perceived hassle associated with the process of purchasing and installing solar PV. This factor is commonly cited as a barrier for rooftop PV adoption among residential households. Consumers tend to consider rooftop PV purchase to be a complex issue, because of the effort required to learn about installation procedures, incentive policies, net metering policies, house-owners’ association regulations, and the required paperwork [18]. In the NREL survey, 32% of households that have never considered solar and 30% of those that have at least considered it once, mentioned “perceived complexity” as a barrier to their decision to adopt rooftop PV [15, 16].

Finally, the literature on existing ABMs does not discuss the reasons for excluding factors that are known to influence solar adoption decisions. For example, Pearse and Slade [10] summarize factors incorporated by previously developed ABMs, such as the effect of advertising and media, but they do not justify the exclusion of many of these factors in developing their own ABM. Appendix C summarizes the factor selection approach and methodologies used to develop the ABMs in the 14 papers reviewed in this chapter. This review suggests that the existing ABMs on solar diffusion do not employ a structured approach in selecting factors that influence consumer decision-making process.

6.3 Potential Approach to Factor Selection in ABMs

One approach to systematic factor selection is to classify factors using established behavioral theories that are used to explain the human decision-making process. For example, Wolske et al. 2018 [18] designed an integrated framework and classified the factors influencing solar diffusion (as determined by the NREL survey) into 8 categories using several
complementary behavioral theories, including the Theory of Planned Behavior, Value-Belief Norm Theory, and Theory of Diffusion of Innovations. The framework enables a structured approach to characterizing influencing factors and reduces the possibility of ignoring an important factor. Such theoretical frameworks can be used to develop agent architecture in ABMs to define the rules that govern agent behavior interactions, and the influence of these interactions on their decision making.

This framework could be applied when developing an empirically validated ABM for the City of Livermore in California. The NREL survey data for the State of California (consisting of 1176 adopters, 187 considerers, and 338 general population) and household-level demographic data obtained from Sunrun will be used to characterize the agents in the ABM. Structural and financial attributes of alternate renewable energy models, such as community solar and green pricing programs, that are available for residential consumers through the utilities serving the City of Livermore will also be incorporated in the development of this empirical ABM. Model outputs, such as the number of consumer agents adopting distributed solar at the neighborhood level, will be compared with the actual adoption data from the City of Livermore. Agent-level validation will include a comparison of the demographic characteristics of the adopter consumer agents from the ABM to the demographics of actual adopters, as discussed in the conceptual agent-based models developed on solar adoption [27 – 31]. To achieve this validation, the simulation will be performed through the back dates, starting with the initial adoption data in 2010, and the outputs will be compared to the actual adoption data in 2018, as provided by Sunrun.

References


CHAPTER 7. GENERAL CONCLUSION

This dissertation discusses new approaches to model decentralized sustainable sociotechnical systems with an aim to develop empirically validated ABMs. Two application areas include regional food supply chains and renewable energy systems, in line with the United Nations Sustainable Development goals of responsible consumption and production, climate action, and affordable and clean energy for all.

A comprehensive literature review of regional food supply chain literature in Chapter 2 suggested the need of quantitative and data-driven methods to help RFSC practitioners make smart logistics management decisions. Inspired by the existing gaps in Chapter 2, Chapter 3 describes a novel hybrid simulation model using discrete event and agent-based model to study inbound warehouse operations of a food hub in Iowa. The model was validated using empirical data from the food hub.

In studying the residential renewable energy systems, agent-based modeling approach was identified as highly appropriate in studying consumers’ behaviors and motivations and their impacts on the viability of the existence of multiple competing renewable energy models. As described in Chapter 4, this research recommended extending the concept of Zero Energy Building to having Zero Energy Communities through introduction of shared community solar programs. This requires a customer-oriented approach to support effective ZEC design decisions. An empirical agent-based model was developed to study ZEC design decisions at a neighborhood in Des Moines, Iowa. The results from the model identified the need of introducing community solar program by utilities for their customers and relaxing policy barriers on shared solar for solar project developers. Also, in making design decisions of these shared solar models such as community solar, simulation results from the ABM also emphasizes the
need to identify the tradeoffs between achieving business targets of involved stakeholders while managing timelines of achieving ZEC targets.

While community solar offered a potential solution to achieving zero energy goals, the research further delved into understanding the impact of having multiple renewable energy models on various stakeholders including customers, utilities, policymakers, and other private players such as solar installers. All stakeholders have different objectives to meet, are operating under different constraints, and exhibit varying behavior. Chapter 4 describes an ABM developed to study the impact of consumer decision-making in presence of multiple competing renewable energy models on various stakeholders’ objectives. The proposed modeling approach can help to inform design decisions of distributed solar energy models that avoid benefiting some stakeholders at the unnecessary expense of others.

Ongoing and future research include development of an empirically validated ABM of residential consumers renewable energy adoption for the City of Livermore in California. To develop a validated ABM of residential solar diffusion, Chapter 6 in this dissertation has provided a systematic approach to shortlist various behavioral and social factors which are important to consider in modeling consumers decision-making. Upon building the empirical model using systematic approach of factor selection, model outputs, such as the number of consumer agents adopting distributed solar at neighborhood level will be compared with the actual adoption data from the City of Livermore, provided by Sunrun, a national level solar installer in the U.S.


## APPENDIX A. SUMMARY OF STATE VARIABLES ASSOCIATED WITH CONSUMER AGENTS IN THE ABM IN CHAPTER 5

Table A.1 summarizes the description of state variables associated with consumer agents in the agent-based model (ABM), along with their possible values and data sources. Subscript $i$ for each variable is used to represent unique values of the state variables for the 300 consumer agents in the ABM, where $i$ varies from zero through 299.

<table>
<thead>
<tr>
<th>State variables</th>
<th>Description</th>
<th>Possible values</th>
<th>Static/Dynamic</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i$</td>
<td>Unique ID number</td>
<td>300 agents are assigned ID’s starting from 0 through 299</td>
<td>Static</td>
<td>N/A</td>
</tr>
<tr>
<td>$C_i$</td>
<td>Community identification number</td>
<td>0 - 6 for community 1 through 7</td>
<td>Static</td>
<td>N/A</td>
</tr>
<tr>
<td>$A_i$</td>
<td>Age level</td>
<td>0 - 6 for age range 18 – 24, 25 – 34, 35 – 44, 45 - 54, 55 - 64, 65 - 74, and above 75, respectively</td>
<td>Dynamic</td>
<td>Derived from Data USA (<a href="https://datausa.io/">https://datausa.io/</a>)</td>
</tr>
<tr>
<td>$E_i$</td>
<td>Education level</td>
<td>0 - 5 corresponds to No High School, Some High School, Some College, Associate Degree, Bachelor’s Degree, and Graduate Degree, respectively.</td>
<td>Static</td>
<td>Derived from Data USA (<a href="https://datausa.io/">https://datausa.io/</a>)</td>
</tr>
<tr>
<td>$R_i$</td>
<td>Race</td>
<td>0 - 7 corresponds to Multi-race, Asian, Black, Hawaiian, Latino, Native, Other, and White, respectively</td>
<td>Static</td>
<td>Derived from Data USA (<a href="https://datausa.io/">https://datausa.io/</a>)</td>
</tr>
<tr>
<td>$Q_i$</td>
<td>Monthly electricity consumption (kWh)</td>
<td>241 - 1445</td>
<td>Static</td>
<td>Derived from (Neighborhood Scout (2018); U.S. EIA (2018))</td>
</tr>
<tr>
<td>$AW_i$</td>
<td>Awareness index</td>
<td>0 – 1</td>
<td>Dynamic</td>
<td>Assumption</td>
</tr>
</tbody>
</table>
Table A.1 (continued)

<table>
<thead>
<tr>
<th>State variables</th>
<th>Description</th>
<th>Possible values</th>
<th>Static/Dynamic</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$AW_h$</td>
<td>Threshold awareness</td>
<td>0.6</td>
<td>Static</td>
<td>Assumption</td>
</tr>
<tr>
<td>$CS_i$</td>
<td>Community Solar Awareness</td>
<td>0, 1</td>
<td>Dynamic</td>
<td>Assumption</td>
</tr>
<tr>
<td>$PC_i$</td>
<td>Perceived complexity</td>
<td>0 – 1</td>
<td>Dynamic</td>
<td>Assumption</td>
</tr>
<tr>
<td>$O_i$</td>
<td>Energy infrastructure ownership index</td>
<td>0 – 1</td>
<td>Static</td>
<td>Assumption</td>
</tr>
<tr>
<td>$AB_i$</td>
<td>Age-based index</td>
<td>0 – 1</td>
<td>Dynamic</td>
<td>Assumption</td>
</tr>
<tr>
<td>$T_x$</td>
<td>Consumer agent type</td>
<td>$T_1, T_2, T_3, T_4$</td>
<td>Static</td>
<td>Adapted from Sigrin (2013)</td>
</tr>
<tr>
<td>$PG_i$</td>
<td>Perceived annual growth rate (%) of electricity from the utility company</td>
<td>0, 2.6, 3.3, and 5 for agent types $T_1$ through $T_4$ respectively</td>
<td>Static</td>
<td>Adapted from Sigrin (2013)</td>
</tr>
<tr>
<td>$PM_i$</td>
<td>Perceived annual maintenance cost (%) involved in rooftop PV</td>
<td>0.5, 0.25, 0.15, and 0 for agent types $T_1$ through $T_4$ respectively as a percentage of up-front installation cost</td>
<td>Static</td>
<td>Adapted from Sigrin (2013)</td>
</tr>
<tr>
<td>$AF_i$</td>
<td>Affordability factor for a consumer agent</td>
<td>0 – 1</td>
<td>Static</td>
<td>Assumption</td>
</tr>
<tr>
<td>$S_i$</td>
<td>Size of the solar panel array (DC) for rooftop PV or community solar program</td>
<td>$Q_i/109$</td>
<td>Static</td>
<td>NREL (2018)</td>
</tr>
</tbody>
</table>
APPENDIX B. SENSITIVITY ANALYSIS OF THE ABM OUTPUTS IN CHAPTER 5

Sensitivity analysis was performed to determine whether the change of input parameters values lead to reasonable changes in the corresponding model outputs. Specifically, as agent-based models are generally sensitive to the social network topology been used to connect the agents, effect of change in rewiring probability of the small-world network and probability of interaction between agents connected via the network was determined on the stakeholders’ metrics (present value of utility company’s revenue and total green power addition, total number of rooftop PV and community solar adopters, percentage of restricted population participating in distributed generation and present value of solar installers revenue) for each of the six experiments as described in Table 5.3. In addition, the effect of change in the awareness threshold ($AW_h$) on the model outputs was also captured. Sensitivity of a parameter was evaluated only by varying one parameter at a time and keeping others constant. The output of the sensitivity analysis performed is summarized in Table B.1. Results from the sensitivity analysis of each parameter demonstrate similar pattern of outputs with respect to the stakeholders’ metrics: utility company’s revenue was greatest in the BLC(3) and BLC(4) experiments, with no significant difference between these two experiments; BLC(2), BLC(3) and BLC(4) led to maximum green power addition, and yielded the largest number of residential solar power adopters and percentage participation by the restricted population in renewable energy; solar installers revenue was greatest in the BLC(4) and BLC(5) experiments as compared to B, BL, BLC(2) and BLC(3) experiments. The results from the sensitivity analysis demonstrate that the pattern of the model outputs discussed in the results and discussion section with respect to different stakeholder’s metrics are not as a result of outcome from specific set of input parameter values.
Table B.1: Model outputs with respect to stakeholders’ metrics from the sensitivity analysis on three input parameters: rewiring probability of the small-world network \((p)\), probability of interaction between agents connected within the social network and threshold awareness \((\text{AW}_\text{i})\). The output metrics shown are mean values over 50 replications. Values in brackets represent standard deviation of the mean.

<table>
<thead>
<tr>
<th>Parameter (value)</th>
<th>Experiment (Table 5.3)</th>
<th>Present value of utility company's revenue ($1000)</th>
<th>Total green power added (kW)</th>
<th>Total adopters (rooftop PV &amp; community solar)</th>
<th>Participation by restricted population (%)</th>
<th>Present value of solar installers revenue ($1000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rewiring probability ((p = 0.25))</td>
<td>B</td>
<td>3139.2 (59.6)</td>
<td>307.6 (68.3)</td>
<td>40.6 (9.1)</td>
<td>0 (0)</td>
<td>799.7 (161.4)</td>
</tr>
<tr>
<td></td>
<td>BL</td>
<td>3123.2 (70.5)</td>
<td>309.8 (76.4)</td>
<td>41.2 (10.1)</td>
<td>0 (0)</td>
<td>812.1 (190.6)</td>
</tr>
<tr>
<td></td>
<td>BLC(2)</td>
<td>3206.9 (54.0)</td>
<td>1514.3 (106.0)</td>
<td>199.5 (13.6)</td>
<td>57.1 (4.6)</td>
<td>854.4 (124.8)</td>
</tr>
<tr>
<td></td>
<td>BLC(3)</td>
<td>3259.4 (62.3)</td>
<td>1510.1 (121.8)</td>
<td>199.0 (16.3)</td>
<td>57.2 (5.8)</td>
<td>895.4 (156.2)</td>
</tr>
<tr>
<td></td>
<td>BLC(4)</td>
<td>3262.3 (67.7)</td>
<td>1534.0 (127.3)</td>
<td>201.9 (17.0)</td>
<td>57.6 (6.1)</td>
<td>1034.8 (166.8)</td>
</tr>
<tr>
<td></td>
<td>BLC(5)</td>
<td>3218.9 (57.0)</td>
<td>1128.6 (111.2)</td>
<td>148.7 (14.4)</td>
<td>34.0 (4.8)</td>
<td>1088.3 (148.6)</td>
</tr>
<tr>
<td>Rewiring probability ((p = 0.75))</td>
<td>B</td>
<td>3151.7 (59.0)</td>
<td>283.9 (60.3)</td>
<td>37.7 (7.6)</td>
<td>0 (0)</td>
<td>754.7 (155.1)</td>
</tr>
<tr>
<td></td>
<td>BL</td>
<td>3118.7 (62.3)</td>
<td>306.9 (57.5)</td>
<td>40.6 (7.1)</td>
<td>0 (0)</td>
<td>815.5 (154.0)</td>
</tr>
<tr>
<td></td>
<td>BLC(2)</td>
<td>3193.9 (67.4)</td>
<td>1513.9 (122.2)</td>
<td>199.4 (15.5)</td>
<td>57.1 (5.4)</td>
<td>877.8 (159.6)</td>
</tr>
<tr>
<td></td>
<td>BLC(3)</td>
<td>3280.2 (51.3)</td>
<td>1515.8 (136.8)</td>
<td>199.2 (17.8)</td>
<td>56.5 (6.6)</td>
<td>864.9 (131.7)</td>
</tr>
<tr>
<td></td>
<td>BLC(4)</td>
<td>3287.1 (50.2)</td>
<td>1552.0 (133.4)</td>
<td>204.3 (17.0)</td>
<td>58.5 (5.8)</td>
<td>994.5 (136.6)</td>
</tr>
<tr>
<td></td>
<td>BLC(5)</td>
<td>3222.3 (59.5)</td>
<td>1137.4 (104.0)</td>
<td>150.3 (13.9)</td>
<td>34.3 (5.1)</td>
<td>1085.4 (147.2)</td>
</tr>
<tr>
<td>Probability of interaction (0.25)</td>
<td>B</td>
<td>3174.6 (46.7)</td>
<td>226.5 (41.1)</td>
<td>30.3 (5.5)</td>
<td>0 (0)</td>
<td>658.8 (117.0)</td>
</tr>
<tr>
<td></td>
<td>BL</td>
<td>3165.7 (58.7)</td>
<td>228.4 (56.7)</td>
<td>30.6 (7.6)</td>
<td>0 (0)</td>
<td>651.0 (152.6)</td>
</tr>
<tr>
<td></td>
<td>BLC(2)</td>
<td>3244.0 (48.9)</td>
<td>975.5 (115.7)</td>
<td>129.1 (15.2)</td>
<td>34.0 (4.9)</td>
<td>651.5 (120.3)</td>
</tr>
<tr>
<td></td>
<td>BLC(3)</td>
<td>3272.9 (56.8)</td>
<td>1018.1 (123.2)</td>
<td>134.7 (15.4)</td>
<td>35.8 (4.8)</td>
<td>710.6 (133.1)</td>
</tr>
<tr>
<td></td>
<td>BLC(4)</td>
<td>3276.9 (69.6)</td>
<td>1054.3 (118.7)</td>
<td>139.3 (15.9)</td>
<td>37.6 (5.0)</td>
<td>806.8 (172.3)</td>
</tr>
<tr>
<td></td>
<td>BLC(5)</td>
<td>3236.1 (60.8)</td>
<td>823.4 (106.6)</td>
<td>108.4 (14.0)</td>
<td>23.2 (4.2)</td>
<td>884.5 (147.3)</td>
</tr>
</tbody>
</table>
Table B.1 (continued)

<table>
<thead>
<tr>
<th>Parameter (value)</th>
<th>Experiment (Table 5.3)</th>
<th>Present value of utility company’s revenue ($1000)</th>
<th>Total green power added (kW)</th>
<th>Total adopters (rooftop PV &amp; community solar)</th>
<th>Participation by restricted population (%)</th>
<th>Present value of solar installers revenue ($1000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of interaction (0.75)</td>
<td>B</td>
<td>3106.5 (71.8)</td>
<td>351.6 (65.0)</td>
<td>47.0 (8.8)</td>
<td>0 (0)</td>
<td>898.0 (181.0)</td>
</tr>
<tr>
<td></td>
<td>BL</td>
<td>3065.8 (73.2)</td>
<td>394.2 (75.6)</td>
<td>52.3 (10.4)</td>
<td>0 (0)</td>
<td>995.6 (191.8)</td>
</tr>
<tr>
<td></td>
<td>BLC(2)</td>
<td>3171.9 (60.7)</td>
<td>1767.3 (93.5)</td>
<td>231.7 (11.6)</td>
<td>68.1 (4.7)</td>
<td>975.1 (139.8)</td>
</tr>
<tr>
<td></td>
<td>BLC(3)</td>
<td>3258.9 (59.3)</td>
<td>1764.8 (76.8)</td>
<td>231.7 (10.0)</td>
<td>68.1 (4.0)</td>
<td>987.0 (122.8)</td>
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<td></td>
<td>BLC(4)</td>
<td>3281.5 (59.2)</td>
<td>1782.2 (91.3)</td>
<td>234.0 (11.5)</td>
<td>68.9 (4.9)</td>
<td>1120.0 (130.8)</td>
</tr>
<tr>
<td></td>
<td>BLC(5)</td>
<td>3201.3 (45.7)</td>
<td>1318.2 (93.9)</td>
<td>173.6 (12.4)</td>
<td>41.7 (4.4)</td>
<td>1228.8 (109.1)</td>
</tr>
<tr>
<td>Threshold awareness (AWh = 0.8)</td>
<td>B</td>
<td>3337.7 (36.5)</td>
<td>88.6 (37.8)</td>
<td>11.6 (4.8)</td>
<td>0 (0)</td>
<td>250.5 (98.2)</td>
</tr>
<tr>
<td></td>
<td>BL</td>
<td>3336.4 (39.0)</td>
<td>86.3 (35.2)</td>
<td>11.6 (4.7)</td>
<td>0 (0)</td>
<td>240.1 (94.2)</td>
</tr>
<tr>
<td></td>
<td>BLC(2)</td>
<td>3353.7 (32.6)</td>
<td>510.0 (125.0)</td>
<td>67.8 (17.1)</td>
<td>17.4 (5.5)</td>
<td>306.4 (99.5)</td>
</tr>
<tr>
<td></td>
<td>BLC(3)</td>
<td>3379.1 (33.5)</td>
<td>466.4 (97.9)</td>
<td>62.0 (12.7)</td>
<td>16.2 (3.9)</td>
<td>286.5 (89.5)</td>
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<tr>
<td></td>
<td>BLC(4)</td>
<td>3371.2 (36.4)</td>
<td>508.9 (119.7)</td>
<td>66.9 (15.0)</td>
<td>17.5 (4.3)</td>
<td>348.5 (100.4)</td>
</tr>
<tr>
<td></td>
<td>BLC(5)</td>
<td>3358.5 (35.7)</td>
<td>375.1 (88.4)</td>
<td>49.6 (11.4)</td>
<td>10.2 (3.1)</td>
<td>373.2 (102.6)</td>
</tr>
</tbody>
</table>
TABLE C.1: Factor selection approach and methodology used to develop ABMs in the 14 journal articles reviewed in Chapter 6

<table>
<thead>
<tr>
<th>Literature</th>
<th>Empirical data collected</th>
<th>Discussion on consideration of other known behavioral factors</th>
<th>Empirical or applied model</th>
<th>Validation of model with empirical adoption data</th>
</tr>
</thead>
<tbody>
<tr>
<td>[10]</td>
<td>No</td>
<td>Summarizes factors considered by previous ABMs on solar adoption but does not discuss why the authors have chosen only the factors they have considered in their ABM and not the others</td>
<td>Applied: Great Britain</td>
<td>Calibrated the model from 2010 to 2016 and then made predictions from 2016-2022. Agents were not geographically coded and the results from 5000 agents were scaled to the population of Great Britain to calibrate the model with actual adoption data</td>
</tr>
<tr>
<td>[9]</td>
<td>No</td>
<td>No</td>
<td>Applied: Germany</td>
<td>First calibrated the model from 2003 to 2011 and then used it for predictions of alternative policies in the same time period</td>
</tr>
<tr>
<td>[7]</td>
<td>Yes (616 adopters in Austin)</td>
<td>No: authors highlights that early adopters are not primarily motivated to adopt based on economic benefits of solar. However, the model does not consider this approach to model agents’ behaviors in the initial time-steps</td>
<td>Applied: Austin, TX</td>
<td>Validated the model outputs by running between 2008 and 2014</td>
</tr>
<tr>
<td>[22]</td>
<td>No</td>
<td>No</td>
<td>Applied: Cambridge, Massachusetts and Lancaster, California</td>
<td>No: the model forecast adoption for next 20 years without calibrating for past years</td>
</tr>
<tr>
<td>[20]</td>
<td>No</td>
<td>No</td>
<td>Applied: Doha, Qatar</td>
<td>No</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Literature</th>
<th>Multiple competing renewable energy models for agent’s adoption</th>
<th>Agent population</th>
<th>Behavioral theories</th>
</tr>
</thead>
<tbody>
<tr>
<td>[10]</td>
<td>No: the paper describes two generation of solar panels: crystalline (first generation) and thin film (second generation) but do not differentiate them in the decision-making of households</td>
<td>Residential households: not a specific geography was studied. 5000 agents were generated, and demographics were assigned from the continuous or discrete probability distributions drawn from the UK demographic data</td>
<td>Multi-criteria utility function: if an agent’s total utility exceed the threshold they will install a PV system</td>
</tr>
<tr>
<td>[9]</td>
<td>Considered two different PV technologies: crystalline silicon and thin film solar, as well as rooftop PV and open-space installation (as net metering policy differs based on type of installation, i.e. for rooftop and open space)</td>
<td>Small-scale rooftop investors (homeowners) as well as large and medium scale investors (farmers, financial investors and also supermarket chains)</td>
<td>None</td>
</tr>
<tr>
<td>[7]</td>
<td>No: rooftop PV buying option</td>
<td>Residential households: 173,466</td>
<td>Theory of Planned Behavior. Also, Relative Agreement algorithm has been used to model agents’ interactions</td>
</tr>
<tr>
<td>[8]</td>
<td>No: rooftop PV buying option</td>
<td>Residential households: 173,466</td>
<td>Theory of Planned Behavior. Also, Relative Agreement algorithm has been used to model agents’ interactions</td>
</tr>
<tr>
<td>[22]</td>
<td>No</td>
<td>Residential and non-residential energy consumers: all the buildings are modeled in both the cities and each building is considered as an agent</td>
<td>None</td>
</tr>
<tr>
<td>[20]</td>
<td>No</td>
<td>Residential households: 150,000 residential buildings in total of 4345 census blocks</td>
<td>Linear threshold model for diffusion of innovation</td>
</tr>
<tr>
<td>Literature</td>
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<td>Social network structure</td>
<td></td>
</tr>
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</tr>
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</table>
| [10]       | a) Income utility  
b) Social utility - number of households an agent is connected to have adopted PV  
c) Economic utility - payback period  
d) Capital cost utility - function of capital cost of the system and agent’s income | An agent is assumed to be connected to 10 other agents |
| [9]        | Net present value of investments  
a) Control Module: payback period  
b) Attitude Module: classified into financial (payback period, profitability of the system and net monthly bill savings), environmental (overall environmental concern, amount the individual is willing to pay for protecting the environment and level of concern for environment in an individual’s neighborhood) and social aspects (number of PV adopters in and outside the neighborhood, and degree of motivation and confidence from neighborhood systems) | None |
| [7]        | Similar to Rai and Robinson 2015 [7]. However, the model was also tested only using the Control Module of Rai and Robinson 2015 [7] and leaving the Attitude Module  
a) Payback period  
b) Attitude (number of residential consumer adopters in the geographical vicinity/neighborhood, is used as a proxy to attitude): attitude component is only applied to residential consumer agents | Small-world network: local (neighbors) as well as non-local connections were established between agents |
| [22]       | a) Cost of PV system and future electricity prices  
b) Influence from two social networks: Twitter and city neighborhood | Neighborhood for a residential household agent is defined as number of buildings within a radius of 90 ft. |
<p>| [20]       | | Barabási–Albert Preferential Attachment Model |</p>
<table>
<thead>
<tr>
<th>Literature</th>
<th>Empirical data collected</th>
<th>Discussion on consideration of other known behavioral factors</th>
<th>Empirical or applied model</th>
<th>Validation of model with empirical adoption data</th>
</tr>
</thead>
</table>
| [14]       | Yes (from Tiajin, Shanxi, Henan and Hunan) | No: the paper highlights the several limitations of the model:  
a) Limited number of social factors considered in the model  
b) Survey data is partially used to fully understand the agent’s preferences towards adopting PV | Abstract: Countryside in Beijing | No |
<p>| [23]       | No                       | No                                                          | Applied: Bracknell, UK      | No |
| [21]       | No: the weights in the multi-attribute utility function were determined based on survey data by [24] | No                                                          | Applied: Tucson, Arizona and New York City | No: the threshold value for adoption in a multi-attribute utility theory is determined by running the model for 10 years and comparing it with the global rooftop PV adoption rate among residential households |
| [6]        | No                       | No                                                          | Abstract                    | No |</p>
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<th>Agent population</th>
<th>Behavioral theories</th>
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<tr>
<td>[14]</td>
<td>No</td>
<td>Residential households: 1000 agents</td>
<td>Multi-criteria utility function: if an agent’s total utility exceed the threshold they will install a PV system</td>
</tr>
<tr>
<td>[23]</td>
<td>Solar PV and electric vehicle</td>
<td>Residential households in Bracknell, UK: 44 low voltage feeders (aka neighborhoods were modeled), 18441 total properties (out of which 71 are commercial properties and are not considered as potential PV or electric vehicle adopters)</td>
<td>None</td>
</tr>
<tr>
<td>[21]</td>
<td>No</td>
<td>Residential households: the number of agents is assumed based on Census Bureau population estimates for the next 20 years</td>
<td>Multi-attribute utility function was used to incorporate the effect of four factors in adopting solar</td>
</tr>
<tr>
<td>[6]</td>
<td>Renewable energy (solar) and conventional energy technologies: the authors mention that the factors affecting the effectiveness of diffusion of innovation are unclear because of the complexity residing in the competition among different technologies</td>
<td>Residential households: 1000 agents</td>
<td>Disruptive Innovation Theory and Bass Diffusion Model</td>
</tr>
</tbody>
</table>
Table C.1 (continued)

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<tr>
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<th>Social network structure</th>
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</table>
| [14]       | a) Riskiness in adopting solar (influenced through agents connected through the social network), risk in expected revenue, risk in damage of the PV panels  
b) Self attitude or personal preference of an individual (binary variable: 0 or 1): considered to be influenced by mass media and educations  
c) Social effect: based on self-attitudes of agents connected to an agent in the social network | Barabase-Albert scale-free networks |
| [23]       | Social influence from the agents only from their neighborhood agents (the ABM has modeled 44 neighborhoods) | None: agents within the neighborhood are all connected to each other |
| [21]       | a) Advertising  
b) Neighborhood social network (word-of-mouth)  
c) Household income  
d) Payback period | None: deterministic equation has been used to evaluate the effect of number of households adopting solar in a neighborhood on an agent desire to adopt solar |
- From other adopters  
- From external sources (e.g. mass media)  
b) Performance of technology  
c) Speed of technology progress  
d) Non-conventional dimension: aggregate of environmental friendliness technology, having green image, having high-tech appearance, independence from the grid, having an integrated smart energy service  
e) Reservation price (highest price an individual is willing to pay for buying a technology) | Random network - Erdos-Renyi model |
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<tbody>
<tr>
<td>[12]</td>
<td>No</td>
<td>No: the authors acknowledge that factors influencing PV adoption have been the subject of various publications. Also, the authors mentioned about certain factors such as effect of mass media can quickly create awareness among households to adopt solar but communication between households is most effective for persuading adopters</td>
<td>Applied: Italy</td>
<td>Yes: the model was calibrated with the actual adoption data from 2006 to 2011 by adjusting the utility thresholds and weights on the individual utilities across the eight personas created in the model. Upon calibration the model was used to forecast from 2012 to 2026</td>
</tr>
<tr>
<td>[13]</td>
<td>Yes (5 regions in Botswana: two villages (Kang and Motsegaletau), two towns (Ghantsi and Maun) and city of Gaborone)</td>
<td>No</td>
<td>Applied: Botswana</td>
<td>No</td>
</tr>
<tr>
<td>[19]</td>
<td>No</td>
<td>No</td>
<td>Abstract</td>
<td>No</td>
</tr>
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<tr>
<td>[12]</td>
<td>No: silicon solar cells have been considered as potential rooftop PV adoption model as they had a share of 93% of the Italian market in 2011</td>
<td>Residential households: all Italian households, 10 million in 2006 (agent population increase/decrease based on population of Italy). However, one agent is considered to represent a group of agents to reduce the computational complexity involved in running the simulations</td>
<td>Multi-attribute utility function was used to incorporate the effect of four factors in adopting solar</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Residential household agents</td>
<td></td>
</tr>
<tr>
<td>[19]</td>
<td>PV systems with and without battery</td>
<td>Residential households</td>
<td>None</td>
</tr>
<tr>
<td>[11]</td>
<td>No</td>
<td>Residential households</td>
<td>Multi-criteria utility function: if an agent/s total utility exceed the threshold they will install a PV system</td>
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<td>[12]</td>
<td>The model is built by extending the decision-making framework by Zhao et al. 2011 [21]</td>
<td>Small-world network</td>
</tr>
<tr>
<td></td>
<td>Four factors affect the decision-making of agents:</td>
<td>Total 8 personas (adapted from [25, 26]) were developed to categorize agents having different socio-economic backgrounds and lifestyles. Most of the links in the small-world network were established between agents belonging to the same persona</td>
</tr>
<tr>
<td></td>
<td>a) Payback period</td>
<td>Interactions of households are modeled with immediate neighbors:</td>
</tr>
<tr>
<td></td>
<td>b) Concern to protect the environment</td>
<td>a) Von Neumann Neighborhood</td>
</tr>
<tr>
<td></td>
<td>c) Household income</td>
<td>b) Moore neighborhood</td>
</tr>
<tr>
<td></td>
<td>d) Number of links with the total population and with the rooftop PV adopters</td>
<td>c) Barabási’s Preferential Attachment Model (PAM)</td>
</tr>
<tr>
<td>[13]</td>
<td>Influence from the ten driver agents as described in the agent population</td>
<td>Each agent is assumed to interact with eight adjacent neighbors</td>
</tr>
<tr>
<td></td>
<td>a) Positive and negative interactions between consumers will affect the intention variable ( I ) of an agent to adopt solar. Interactions are determined if an agent is having net metering restrictions in installing solar</td>
<td>None: effect of social interactions was evaluated based on number of solar adopters in the geographic vicinity, measured by a radius around a household</td>
</tr>
<tr>
<td></td>
<td>b) Influence of the government agent/expert advice to motivate people to go solar (i.e. increase intention ( I ) of agents to adopt solar)</td>
<td></td>
</tr>
<tr>
<td>[19]</td>
<td>a) Economic utility: net present value</td>
<td></td>
</tr>
<tr>
<td></td>
<td>b) Income utility: home value is used as a proxy</td>
<td></td>
</tr>
<tr>
<td></td>
<td>c) Environmental utility: among of CO(_2) solar installation will save</td>
<td></td>
</tr>
<tr>
<td></td>
<td>d) Communication utility: solar installers density around the agent</td>
<td></td>
</tr>
</tbody>
</table>