Supply Chain Optimization and Economic Analysis of Using Industrial Spent Microbial Biomass (SMB) in Agriculture

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To My Family...

Abstract

This thesis uses a mixed integer program to minimize the transport and storage cost of delivering spent microbial biomass (SMB), a bio-coproduct resulting from the production of 1,3-propanediol, to farm fields as a soil amendment and fertilizer substitute. The case study examines focuses on a bioprocessing facility and corn production in East Tennessee. The results indicate on-farm storage of SMB minimizes transport and storage costs of the material. A one percent decrease in the moisture content of SMB results in less than five percent decrease in the total transport and storage costs. Future research should investigate farmers' willingness to adopt the practice, cost sharing design, and to apply SMB to other crop production.

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Chapter 1

Introduction

1.1 The Emerging Bioeconomy and Challenges

Bioeconomy solutions could pave a pathway towards increased economic and environmental sustainability and address global and regional challenges of food security, climate change, and resource scarcity [32]. As many as 37 regions and countries have developed strategic plans to promote the growth of the bioeconomy by encouraging biotechnology development and the production of biobased products [41]. The definitions and scope of these plans and strategies are diverse [79]. For example, the Netherlands pioneered the promotion of a biobased economy since 2005. In 2009, the OECD published the *Bioeconomy to 2030-Designing a Policy Agenda*, a report that focusd on promoting biotechnology development. In 2012, the United States White House's *National Bioeconomy Blueprint* proposed a broad approach to support growth of the bioeconomy, including six priorities [55]: 1) funding relevant research and development of a bioeconomy; 2) facilitating the adoption of bioinventions; 3) reducing barriers constraining the growth of biobased industries by developing and reformulating regulations; 4) training a workforce required for the bioeconomy's development; 5) supporting facility upgrades that aligne with research incentives and training led by academic institutions; and 6) identifying and supporting opportunities for the development of public-private partnerships and multi-institutional collaborations. In 2014, Germany released their *National Policy Strategy on Bioeconomy*. Germany's report proposed a comprehensive societal transition toward a bioeconomy, including industries such as agriculture, forestry, horticulture, fisheries, plant and animal breeding, food processing, wood, paper, leather, textile, chemical, and the pharmaceutical industries, and energy sectors. France declared its national bioeconomy strategy in *A Bioeconomy Strategy for France* [6] following previous efforts by the government supporting biotechnology, and renewable energy sources [29].

Although a bio-based economy ("bioeconomy") is a fairly new concept but active field of research [24], questions remain with respect to its definition. However, a unifying theme is the replacement of non-renewable fossil fuel resources that are currently used in industrial production processes and energy supply [63]. Firms in the private industrial sector currently using or experimenting with renewable biological materials will eventually assume leadership roles in development of the bioeconomy and ultimately its success [61]. Depending on the type of renewable materials considered, bioeconomy proponents frequently refer to feedstock materials as first-generation biomass (agricultural crops), second-generation biomass (agricultural crop residues and perennial grasses), and third-generation biomass (algae). These materials can be processed with technologies including anaerobic digestion, pyrolysis, torrefaction, and fermentation.

Among the above mentioned processes and different feedstocks, the most mature and commercialized pathways is currently fermentation using agricultural crops. Advances in microbial bioengineering has also expanded the frontier of fermentation science with respect to the production scale of multifunctional bioenergy products such as ethanol, biodiesel, and other fuels. Non-energy biomaterials such as bioplastics, biofoams and biorubbers; and biochemicals such as 1,3-propanediol, antibodies, and vaccines can also be produced with the recent technology innovations.

In recent years, biotechnologies have revolutionized the bioprocessing industry by expanding product quantity and improving quality. A wide range of bulk and fine chemicals are produced using biotechnologies. In addition, the number of industrial bioprocessing plants is increasing each year, with smaller and more efficient plants and lower market entry barriers [26]. The United States Department of Agriculture (USDA) projected that biochemical production could grow from its current share 2% to 22% of the total market share by 2025 [27]. Economic analyses demonstrate that the annual economic impact of biobased products industry reached $369 billion in the US in 2013, with the biobased chemical sector contributing $5,032 million to the total direct economic value added [45]. Biobased chemicals can also be used as feedstock for many biobased products. The bioprocessing industry is therefore likely going to play an important role in the continued development of the bioeconomy.

However, food security remains an ongoing issue raised by those concerned with expansion of bioprocessing industry development because of its close relationship with the agricultural sector and land use. In 2017, there were 216 biorefineries in United States, with a total operating capacity of 15,737 million gallons ethanol per year. The majority of these biorefinaries used corn as the primary feedstock. About 32% of U.S. corn production was to produce ethanol, but only about 8% of total corn production was used for food, seed, or productio of other goods in 2016-2017 (Figure 1.1). As consumption of corn by the non-food sector increases, it is reasonable to ask the question: will the food and fiber sectors compete with bioprocessing industries for the same or similar resources, such as land and water? If so, what policies are appropriate to maximize producer and consumer surplus? Some studies report that food and biobased production does not compete for land and water. For example, [84] addressed the food security issue, assuming that cellulosic feedstock could be planted on marginal land and have a lower impact on food prices than corn. [4] considered the food security in an optimization model that confined the quantity of domestic biomass dedicated to biofuel production. These approaches may be helpful for moderating concerns pertaining to land and other resource used. However, some argue that obtaining simultaneously the goals of food security and expansion of a biobased economy using agricultural output depends on the coordination of objectives among bioeconomy research, industry, and policy makers [88]. The concept is easy to imagine, but *ex ante* convergent empirical analyses of full scale implementation, logistics, and the economics of using agricultural co-products and residues is limited [65]. A comprehensive understanding of the nexus linking food, feedstock production, and environmental and natural resources is needed to tackle these issues and requires policymakers and bioprocessing industry managers to identify and exploit new ideas and opportunities.

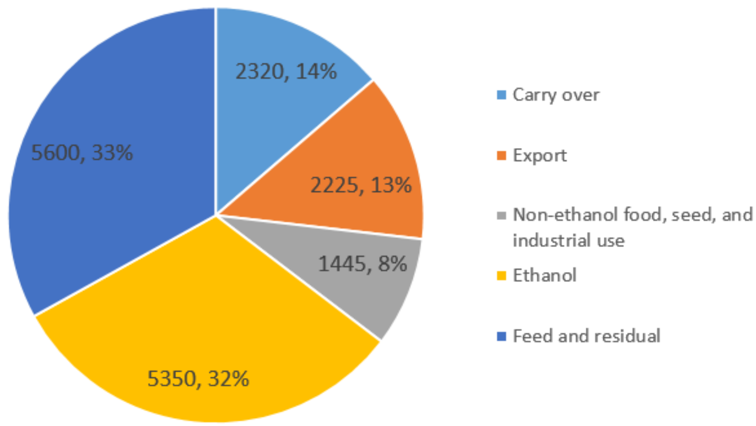


Figure 1.1: U.S. corn use (million bushels and percentage) in 2016-2017 (source: [96]).

Linking the bioeconomy with circular economy principles [76] has become of topical interest in recent academic research. The circular economy approach aims to link different economic sectors in order to minimize losses from waste and to maximize value chains [19]. A novel "biomass-based value web" concept developed by [97] and [85] exemplify this process with sugarcane. This concept encompasses a cascade of feedstock usage and the recycling of co-product streams from feedstock processes and end users. Nonetheless, the food-versus-feedstock concern is a complex issue that requires understanding the complexities between food and bioprocessing feedstock production [75]. This thesis investigates a relevant interaction between agricultural and biochemical production that uses corn grain as a feedstock to produce a certified bioproduct, 1,3-propanediol, or BioPDO$^{\mathrm{TM}}$.

1.2 Utilization of Spent Microbial Biomass (SMB) and Closed Loop Supply Chain (CLSC)

Spent Microbial Biomass (SMB) are co-products generated from fermentation of primary agricultural products in a bioprocessing plant. These co-products can be used as inputs for the production of cellulosic biofuels, animal feeds, and soil amendments because they are abundant in organic material, and contains macro and micro-nutrient. Reuse of SMB could provide a new value chain for bioprocessing plants. However, these co-products resulting from the conversion of biomass to energy or other products are typically non-discrete products, bulky, and of low texture density. Existing research on the use of SMB or similar products are limited to the lab environment or pilot scale [92]. The industries contributing to the bioeconomy's sustainability require research on the economic and logistic feasibility to up-scale operations.

Cost effective recovery of SMB could increase firm profit margins, positively promote the public image of companies, and provide an alternative source of livestock feed or low cost fertilizers. For example, Tennessee's craft beer and spirit industry has continued to expand led by consumer demand for locally produced beer, wine, and spirits. Brewers, distillers, local and regional development agencies, and researchers are beginning to ask how fermentation co-products can add value to their profit margin as well as regional economies. Every year, more than 4.5 million tons of brewer spent grain are generated in US. These brewery and distillery spent grains contain about 20% protein and up to 60% fiber by dry weight [18]. Brewery and distiller spent grain can therefore be used as a source of protein and fiber in livestock feed [100, 17], as a soil amendment by adding nitrogen and organic matter to soils [91, 50, 92], or as feedstock to produce biofuels[23]. Bioprocessing companies can generate revenue from selling co-products such as SMB. Companies can also give away SMB to bolster public image. These types of activities can help the bioprocessing industry secure medium and long term sustainability and profitability, as well as good public reputation. For example, nearly 20% of corn-based dry milling ethanol plant's revenue is generated from distillers dried grains (DDG) sales [94]. The biotechnology company Novozymes distributes 84% of their inactivated SMB to farmers as the fertilizer NovoGro™. The product is currently used by farmers in Denmark and Brazil [7, 71, 72, 73]. [101] studied land application of Novozymes's lime-stabilized SMB on corn and soybeans in the U.S. Their research validated its use as a source of soil amendment for crops. The abundant quantities of SMB resulting from white biotechnology processes suggest there are substantial opportunities for its reuse as a source of crop nutrients. However, these opportunities can be realized if farmers can maintain or surpass break-even crop yields and if concerns about DNA transfer to the environment are addressed [92].

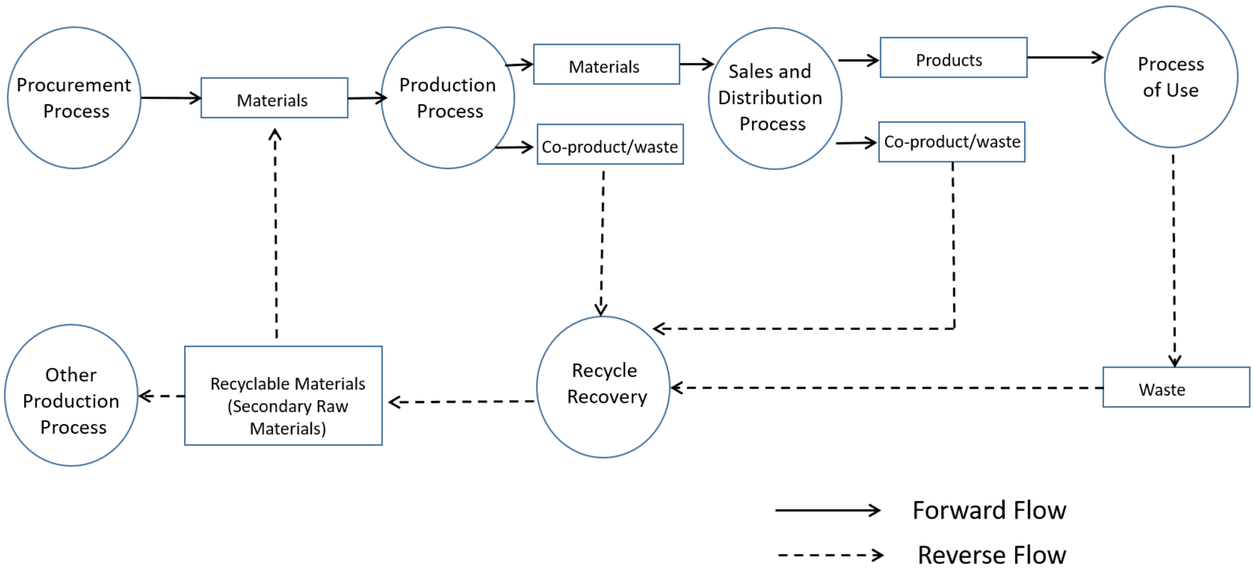


Figure 1.2: Closed Loop Supply Chain (CLSC) Scheme (modified from [86])

Analyzing the value-added pathways resulting from the reuse of SMB is a Closed-loop Supply Chain (CLSC) or reverse logistics (RL) analysis problem [49, 78]. [49] defined CLSC as "the design, control, and operation of a system to maximize value generation over the entire life cycle of a product with recurring recovery of value over time". A CLSC system is composed of forward and reverse supply chains. Forward supply chains are a combination of processes fulfilling customer demand, comprised of entities including suppliers, manufactures, transportation, distribution centers, retailers, and end users [25]. The reverse flow of supply chain is "the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal" [81]. [78] further extended the reverse flow concept to include streams that recover value from goods entering into novel supply chains. Figure 1.2 depicts a CLSC flow, showing that co-products can be produced and marketed at different stages along the forward supply chain and how co-product stream values can be structured to recover and enter reverse flows.

CLSC research is a relatively new direction for solving supply chain management problems, gaining increased attention by academic researchers and private companies in the past decade. A Web of Science search indicates more than 170 papers were published on CLSC in 2017, compared with 30 in 2007. The driving forces behind the growth in CLSC research are economics, legislation, and corporate citizenship [78]. Most research pertains to internal product recycling or remanufacturing, and the creation of secondary markets for recycled and remanufactured goods (e.g., [38, 40, 44, 16, 87, 56, 56, 28, 9, 36, 98, 37, 10, 77, 99]). Some research has focused on co-product (or misnomer "waste") management and other related non-discrete goods (e.g., [62, 90, 86, 93, 47, 2]). [47] provided more recent reviews of RL and CLSC progress.

The existing research focusing on remanufacturing and recycling operational system suggest the following commonalities: 1) a set of similar activities is required for reverse logistic planning problems; e.g., product acquisition, flow of materials, testing, sorting and grading, remanufacturing/reconditioning, and distribution and selling [48]; 2) there are also centralized and decentralized forms of reverse flow of supply chains [66]; 3) conventional location models are useful for planning network structures from a limited number of supply origins to dispersed demand points [60, 89, 39, 40]; 4) the capacity of production and storage and uncertainty in demand for remanufactured goods can be addressed using scenario-based approaches [82] and dynamic and stochastic programming [59, 34, 21, 67]; 5) companies will be most favorable towards CLSC processes and recycle materials if they benefit from the economic and business perspectives [89, 49]. Nonetheless, CLSC research is moving from focusing on remanufacturing operational systems towards understanding markets and firm profitability of recovered products [49]. This movement is slow, and much research on modelign and data is needed [49].

Given that conventional CLSC analysis rely heavily on the internal closed-loop of the company (such as remanufacturing or parts recycling) and the flow of remanufactured goods in secondary markets [38], some researchers have started to examine the value recovered from the production co-products that could be used differently in supply chain pathways on a much broader scales (e.g., [62, 93, 86]). For example, [90] reviewed CLSC research in process industries. They concluded that the current CLSC models were insufficient to address the diversity of the problems faced by today's industries. They further recommended the examination of different "players" within the industry and case study approach. [62] proposed managing industrial and urban waste streams using the CLSC framework. [93] pointed out the CLSC in food processing and manufacturing is very different from other sectors. [86]

focused on the meat processing industry and proposed a CLSC model to evaluate investments to construct infrastructure that recovers unavoidable waste from meat processing to use it for energy production.

It is not surprising to find that there is limited research of CLSC pertaining to SMB or similar co-products generated from the bioprocessing industry. This may be due to the relative small scale and idiosyncratic of the sector. For example, the value recovery and potential use of brewery spent grain [12, 69, 70, 74, 23, 20, 1, 68, 102, 13, 46], could be very different from the value of using brewery spent diatomite sludge [30]. Spent coffee grounds have the potential to be used as soil amendments or as feedstock for producing other biobased products [103], but coffee grounds can actually diminish plant growth if grounds are not pretreated to accommodate soil conditions [53].

In summary, the literature of examples, pilot-scale trials and lab experiments, and technology paths for recovering and recycling organic co-products of industrial processes is rich and instructive [65, 42]. These studies provide a solid foundation and opportunities for researchers to explore the economic and logistic feasibility as a full-scale problem. Comprehensive analyses should include the geographic location of the bioprocessing facilities and demand points, and the cost of handling and distribution. [80] researched spent microalgal biomass as a biofuel production feedstock, indicating the importance of coordinating upstream and downstream processing and techno-economic analysis. [23] studied the economic market and supply chain system for the reuse of brewery spent grain as a feedstock for cellulosic biofuel production. He proposed a conceptual "hub and spoke" model that integrated potential suppliers and end-use customers.

The objectives of this research are 1) to understand the physical characteristics of SMB generated from producing Bio-PDO (1,3-propanediol); and 2) to develop a supply chain network that minimizes the logistic costs of using SMB for field crop production. In many cases, SMB is bulky and exist in different shapes or forms. The primary research question is: how can a company producing Bio-PDO supply SMB to agricultural producers in the right quantities at the right time at the lowest cost.

Chapter 2

Facility Location Model And Strategic Supply Chain Network Design

2.1 Introduction

This research frames the reuse of co-products from bioprocessing plants that depend on agricultural sector as a closed-loop-supply-chain (CLSC) problem. The feasibility of utilizing SMB to fertilize crops depends on the logistical costs of distributing SMB to downstream users; e.g. farmers. The core problem is to identify an effective and efficient infrastructure configurations. Network design theory can establish the connections between existing and/or potential supply chain actors. The cumulative effects of these interactions determine the cost minimizing physical flows associated with the supply and demand of SMB. This background is context to the following questions:

a) How many storage sites are required to deliver available SMB ?

b) Where should storage sites be located?

c) If there are multiple plants providing SMB, which storage sites should be assigned to each plant?

d) How large should each storage site be?

e) How should SMB flows be allocated among the plants, storage sites, and farms?

If SMB is to be used as a crop fertilizer or soil amendment, the key to developing a cost-minimizing distribution network is to determine where SMB can be stored before farmers use it to fertilizer their fields and how big storage sites should be. Optimal SMB storage location and capacity minimizes the cost of meeting farmer demand for SMB subject to the product's availability, existing infrastructure (road system), and system capacity. System capacity refers to the bioprocessing facility's production of SMB and total demand for SMB by farmers. Given the bulkiness and non-discrete form of SMB, transportation and storage facility costs will drive the firm's decision of where to locate storage facilities and where to deliver SMB. It is therefore necessary to determine how many storage facilities are required, storage capacity, the cost of storing SMB, and the travel distance to fields (demand nodes). This is a classic facility location problem in the context of strategic supply chain network design [64]. The problem can be conveniently solved as a Capacitated Facility Location (CFL) model. The CFL model is rooted in the general class of p-median problem.

2.2 The p-median Problem and Capacitated Facility Location Model

There are various types of facility location problems with different measurements of effectiveness of a facility location [31]. One way to measure a facility's effectiveness is the average distance or time that products or services must travel from a facility to the end users. In 1964, Hakimi [51] introduced the p-median problem. He called a set of p points (facilities) as "medians of the network" if the set of points (facilities) results in a minimum total weighted distance between facilities and product demand nodes. The objective of a p-median problem is to minimize the sum of the weighted distances between facility and demand points, subject to a fixed number of facility locations given a distance matrix and candidate locations. The number of facilities is predetermined, but the location of facilities is endogenous. Figure 2.1 illustrates a typical input and output of a p-median problem. The inputs for a p-median problem are demand points (nodes) indicating where the demand is concentrated, and the quantity demand at the location, and candidate median sets indicating

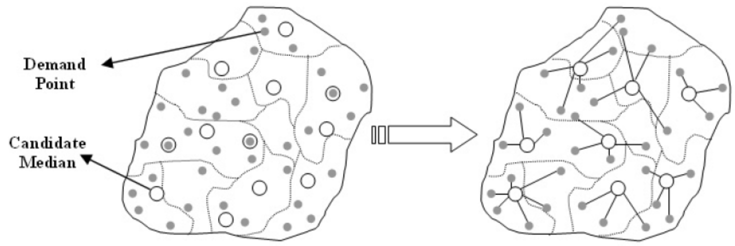


Figure 2.1: Typical input (left figure) and output (right figure) of the p-median problem (source: [43])

possible facility locations. The optimal solution of the p-median problem is a set of facilities and locations that minimize the sum of weighed distance traveled between the selected facility and the demand nodes served.

The p-median problem can be expanded to include more realistic constraints, such as the maximum travel distance from the facility to customers [57] and consideration of transportation and facility setup costs [15, 11]. The Capacitated Facility Location (CFL) model is an extension of p-median problem and has been considered one of the most important location model used extensively by public organizations and private industries [35]. A typical CPLM problem composed of the following aspects:

a) A product is produced at one plant;

b) This product is distributed to facilities in various locations with limited capacities before reaching the end users;

c) Demand at each location is known;

d) The p locations of facilities are determined from a finite set of candidate locations in order to effectively distribute the product with the objective of minimizing cost.

In another words, the CFL model aims to determine an optimal set of capacitated facilities such that the sum of facility construction and transportation costs is minimized. The mathematical formulation of the CFL model is a mixed integer programming problem with facility locations entering the solution as binary variables:

$$\text{minimize} \quad \sum_{i \in U} \sum_{j \in V} + \sum_{i \in U} c_{ij} x_{ij} + \sum_{i \in U} f_i y_i \tag{2.1}$$

subject to:

$$\sum_{i \in U} x_{ij} = 1 \qquad \forall j \in V \tag{2.2}$$

$$\sum_{j \in V} d_j x_{ij} \leq q_i y_i \qquad \forall i \in U \tag{2.3}$$

$$\sum_{i \in U} y_i = p \tag{2.4}$$

$$x_{ij} \geq 0 \qquad \forall i \in U, j \in V \tag{2.5}$$

$$y_i \in \{0, 1\} \qquad \forall i \in U \tag{2.6}$$

where x_{ij} is a positive continuous decision variable determining the amount of products shipped from facility location i to meet the demand by client j, and y_i is a binary variable equal to 1 if the facility is sited in i, and zero otherwise. The symbol U is the set of candidate locations for i; and V is the set of customers for j. The parameter d_j is the demand by client j. The paramter q_i is the capacity of facility i. The symbol c_{ij} denotes the cost of delivering products from facility i to customer j, and f_i is a fixed cost associated with setting up facility i.

The objective function (Eq. 2.1) minimizes the total costs of transportation and facility setup. Eq. 2.2 ensures that the demand of each customer is satisfied. Eq. 2.3 represents the connection between product shipments and facility capacity; i.e., the demand for the product cannot exceed the facility's supply capacity. Eq. 2.4 sets the total number of facilities to p. Eq. 2.5-2.6 define x_{ij} as a positive variable and y_j an integer variable of 1 or 0.

The basic CFL model assumes as single planning horizon, deterministic parameters (i.e., demands and costs), a single product, and one type of facility. The CFL problem provides a reasonable starting point for models including more constraints compared with the typical p-median problem. However, the CFL model is still insufficient for dealing with the complex real-world facility location contexts. Hence, many extensions to the CFL formulation have been suggested and extensively studied, especially during supplying chain planning stage [64].

2.3 Linking Supply Chain Network Design with a Facility Location Model

Determining the optimal locations and capacity of SMB storage facilities is a special case of the CFL problem, given that storage facilities need to be strategically located to meet fertilizer demand of farmers. Storage capacity is limited because the demand and supply of SMB is finite and there are different costs associated with the capacity of storage facilities. Storage capacity does not have to be uniform, and there is no need to constrain the total number of storage sites. To transport SMB, dumpster trucks with specific load capacities are required. There is a limit on the maximum travel distance for the type of truck used and each truck load.

SMB is a new material for crop production for many farmers. Demand for SMB is uncertain at this point. There is limited information about farmer's willingness to adopt this product as a soil amendment. However, crop acreage maps are a reasonable prior on distribution of potential demand. Another uncertain aspect is how much SMB a farmer is willing to apply on each acre. Farmers are generally risk averse [8]; they need some assurance that SMB is a reliable substitute for conventional fertilizers. In order to find the optimal number of facilities and location and capacity these facilities, a mathematical programming model should be able to take into consideration the non-discrete characteristics SMB as a commodity product and the uncertainty in product demand.

Chapter 3

Supply Chain and Logistic Optimization of Spent Microbial Biomass (SMB) Distribution as a Soil Amendment

3.1 Introduction

The logistic feasibility of distributing SMB to farmers to replace part or all of the commercial nitrogen fertilizer used for corn production is considered in this chapter. Most bioprocessing plants are operated on a daily basis and at fixed levels of output. Therefore, this analysis assumes the supply of SMB is also constant. However, demand for SMB by farmers would be periodical, probably occurring after harvest or before planting. For corn production, suitable field days are limited to at most three months (March, April, and November). During this time, fields must be prepared, fertilized, planted, and harvested. Designing an optimal supply chain network that ensures the appropriate storage and timely delivery of SMB to meet farmer demand is an important logistical cost problem to be determined before large-scale implementation of SMB distribution to farmers as a closed-loop supply chain system is feasible.

This chapter describes the modeling framework used to identify optimal SMB supply chain network configurations that minimize the logistic costs of SMB distribution to storage

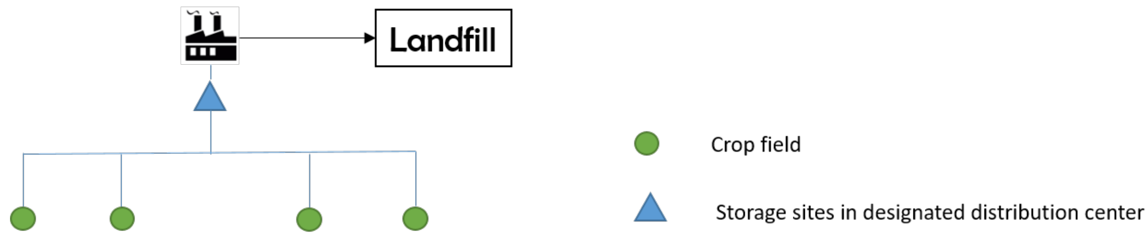


Figure 3.1: Single Distribution Center (SDC).

sites and fields. The modeling framework applies to a case study of SMB transport to row crop farmers in East Tennessee from the DuPont Tate & Lyle facility in Loudon, Tennessee to growers in the region.

3.2 Potential Supply Chain Configuration

3.2.1 Distribution through a single distribution center

A single distribution center (SDC) stored and shipped SMB at a single location. The capacity of this location should be large enough to hold all the SMB shipped from the bioprocessing plant to the distribution center (storage site) over a specific time period. SMB is subsequently distributed from the storage location to a field if the farmer is willing to apply the material. Figure 3.1 illustrates the SDC network concept. Large-capacity storage systems may require larger facility investment and additional management costs to coordinate shipments from a centralized storage location to farm fields on demand. The window of demand for SMB is approximately 90 days.

3.2.2 Distribution through multiple distribution center

Consider now multiple distribution centers (MDC). SMB is stored in more than one location. Storage capacities and locations vary, depending on SMB demand by farmers and field locations (Figure 3.2). This is a decentralized system. Candidate (or potential) sites could be specific locations designated as distribution centers (DC) or farms that are willing to store SMB on site. The on-farm storage (or DC) of SMB would be applied to the farmer's field on demand. That is to say, if SMB is stored on the farm, demand at that location is

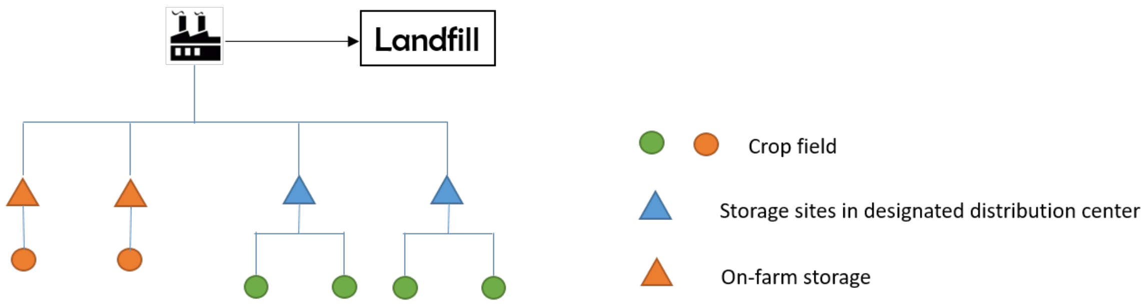


Figure 3.2: Multiple Distribution Center (MDC).

known. However, if the SMB is stored at designated DCs, it can be shipped to other farm locations on demand.

3.3 Mathematical Models

Two models were developed to optimize the SDC and MDC systems using Mixed Integer Linear Programming (MILP). For both models, total costs of storage and delivery of SMB, subject to a set of constraints including supply, demand, and storage capacity, are minimized. Stochastic analysis and a Monte Carlo simulation was conducted to characterize the distribution of locations of SMB distribution centers under uncertain demand and the corresponding logistic costs.

3.3.1 The Single Distribution Center (SDC) model

The SDC model minimizes the total of storage, transportation, and landfill costs (Eq. 3.1), subject to a set of constraints on supply, demand, shipping routes, and candidate storage site constraints.

The objective function is:

$$\text{minimize} \qquad CS + CT + CL \tag{3.1}$$

where

CS: total cost of storage facilities (\$);

CT: total cost of transportation (\$);

CL: total landfill cost if not for agricultural use($);

Total storage cost, CS, is the sum-product of a binary variable, b_{js}, and H_s, the annual cost of a storage facility with capacity type s (Eq.3.2). The binary variable b_{js} denotes the selection of storage location j and its associated capacity type s.

$$CS = \sum_{j \in J} \sum_{s \in S} b_{js} \cdot H_s \tag{3.2}$$

The transportation cost, CT includes transportation from bioprocessing plant i to storage location j and then from storage j to field k (Eq. 3.3). The unit costs of delivering SMB from bioprocessing plant i to storage j is c_{ij}, and the shipment volume between i and j is v_{ij}. The transportation cost of delivering SMB from storage to crop fields is the sum-product of unit shipment costs c_{jk} and the shipment of SMB from j to k (v_{jk}). In the SDC model, only one storage location is selected, therefore $J = 1$.

$$CT = \sum_{i \in I} \sum_{j \in J} c_{ij} \cdot v_{ij} + \sum_{j \in J} \sum_{k \in K} c_{jk} \cdot v_{jk} \tag{3.3}$$

Total landfill costs, CS, are the sum-product of the amount of SMB sent to landfill location from bioprocessing plant i (y_i), and the unit cost of landfill per ton, l (Eq. 3.4). It is assumed that only one landfill location is available.

$$CL = \sum_{i \in I} y_i \cdot l \tag{3.4}$$

Eq. (3.5 - 3.8) are model constraints. Given an SMB application rate γ, the SMB shipped from storage j to farm k (v_{jk}) cannot exceed the total SMB farmer demand ($\gamma \cdot \bar{x}_k$) (Eq.3.5, where $\bar{x}_k$ is the corn production area in k). The total shipment volume of SMB from bioprocessing plant i to j is $\sum_{j \in J} v_{ij}$ plus the amount of SMB sent to landfill equals to total available of SMB in i (G_i) (Eq.3.6). The shipment of SMB received by storage site j is $\sum_{i\in I} v_{ij}$. This quantity cannot exceed the storage capacity of location j ($\sum_{s\in S} \eta_s \cdot b_{js}$ in Eq. 3.7, where η_s is the capacity of storage type s). Eq. 3.8 shows that the amount of SMB shipped from storage site j to farm field k should not exceed the amount shipped into j from plant i. The following constraints depict this pathway:

$$v_{jk} \leq \gamma \cdot \bar{x}_k \qquad \forall k \in K \tag{3.5}$$

$$\sum_{j\in J} v_{ij} + y_i = G_i \qquad \forall i \in I \tag{3.6}$$

$$\sum_{i\in I} v_{ij} \leq \sum_{s\in S} \eta_s \cdot b_{js} \qquad \forall j \in J \tag{3.7}$$

$$\sum_{k\in K} v_{jk} \leq \sum_{i\in I} v_{ij} \qquad \forall j \in J \tag{3.8}$$

Given candidate storage locations, only one storage unit is allowed in each candidate location (Eq. 3.9). Eq. 3.9 shows also that only one capacity type is permitted in the SDC model. This capacity type ($s = S$) must be greater or equal to the total SMB that needs to be stored. Here, S is the storage capacity type that is large enough to hold all the SMB demanded by farmers. The remaining SMB is shipped to a landfill.

$$\sum_{j\in J} \sum_{s\in S} b_{js} \leq 1 \tag{3.9}$$

3.3.2 The Multiple Distribution Centers (MDC) model

The MDC model is structured similarly to the SDC model, except that this model permits more than one distribution center and single storage site. The capacity of each storage site is varied and depends on farmer demand.

The objective function is:

$$\text{minimize} \qquad CS + CT + CL \tag{3.10}$$

where

CS: total storage cost ($);

CT: total transportation cost ($);

CL: total landfill cost ($);

Total storage cost, CS, are composed of the storage costs of distribution centers j, $\sum_{j \in J} \sum_{s \in S} b_{js} \cdot H_s$, and storage costs at the farm location k, $\sum_{k \in K} \sum_{s \in S} f_{ks} \cdot H_s$ (Eq. 3.11). The variable f_{ks} is binary, selecting only storage locations at site k.

$$CS = \sum_{j \in J} \sum_{s \in S} b_{js} \cdot H_s + \sum_{k \in K} \sum_{s \in S} f_{ks} \cdot H_s \tag{3.11}$$

The transportation cost, CT, is composed of three parts: 1) the cost of delivering SMB from bioporcessing plant i to distribution centers indexed by j; 2) the cost of delivery of SMB from bioprocessing plant i to one or more on-site farm storage locations k; and 3) delivering SMB from distribution center j to a field located at k. Eq. 3.12 calculates total transportation costs. The parameters c are the unit transportation costs and v are shipments volumes. The variable CL is calculated as in Eq. 3.4.

$$CT = \sum_{i \in I} \sum_{j \in J} c_{ij} \cdot v_{ij} + \sum_{j \in J} \sum_{k \in K} c_{jk} \cdot v_{jk} + \sum_{i \in I} \sum_{k \in K} c_{ik} \cdot v_{ik} \tag{3.12}$$

Eq. 3.13 -19 are the main constraints of the MDC model. Eq. 3.13 is the demand constraint, which is similar to Eq.3.5. Here, demand equals to shipment from storage j to farm location k and direct shipment from i to k, denoted by v_{jk} and v_{ik}, respectively.

$$\sum_{i \in I} v_{ik} + \sum_{j \in J} v_{jk} \leq \gamma \cdot \bar{x}_k \qquad \forall k \in K \tag{3.13}$$

Eq. 3.14 ensures that the total shipment from bioprocessing plant i to storage j, to farm location k, and to a landfill cannot exceed the total SMB available from the bioprocessing plant i. The variable v_{ij} is the shipment volume of SMB from bioprocessing plant i to DC j, and v_{ik} is the shipment volume of SMB material from plant i to farm location k for on-site storage. The parameter G_i is the total available SMB.

$$\sum_{j \in J} v_{ij} + \sum_{k \in K} v_{ik} + y_i \leq G_i \qquad \forall i \in I \tag{3.14}$$

Eq. 3.15-16 ensure that SMB shipment to storage j and farm location k does not exceed storage capacity. In these equations, b_{js} is a binary variable indicating the storage at different capacity types s in location j, and f_{ks} is a binary variable identifying on-farm storage location and capacity. The parameter η_s is storage capacity indexed by type s.

$$\sum_{i \in I} v_{ij} \leq \sum_{s \in S} \eta_s \cdot b_{js} \qquad \forall j \in J \tag{3.15}$$

$$\sum_{i \in I} v_{ik} \leq \sum_{s \in S} \eta_s \cdot f_{ks} \qquad \forall k \in K \tag{3.16}$$

Eq. 3.17 ensures that SMB shipment volume from storage j to location k does not exceed the shipment received by DC j.

$$\sum_{k \in K} v_{jk} \leq \sum_{i \in I} v_{ij} \qquad \forall j \in J \tag{3.17}$$

Only one facility regardless of capacity type is allowed in each location (Eq. 3.18-19).

$$\sum_{s \in S} b_{js} \leq 1 \qquad \forall \quad j \in J, s \in S \tag{3.18}$$

$$\sum_{s \in S} f_{ks} \leq 1 \qquad \forall \quad k \in K, s \in S \tag{3.19}$$

3.3.3 Sample Average Approximation (SAA) and Monte Carlo simulation

Stochastic programming and Monte Carlo simulation were used to evaluate the MDC deterministic model when facing the demand uncertainty. Without knowing where the demand nodes location and demand quantity, a percentage of the total number of candidate demand locations is randomly selected to simulate demand uncertainty for SMB. The right-hand-side of Eq. 3.13 is changed, given different realizations of SMB demand. If demand locations are randomly drawn M times, there will be M sets of "what if" problems. Solving for the M sets of MDC problems independently results in M sets of optimal solutions for SMB storage, quantities delivered to demand locations, and corresponding storage and transportation costs. This is, however, not very useful information because once storage facility sites and capacity types are determined, they are fixed in the short or medium term regardless of changes in demand locations or quantities. It is therefore more revealing to understand how costs change due to changes in demand, holding storage locations and capacities constant. This is a reasonable assumption because once the storage shed is financed and determined, and contracts with owners are signed, it may be relatively more costly to change storage locations and capacities.

The Sample Average Approximation (SAA) method was applied to estimate the location of the storage sites and determine the capacity of each site under uncertainty [3, 58]. The basic idea of SAA is to generate multiple random samples of scenarios from the population and to form a optimization model with expected objective value function that is approximated by the corresponding sample average function. For example, let $D^1, ..., D^N$ be an independently and identically distributed random sample of N realizations of a demand vector D, such as farms demand for SMB, the sample average function can be expressed as in Eq. 3.20:

$$\hat{f}_N(b) := \frac{1}{N}\sum_{n\in N} F(b, D^n) \tag{3.20}$$

where b is a variable to be solved with this model (such as the facility location and capacity type), and $F(b, D^n)$ is the objective function when D^n is realized. The optimization problem is minimizing Eq. 3.21 subject to resource or other constraints.

$$\min \quad \hat{f}_N(b) \tag{3.21}$$

After the SAA problem is solved, the variable solution can be evaluated using Monte Carlo simulation. This approach had been widely used in facility location problems under uncertainty [83].

The following procedure uses a N sets for the proposed "what if " demand problems to form a SAA problem that can be solved to determine a single set of storage location and capacity solution, minimizing the expected total cost of these N set of problems. The solution for storage location and capacity can be viewed as an approximation of the true optimal configuration of the distribution network. To evaluate the cost efficiency of the configuration, the Monte Carlo simulation is conducted by fixing the binary variable pertaining facility location and capacity in the aforementioned optimization model, changing the demand nodes and corresponding quantities based on the M random draws. Note that M is much larger than N.

The mathematical formulation of the SAA model and Monte Carlo simulation steps pertaining to SMB storage site locations and capacities are as follow:

Step 1 : based on a hypothetical participation rate, randomly select fields from all crop fields to generate a new $\bar{x}_k$ for M times;

Step 2 : formulate the SAA mathematical programming model based on the N random draws as follows:

$$\min \qquad \frac{1}{N}\sum_{n\in N} CT^n + CS^n + CL^n \tag{3.22}$$

subject to:

$$\sum_{j\in J} v_{jk}^n + \sum_{i\in I} v_{ik}^n \le \gamma \cdot \bar{x}_k^n \qquad \forall k \in K, n \in N \tag{3.23}$$

$$\sum_{j\in J} v_{ij}^n + \sum_{k\in K} v_{ik}^n + y_i^n \le G_i \qquad \forall i \in I, n \in N \tag{3.24}$$

$$\sum_{i\in I} v_{ij}^n \le \sum_{s\in S} \eta_s \cdot b_{js} \qquad \forall j \in J, n \in N \tag{3.25}$$

$$\sum_{i\in I} v_{ik}^n \le \sum_{i\in I}\sum_{s\in S} \eta_s \cdot f_{ik}^n \qquad \forall k \in K, n \in N \tag{3.26}$$

$$\sum_{k\in K} v_{jk}^n \le \sum_{i\in I} v_{ij}^n \qquad \forall j \in J, n \in N \tag{3.27}$$

$$\sum_{s\in S} b_{js} \le 1 \qquad \forall j \in J \tag{3.28}$$

$$\sum_{s\in S} f_{ks}^n \le 1 \qquad \forall k \in K, n \in N \tag{3.29}$$

where Eq. 3.22 minimizes the total cost of N demand situations, subject to constraints presented in Eqs. 3.23-29. Most of the constraints are the same as in section of MDC for each n.

Step 3 : solve the model formulated in Step 2 with a small N and find the optimal solution for facility location and capacity b_{js}, where b_{js} are set to equal for each n;

Step 4 : solve the individual MDC model with M different random draws from the populations of demand area and locations ($\bar{x}_k$ will be different for each $m \in M$) holding the value of binary variable b_{js} at the optimal solution obtained in Step 3.

This procedure can be iterated over different values of N from one to a larger number as long as the problem is tractable and can be solved in a reasonable time. Then, each iteration may result in a different configuration with respect to different N. The larger N

is, the smaller the gap between the approximate solution to the 'true' configuration. The trade-off is that the computational resources required increases exponentially as N increases [3].

Each network configuration at solution b_{js} obtained in Step 3 can be further evaluated with Monte Carlo simulation using M sets of samples in Step 4, where the integer variables b_{js} are given. The integer values are the same for each simulation. An output of the simulation is the distribution of costs (the objective value) with respect to the M possible demand scenarios. The distributions can be used to tests hypotheses about demand, costs, or other policies that affect firm profitability.

3.4 Case Study on SMB Generated from 1,3 Propanediol Fermentation in Eastern Tennessee

3.4.1 Problem statement

The Dupont Tate & Lyle plant is located in Loudon, Tennessee. The facility is one of the world's largest aerobic fermentation plants with an annual production of 140 million pounds per year of Bio-PDO^{TM} [45]. Each year, approximately 17,000 metric tons of SMB are produced during the fermentation process. As of 2018, the facility is planning to expand their Bio-PDO^{TM} production capacity, which will more than double the annual SMB production. The current protocol is to haul SMB to landfills following heat-deactivation [52]. The facility's SMB contains 50% C on a dry matter basis (DM), 11% N (DM), and trace amounts of other essential plant nutrients including Ca, Cu, K, Mo, P, and Zn [52]. Halter and Zahn's [52] study also traced the DNA degradation of SMB from Bio-PDO™ production in the laboratory and field environments. The researchers concluded that microbial DNA presence was not detectable in the field 14 days after application, and found no evidence of gene transfer into local microbial communities. [52, 92] evaluated the use of SMB from Bio-PDO™ production as a nutrient source for tall fescue and corn production to determine if the material could serve as an N fertilizer source. Their results were encouraging with respect to SMB's potential as a nutrient source for production in agriculture [92].

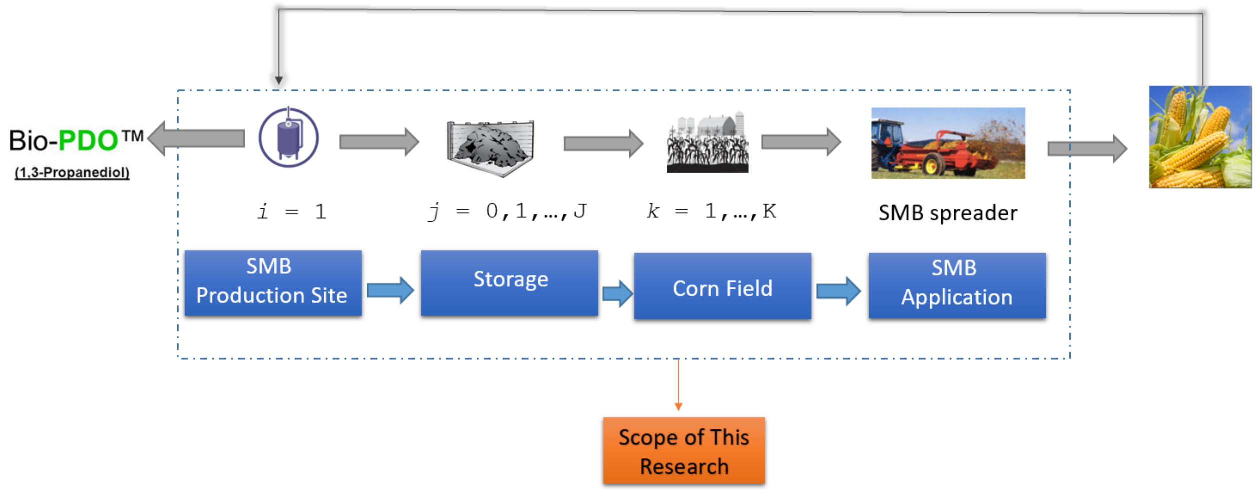


Figure 3.3: Scope of the case study.

This case study focuses on the storage, distribution, and farmer fulfillment for SMB. Figure 3.3 depicts the movement of SMB from the bioprocessing facility to the field as a closed loop supply chain (CLSC) system. The CLSC system encompasses the flow of raw material (corn) from harvest sites to the plant (Tate & Lyle), production and distribution of the main product (Bio-PDO^{TM}) to customers, and the production and distribution of co-products (SMB) to meet farmers' fertilizer demand. The scope of this research focus on the SMB distribution exclude the supply chain of corn from production site the bioprocessing plant.

SMB has a similar moisture content as feedlot manure. The material can be transported using dumpster (roll-off) trucks and stored in sheds. Figure 3.4 shows the type of dumpster truck and storage shed considered in this application.

The main assumptions used in the proposed SDC and MDC models include:

(1) The total supply of SMB is fixed because the production level of SMB is set to a daily fixed amount;

(2) SMB is produced year-around (365 days);

(3) Dumpster trucks are used to transport SMB. The current practice used by the bioprocessing plant is to transport SMB to a landfill with a 12 ton dumpster truck;

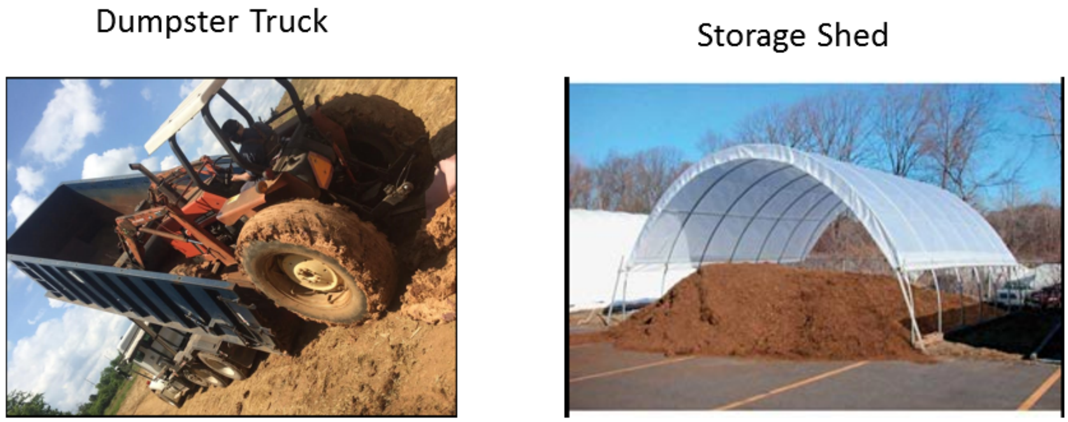


Figure 3.4: Dumpster truck for delivery and storage shed.

(4) Farmer use of SMB is limited to corn production;

(5) There is a single source of SMB serving the study region.

The study region is a 100-mile radius around the bioprocessing plant. The study area was digitized into 5-square-mile hexagons using ArcGIS (Figure 3.5). These polygons are the functional "decision-making units", determining the nodes along optimal transportation pathways. Potential SMB application and storage locations are identified from the distribution of corn-producing land inside the circumscribed research area at the hexagon level. A distance matrix was generated between hexagons using ArcGIS based on existing roads system. The maximum allowable travel distance between hexagons was 75 miles.

The Crop Data Layer generated by the USDA's National Agricultural Statistics Service [95] was digitized and superimposed onto the hexagons to identify areas where corn production occurs (Figure 3.5). Thus, hexagons containing corn production areas are also potential demand sites for SMB.

Hexagons where there is a Farmers CoOP are selected as candidate sites for SMB storage facilities because they are typically located near major roads. In addition, hexagons with corn acres are also candidates for on-farm SMB storage sites. There are currently 46 CoOPs

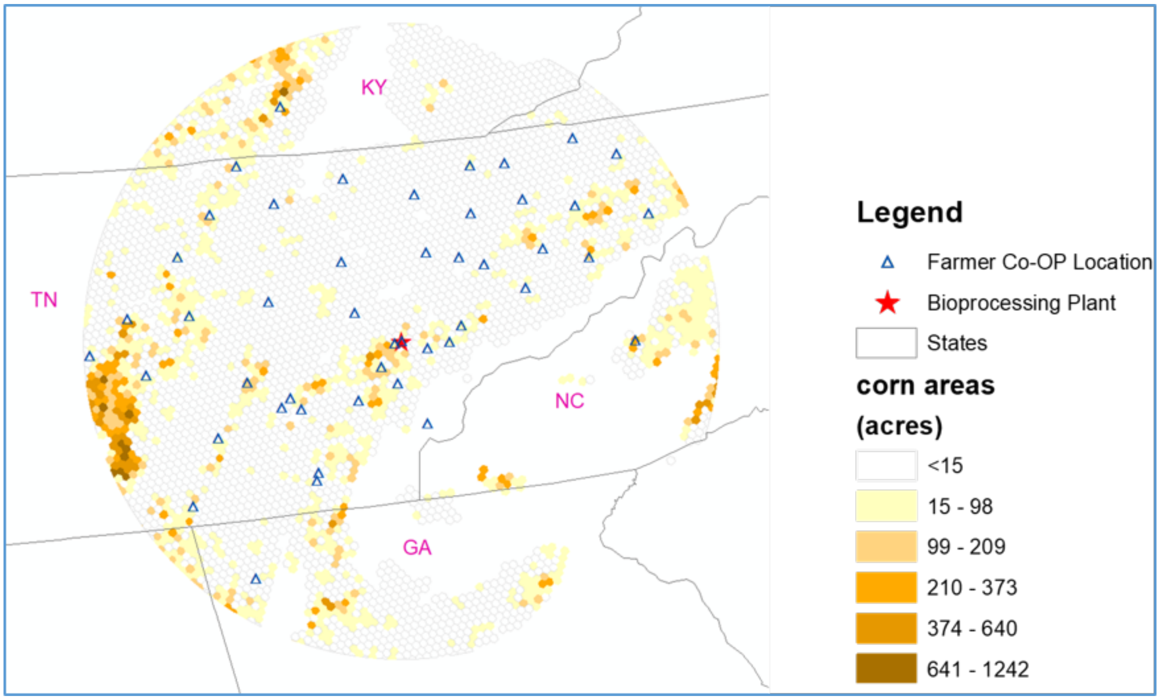


Figure 3.5: Study region, corn production area and location, and farmers CoOP locations.

located in the study region. The geographic resolution of the study area, the location of the Tate & Lyle plant, candidate storage locations, and the distribution of corn acreage are presented in Figure 3.5.

3.4.2 Transportation, storage, and landfill parameters

Table 3.1 summarizes the parameters used to calculate SMB transportation and storage costs. The unit transportation cost per ton-mile is calculated using Eq. 3.31 (below), where \$177.5 is the current pick-up charge per load currently paid by the plant to transport SMB from Loudon, Tennessee to a landfill in Bradley County, Tennessee. In general, there are 0.5 hours of loading/unloading/waiting time during each trip, and this time is measured as a per-trip fixed cost. The current truck use per hour rate is \$75 per hour. Therefore, the fixed cost for each trip is \$37.5 with a variable cost of \$140 including labor and fuel. The one-way distance between these two locations is about 59.1 miles. At a per truck load quantity of 12 tons, the unit cost (\$ per ton-mile) is:

Table 3.1: Parameters of transportation and storage facility

Items	Value
Maximum travel distance (miles)	75
Daily production of SMB (tons per day)	48
Truck load capacity (tons per truck)	12
Truck cost ($ per hour)	75
Storage initial investment cost for 100 ton facility ($)	5000

$$UnitCost = \frac{\$140}{12 \text{ tons} \times 59.1 \text{ miles}} = 0.1974 \text{ ton-mile} \tag{3.30}$$

Given any distance, the transportation cost for each 12 ton of SMB shipment is:

$$\$37.5 + 0.1974 \text{ ton-mile} \times \text{miles} \times 12 \text{ tons} \tag{3.31}$$

Storage costs are amortized from the initial purchasing cost of a storage unit using a discount rate of 6% over 10 years period. The scaling factor of storage capacity is 1.1. This scaling factor exceeds one because the proposed storage facility requires higher management and coordination costs as SMB throughput capacity increases. For example, at a larger storage capacity, a distribution center will need to serve more demand nodes during the application periods. Table 3.2 shows the annual costs with respect to different storage facility capacities.

Landfill unit costs were set to be much large than distribution to farm use for this case study, assuming that all the SMB will be used in agriculture if there are sufficient demand; i.e., the transport of SMB to a landfill is an option when SMB supply exceeds demand. The current annual supply of SMB is 48 tons per day $\times$ 365 days $= 17,520$ tons. Assuming an application rate of 8 tons per acre, about 2,190 acres of corn areas are required to distribute all of the SMB produced by the bioprocessing plant to farms.

Table 3.2: Annual facility costs with respect to different storage facility capacities

Storage Capacity (000 tons)	Annual cost ($)
0.1	679
0.2	1,456
0.3	2,275
0.4	3,121
0.5	3,990
0.6	4,876
0.7	5,777
0.8	6,691
0.9	7,616
1	8,552
2	18,332
3	28,636
4	39,296
5	50,228
6	61,383
7	72,726
8	84,233
9	95,885
10	107,668
11	119,569
12	131,578
13	143,689
14	155,893
15	168,185
16	180,558
17	193,010
18	205,535

3.4.3 SMB Storage Candidate Location and Demand Scenarios

Candidate locations

With respect to the number and location of storage sites, three scenarios are investigated: **singleCP**, **multiCP**, and **multiCPFM** (Table 3.3).

— **singleCP**

This scenario assumes that a single location stores all the SMB farmers demand. The candidate storage sites are Farmers CoOP locations in the study region. Stored SMB is delivered to farmer fields from the selected location. The SDC model is used to solve for the optimal location and farm fields served;

— **multiCP**

This scenario examines the case of multiple storage locations. Storage units can only be located at nodes with Farmers CoOPs. SMB is shipped to fields from these storage facilities. The MDC model and SAA are applied to solve for the optimal locations and farm fields served. The Monte Carlo simulation was used to evaluate the SAA solution on storage site locations and capacities;

— **multiCPFM**

This scenario allows multiple storage locations to be located at Farmers CoOPs or on farms. If SMB is stored at a Farmers CoOP, the SMB is subsequently shipped to farms when required. However, if SMB is stored on-farm, it can only be used at that farm; i.e., there is only ship-in and no ship-out. Farmers cannot re-sell SMB to other farmers after it is stored on their own farm (a "no arbitrage" condition). This scenario is also solved using SAA to determine storage site locations and capacities.

Table 3.3: Location scenarios

scenarios	number of location	candidate location	model/simulation
singleCP	1	Farmers CoOP	SDC
multiCP	> 1	Farmers CoOP	MDC/SAA and Monte Carlo
multiCPFM	> 1	Farmers CoOP, Corn farms	MDC/SAA

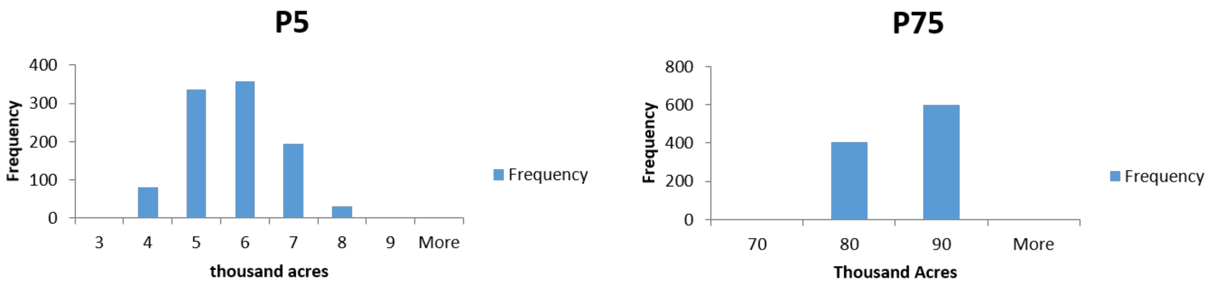


Figure 3.6: Histogram of total corn area (000 acres) from 1000 random draws at participation rates of P5 and P75.

Farmer participation rates and demand for SMB

Scenarios varying farmer demand for SMB is simulated by changing farmer participation (P) and field application (A) rates. It is currently unknown which farms would actually want to use SMB, and subsequently how much SMB they would use in lieu of conventional fertilizers.

A random sampling procedure was used to identify the number of hexagons demanding SMB at different participation rate: from 100% ($P100$) to 5% ($P5$) with 5% decremented change. At participation rates less than 100%, such as 75%, demand locations were randomly drawn from the corn production hexagons in the study region such that the total number of hexagon sampled from the hexagon population was 75%.

Table 3.4 presents the randomly sampled areas at different participation rates based on a single time random drawn from the population. Currently, there are 1,047 hexagons planting more than 15 acres of corn, and the total corn acreage is 107,202 acres. As the participation rate decreases, corn acreage decreases as well and could fall below 4,000 acres. If re-sampling with 1000 draws and setting participation rate to 75%, the average area is 80,375 acres with a minimum of 72,990 acres and maximum of 86,573 acres. At the participation rate of 5%, 1,000 times re-sampling results in the average area of 5,285 acres with a minimum of 3,070 acres and maximum of 8,278 acres. Figure 3.6 presents the frequency and range of corn acres under different participation rates with 1,000 times random draws.

Table 3.4: Participation rates and corresponding hexagon numbers and acres

Participation Rate	Number of Hexagons	Acres (based on a single random drawn)
$P100$	1047	107,202
$P95$	995	101,608
$P90$	942	97,067
$P85$	890	92,552
$P80$	838	86,046
$P75$	785	79,182
$P70$	733	76,585
$P65$	681	63,867
$P60$	628	64,644
$P55$	576	61,814
$P50$	524	57,134
$P45$	471	47,008
$P40$	419	41,166
$P35$	366	36,688
$P30$	314	28,214
$P25$	262	25,822
$P20$	209	22,080
$P15$	157	15,846
$P10$	105	7,359
$P5$	52	3,015

SMB Application Rates

SMB field application rates were varied at 100% ($A100$), 90% ($A90$), 80% ($A80$), 70% ($A70$), 60% ($A60$), and 50% ($A50$). For example, if the application rate is at 50% ($A50$), only 4 tons SMB are applied to each corn acre. At the 100% application rate ($A100$), 8 tons of SMB per acre are applied to fields.

3.5 Software and Solver Routine

The models were programmed in the GAMS (General Algebraic Modeling System) optimization package [22]. The models were solved using the commercial solver CPLEX 10 on the GAMS platform. The relative gap was set to be less than or equal to 0.5%.

3.6 Results

3.6.1 Optimal Solution on the Network

The optimal network solution includes the location of the storage sites and the demand nodes that were served. Given that demand exceeds supply under most of the participation rate assumptions, the model always picked the closest demand point to serve first, followed by the second, and so on.

When the participation rate is higher than 15% ($P15$), if only one distribution center is allowed, the location of this site was either on a hexagon where the bioprocessing plant is currently located or in a candidate hexagon that is about three miles west of the bioprocessing plant. This pattern occurs because both locations are either at the center point or close to the center point of the study region where corn acres are abundant and located within the 75 mile limit.

Figure 3.7 summarizes the network locations and demand areas served under the **singleCP** scenario at low participation rates ($P10$ and $P5$) and the 100% application rate ($A100$). When participation rates were low, the randomly select demand areas are sparsely distributed across the study region. The storage site location is near the demand areas, and clustered southwest of the bioprocessing plant. At the $P10$ and $A100$ levels, the distance between the bioprocessing plant to the storage site is about 52 miles, and 68 miles given $P5$ and $A100$. The red lines on the map connect the storage site and corn field locations served by the storage facility.

When multiple storage locations are considered and candidate locations of storage facilities are sited at Farmers CoOPs (i.e., **multiCP**), the maps of supply network are presented in Figure 3.8 with respect to different participation and application rates. In $P100\_A100$, six CoOP storage sites are selected. Most of the fields served contain more than 99 corn acres. Only a few field locations has small corn acres served. Both storage sites and fields served are proximate to the bioprocessing plant. In the scenario $P75\_A50$, there are nine CoOP storage sites selected. Their locations are further from the bioprocessing plant. In this case, more but smaller fields are served. Pathways between storage and fields are more frequent and distances are longer compared with the $P100_A100$ scenario.

The network configurations of the scenario **multiCPFM** - [$P100\_A100$] and [$P75\_A50$] are presented in Figure 3.9. In these scenarios, most of the storage sites are located on farms instead of Farmers CoOPs. In the $P100\_A100$ scenario, only one CoOP storage site is selected. The remaining storage sites are located on farms. Four CoOP storage sites are selected in the $P75\_A50$ scenario, where most of the on-farm sites have smaller corn field acreages. If there is on-farm storage, SMB will be used at that farm.

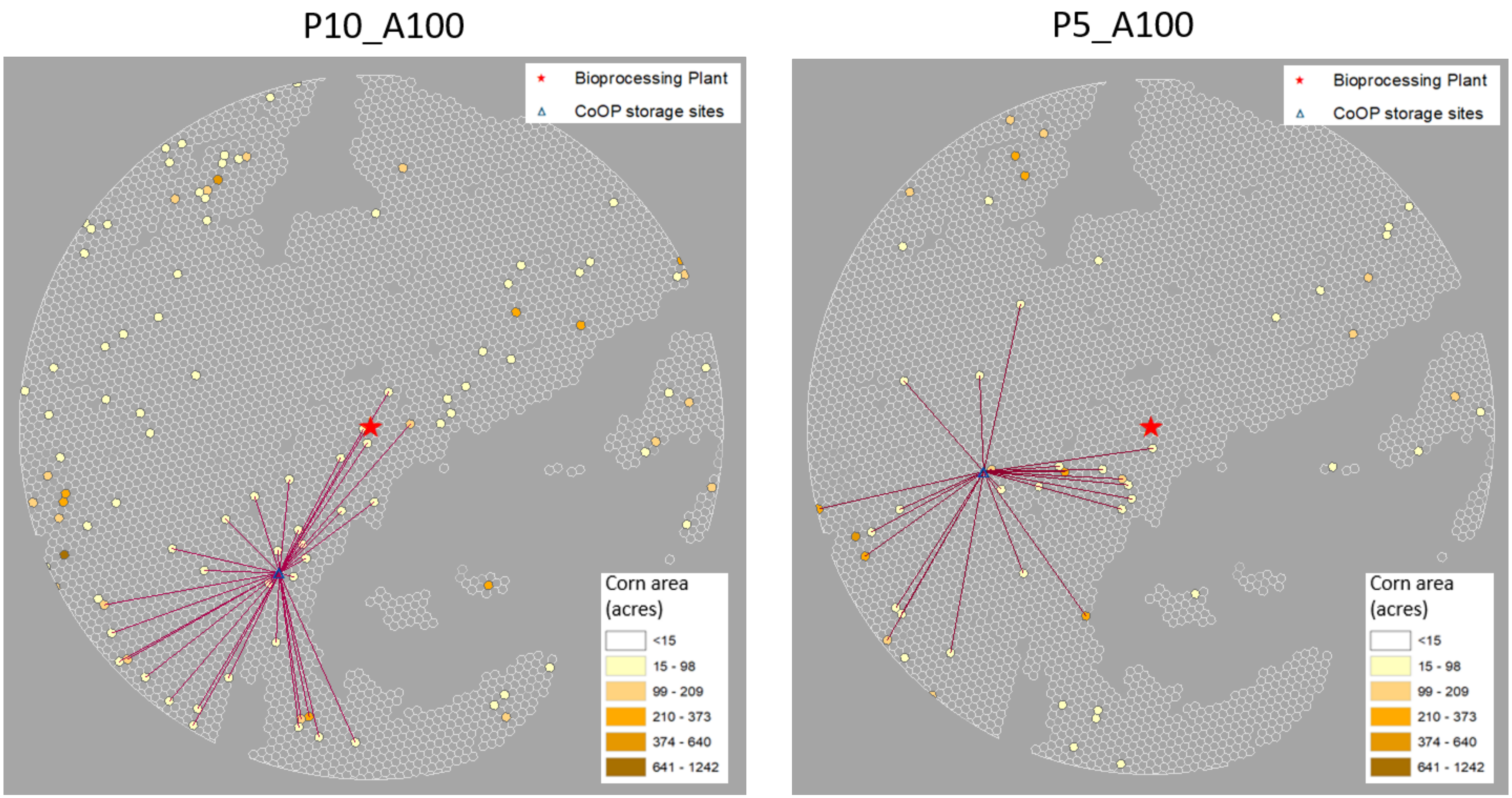


Figure 3.7: Supply network solution under the **singleCP** scenario at a 10% and 5% participation rates and a 100% application rate.

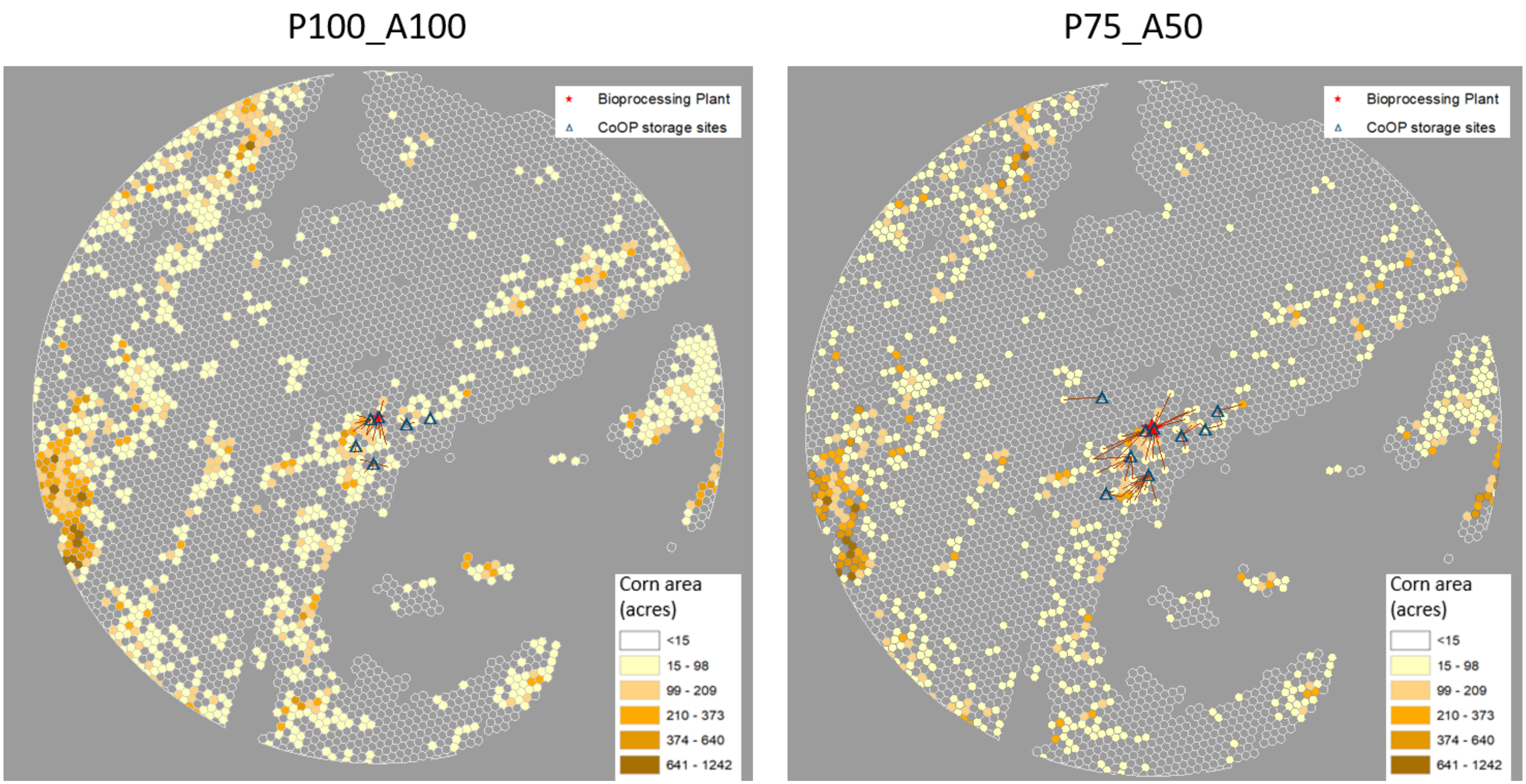


Figure 3.8: Supply network solution under the **multiCP** scenario at a different participation and application rates.

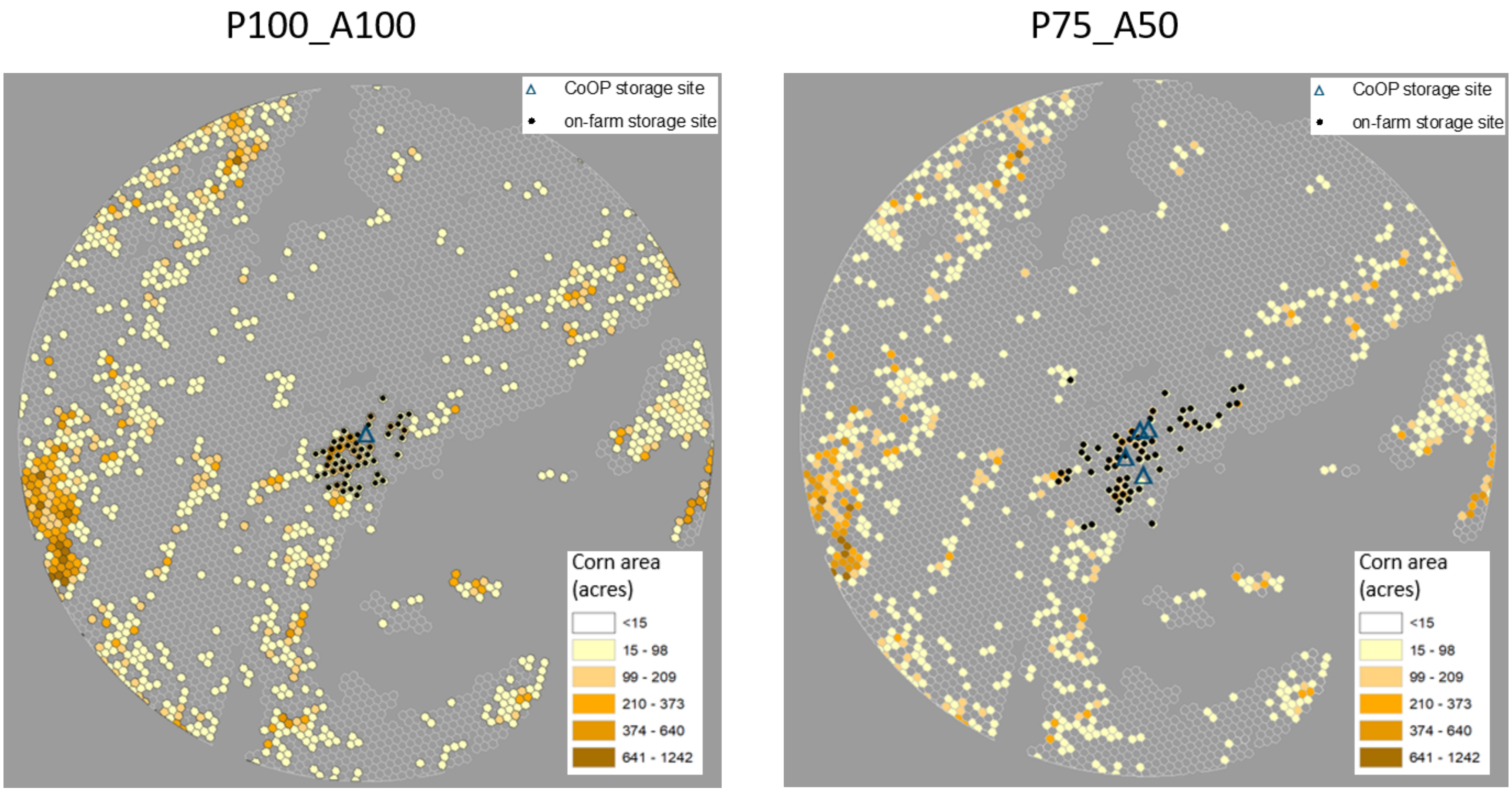


Figure 3.9: Supply network solution under the **multiCPFM** scenario at different participation and application rates.

The total number of storage sites and capacities under [$P100\_A100$], [$P75\_A100$], and [$P5\_A100$] are presented in Table 3.5. In the **singleCP** scenario, only one storage site is allowed. The optimal solution is to site the CoOP in the same hexagon where the bioprocessing plant is located. The storage capacity is 18,000 tons. In the **multiCP** scenario, with [$P100\_A100$], there are six storage sites selected. Two storage sites have a capacity of 7,000 tons; one site 1,000 tons; and another 2,000 tons. There is one site with a storage capacity of 200 tons, and another with a 400 ton capacity. In the **multiCPFM** scenario of $P100\_A100$, most of the storage sites are on-farm and at a smaller capacity. There are 21 sites with capacities of 100 tons, 10 sites at a capacity of 200 tons, 5 sites with a capacity of 300 tons, 4 sites with a capacity of 400 tons, one site with a capacity of 500 tons, two sites with a capacity of 700 tons, three sites with capacity of 800 tons, four sites with capacity of 1,000 tons, and one site with capacity of 2,000 tons. The largest storage capacity is 2,000 tons in this scenario. There is only one CoOP site at capacity of 100 tons and total of 52 sites were located in this scenario. When the participation rate drops to $P75$, the number of CoOP location increases to 10 in the **multiCP** scenario, and to two CoOP locations in the **multiCPFM** scenario. The number of on-farm sites decreased to 47. When the participation rate is very low ($P5$), the number of CoOP sites substantially increases in the **multiCP** and **multiCPFM** scenarios.

At the lower application rate scenario of $A50$, the total number of storage sites and capacities differed from the $A100$ scenario , but at a similar increasing trend (Table 3.6). Lower application rates corresponded with an increase in the number of CoOP sites in the **multiCP** scenario, and an increase in the number of storage facilities on-farm in the **multiCPFM** scenario. As the participation rate decreased to $P5$, the number of CoOP sites increased to 25 in the **multiCP** scenario. There are six more CoOP sites than on-farm sites in the **multiCPFM** scenario.

Table 3.5: Storage capacities and number of storage sites at 100% application rate (A100)

Capacity (000 tons)	P100_A100			P75_A100			P5_A100		
	multiCP	multiCPFM		multiCP	multiCPFM		multiCP	multiCPFM	
	CoOP	CoOP	Farm	CoOP	CoOP	Farm	CoOP	CoOP	Farm
0.1		1	21	1	2	21	1	3	
0.2	1		10	2		8	3	5	8
0.3			5	1		4	3	5	4
0.4	1		4	2		3	3	3	1
0.5			1			2	2	4	
0.6							4	1	1
0.7			2			1	1		1
0.8			3			2	1	1	
0.9							1	1	1
1	1		4	1		4	3		2
2	1		1	1		2	3		1
3									
4									
5									
6				1					
7	2			1					
Total number	6	1	51	10	2	47	25	23	19

Table 3.6: Storage capacities and number of storage sites at 50% application rate (A50)

Capacity (000 tons)	P100_A50			P75_A50			P5_A50		
	multiCP	multiCPFM		multiCP	multiCPFM		multiCP	multiCPFM	
	CoOP	CoOP	Farm	CoOP	CoOP	Farm	CoOP	CoOP	Farm
0.1			32	1	2	30	5	9	9
0.2	1	2	12			10	2	1	4
0.3			1		2	5	1	6	2
0.4			5			5	2	1	1
0.5	1		2				3	1	
0.6			3	1		3	3		
0.7			4			3	1	1	1
0.8			1			2	1	1	1
0.9	1			1		1		1	
1			3	2		2	6	2	1
2	2			1					
3				1					
4				1			1	1	
5				1					
6	2								
7									
Total number	7	2	63	9	4	61	25	24	19

The SAA results for the **multiCP** and **multiCPFM** scenarios at P75_A50 were compared (Figure 3.10). These results are based on $N = 10$ of random draws of demand nodes from the population, assuming a participation rate of 75%. The reason of using 10 draws is because of the computational resource limitations as the problem grows exponentially as N increases. In the **multiCP** scenario, the most likely CoOP storage sites were near the bioprocessing plant. In the **multiCPFM** scenario, only two CoOP storage sites are selected, and most of the storage site are located at farms.

Figure 3.11 provides the SAA solution on locations at 5% participation rate (P5) and 100% of application rate (A100) on $N = 10$. There are total 23 CoOP storage sites were selected with one at 3000 tons, three sites at 2000 tons, two sites at 1000 tons, and the rest with less than 1000 tons. The distance between the bioprocessing plant to CoOP storage sites ranged from one mile (i.e., storage located in the same location of the bioprocessing plant) to as far as 69 miles.

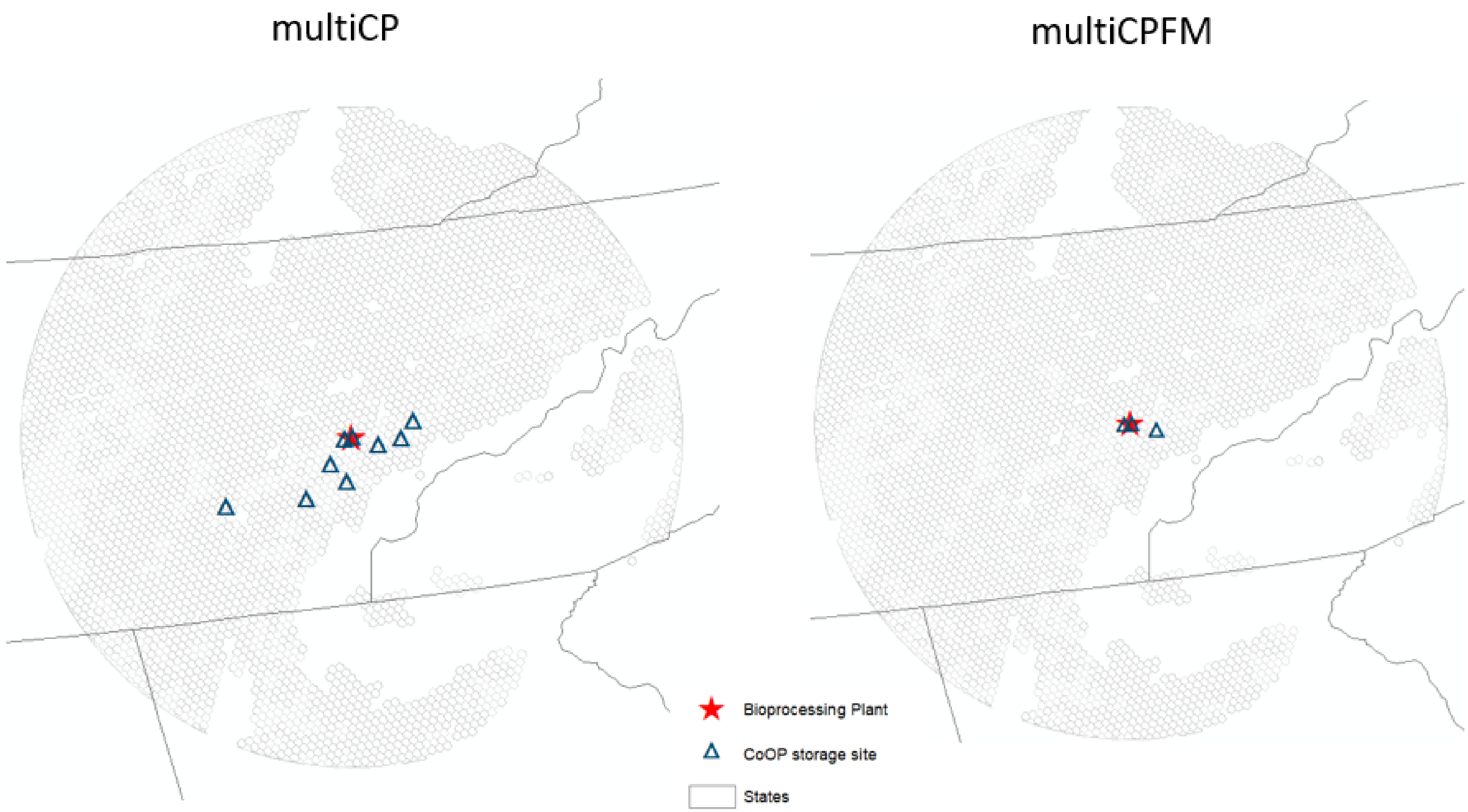


Figure 3.10: Supply network solution under the **mulctiCP** and **multiCPFM** scenarios at P75_A100 with 10 random draws of demand nodes.

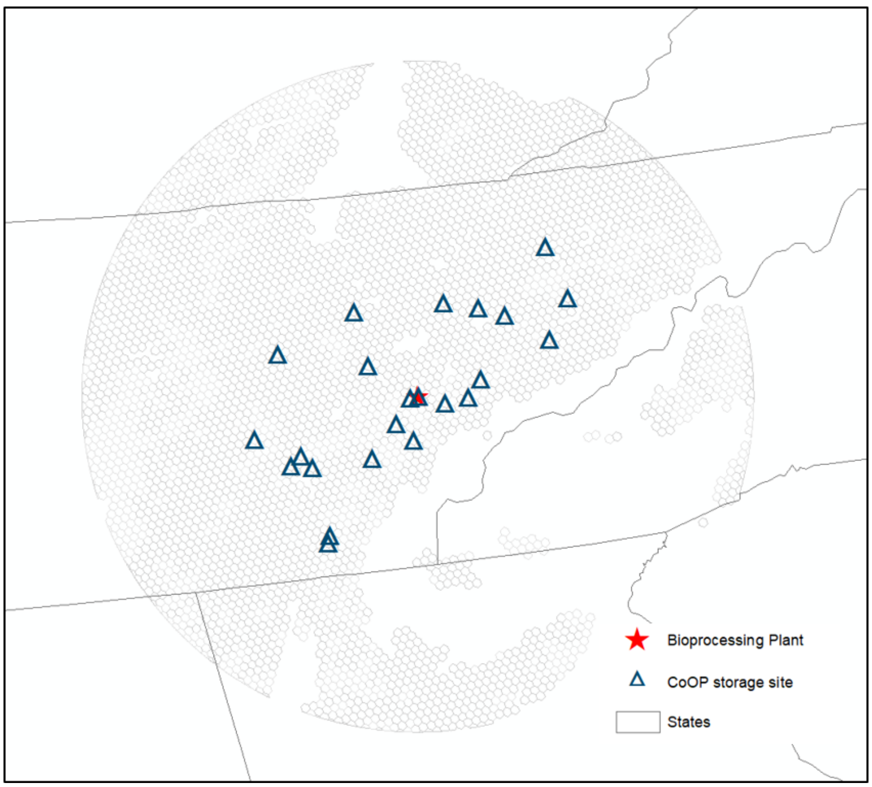


Figure 3.11: Supply network solution under the **multiCP** scenario at P5_A100 with 10 random draws of demand nodes.

3.6.2 Costs

Results of the deterministic programming

The results indicate no significant cost differences as the participation rate was reduced until the participation rate was very low (Figure 3.12). An almost identical pattern appears under the $P100$, $P75$, and $P50$ participation scenarios. However, at specific participation rate and application rates, the cost of transportation and storage diverge among the **singleCP**, **multiCP**, and **multiCPFM** scenarios. For example, when the participation rate is $P100$ and the application rate 100%, the **singleCP** scenario generates the largest storage costs, while the **multiCP** transportation costs are highest. The transportation and storage costs under the **multiCPFM** scenario are always lowest because most of the SMB can be stored at farms in smaller storage units. This substantially reduces the transportation costs compared with the **multiCP** scenario.

Varying the participation rate from 100% to as low as 5%, Figure 3.13 presents the storage and transportation costs, assuming a 100% application rate. There are no significant changes in transportation costs in any scenario until the participation rate is lower than 15% ($P15$). However, when the participation rate is below $P15$, the total transportation cost alone could exceed \$0.5 million in the **singleCP** scenario, and more than \$0.3 million in the **multiCP** and **multiCPFM** scenarios.

Results of the stochastic programming

Figure 3.14 summarizes the Monte Carlo simulation results on transportation costs given that all CoOP storage sites and capacities are fixed and benchmarked to the SAA solution. The simulation used 1000 random draws from the available corn area, assuming a 75% participation rate and a 100% of application rate. The cost distribution shows that the average cost in transportation is around \$152,000. The dotted red lines in the figure are the lower 2.5% and upper 97.5%-tiles for a 95% confidence interval ranging between \$149,000 and \$157,000.

At the 5% participation rate, the Monte Carlo simulation based on 1,000 random draws shows that more than 90% of the time, no SMB is transported to landfill; all the SMB is shipped to meet farmer demand. Where a landfill is required, the amount is less than 1,500 tons (Figure 3.15). Simulation results on transportation costs under this scenario are presented in Figure 3.16. At the 95% confidence interval, the transportation costs range between \$351,000 and \$450,000.

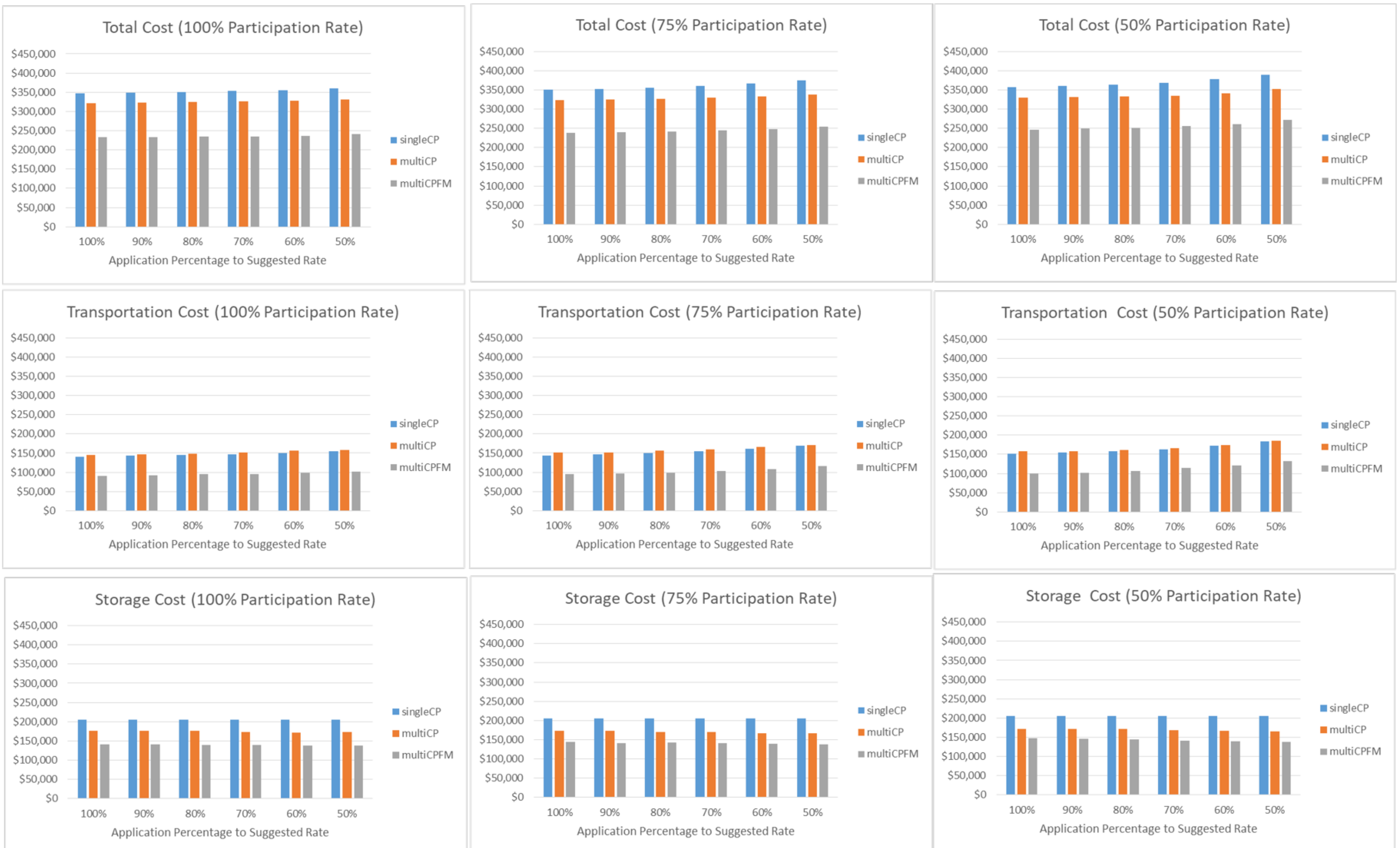
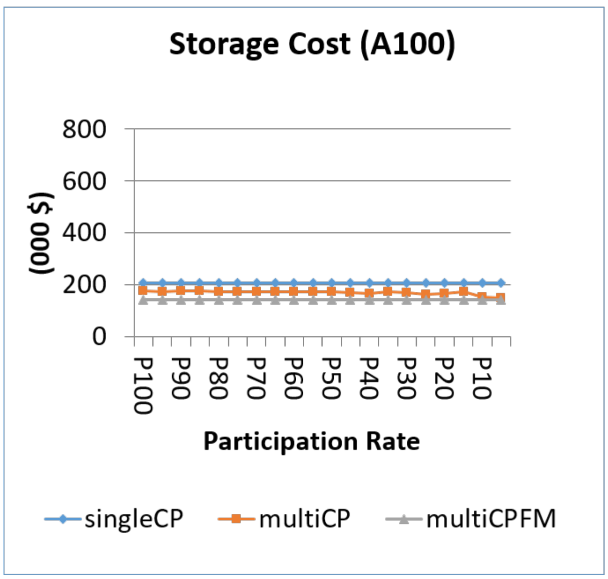


Figure 3.12: Tranportation and storage costs under different SMB participation and application rates.



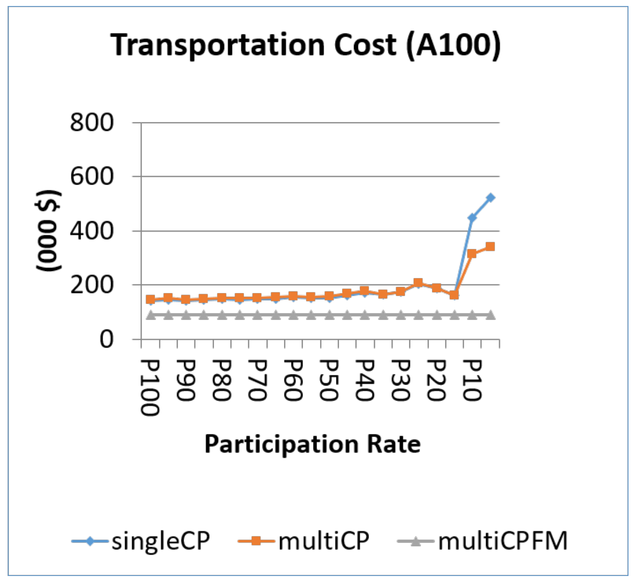


Figure 3.13: Storage and tranportation costs at a 100% application rate (A100) and different participation rates.

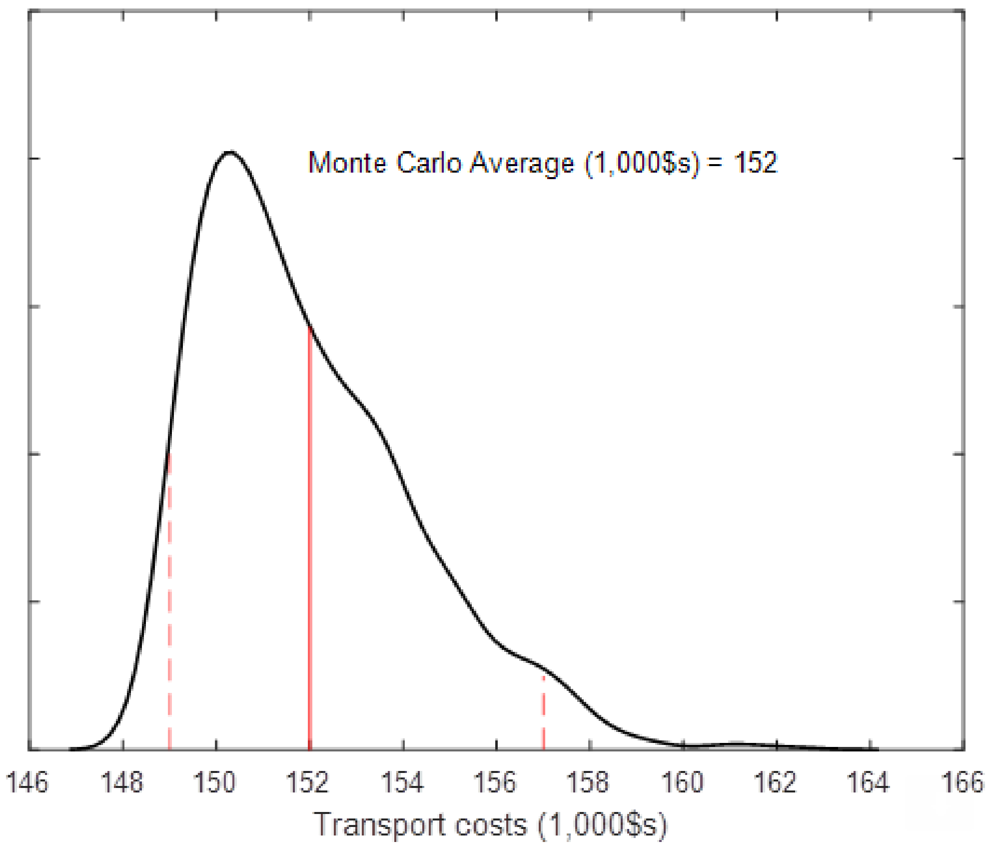


Figure 3.14: Simulation of transportation cost in **multiCP** scenario with 75% participation rate and 100% application rate.

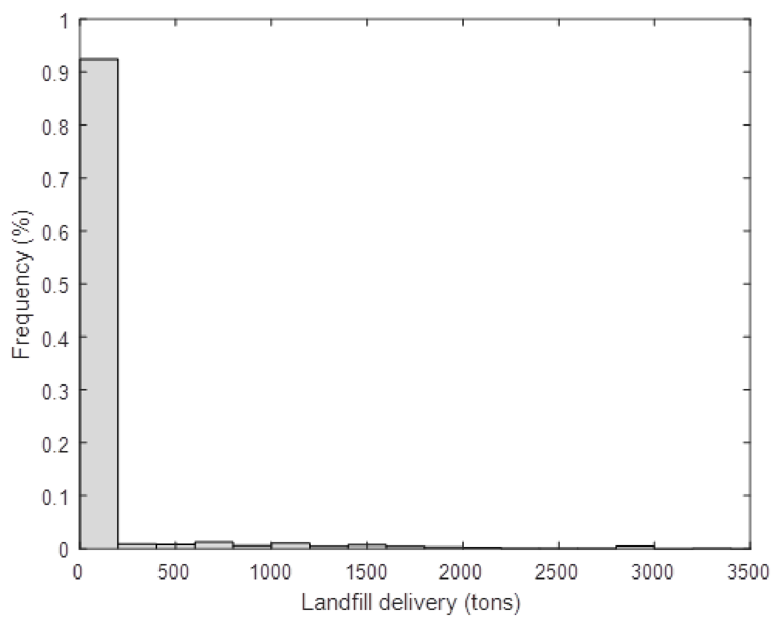


Figure 3.15: Simulation of landfill amount in **multiCP** scenario with 5% participation rate and 100% application rate.

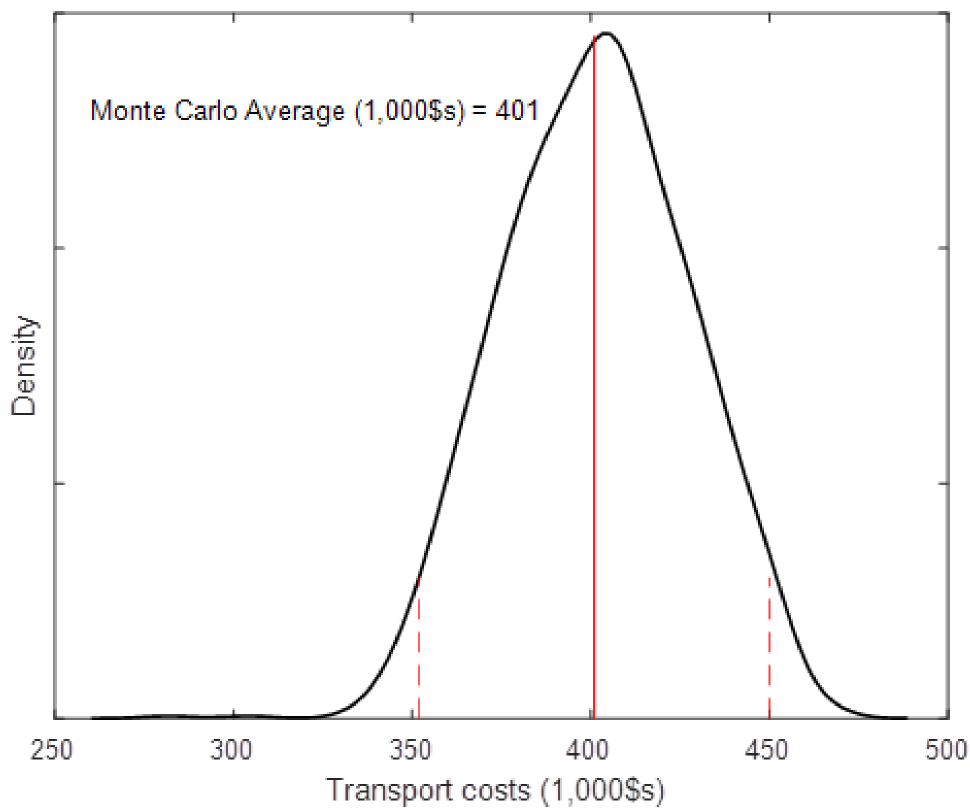


Figure 3.16: Simulation of transportation cost in **multiCP** scenario with 5% participation rate and 100% application rate.

3.6.3 Sensitivity analysis on moisture content of spent microbial biomass

The moisture content of SMB may affect its transportation and storage costs to fields. Lower SMB moisture content means lower application rates and fewer truck trips. However, drying SMB can also be expensive because of energy requirements and drying equipment. The sensitivity analysis on moisture content here focuses on the impact on transportation and storage costs only.

SMB application rates and transport/storage volume under different moisture levels

The current SMB moisture content is 43%. To conduct a sensitivity analysis, SMB moisture content levels were varied at 60%, 55%, 50%, 45%, 43%, 40%, 35%, 30%, and 25% levels. The suggested application rate is eight tons per acre, given the material's current moisture content of 43%. New application rates for corn under different moisture content assumptions are calculated using the following equation.

$$\text{New Application Rate} = 8 \times (1 - 0.43)/(1 - \text{New Moisture Content})$$

The new moisture content is between zero and one. At different moisture levels, the total volume of SMB transported and stored changes as well. The equation below calculates the volume of SMB that needs to be stored and transported, given different moisture content levels. Table 3.7 presents the SMB application rate and total volume corresponding to different moisture content.

$$\text{New Volume} = \text{Current Volume} \times (1 - 0.43)/(1 - \text{New Moisture Content})$$

Table 3.7: Moisture content and corresponding application rates

Moisture Content (%)	Application (tons per acre)	Total SMB Volume (tons)
60%	11.40	24,966
55%	10.13	22,192
50%	9.12	19,973
45%	8.29	18,157
40%	7.60	16,644
43%	8.00	17,520
35%	7.02	15,364
30%	6.51	14,266
25%	6.08	13,315

SMB moisture content impacts on logistic costs

The change in moisture content affects the total transport and storage logistic costs for obvious reasons: there is a change in volume that needs to be stored and transported. The direction and magnitude of changes depend on candidate location scenario, and participation and application rates. Figure 3.17 shows the percent changes in total cost, given different moisture content levels between 60% to 25%. The base case is the current moisture content level of 43%. Changing from 43% to 40%, or 43% to 45% moisture content, then the change of total cost from the base is less than 5% for the **multiCP** scenario. If the SMB moisture content level was decreased to 25%, the total transport and storage cost decrease by more than 20%. Under different participation rates, the percentage change in total costs are the same. However, the absolute change is different because the total costs are higher when participation rate is low.

A similar trend is evident in the **singleCP** and **multiCPFM** scenarios (Figure 3.17). However, the absolute changes in total costs may be higher in the **singleCP** and **multiCP** scenarios, compared with the **multiCPFM** scenario. This occurs because the baseline total costs are lower in **multiCPFM** scenario.

Only storage and transportation costs were considered in this sensitivity analysis. The cost for extra drying equipment was not factored into the total costs. It should be noted that drying will increase energy costs and incur additional investment costs from equipment purchases, especially when the moisture content target is low.

Decreasing moisture content will decrease the amount of SMB that must be stored and transported, assuming demand for the material is strong. A small incremental increase or decrease in the current moisture content will not affect costs substantially (less than 5%). If SMB moisture content is increased to 60%, the total change in distribution costs could increase by more than 15%. Decreasing the moisture content from the current level of 43% to 25% will also decrease total transport and storage costs by more than 15%.

It is too early to conclude if a lower SMB moisture content will benefit the entire logistic process because drying operation and equipment costs were not considered. To better understand how moisture content will affect drying costs, a Techo-Economic Analysis (TEA) would be required.

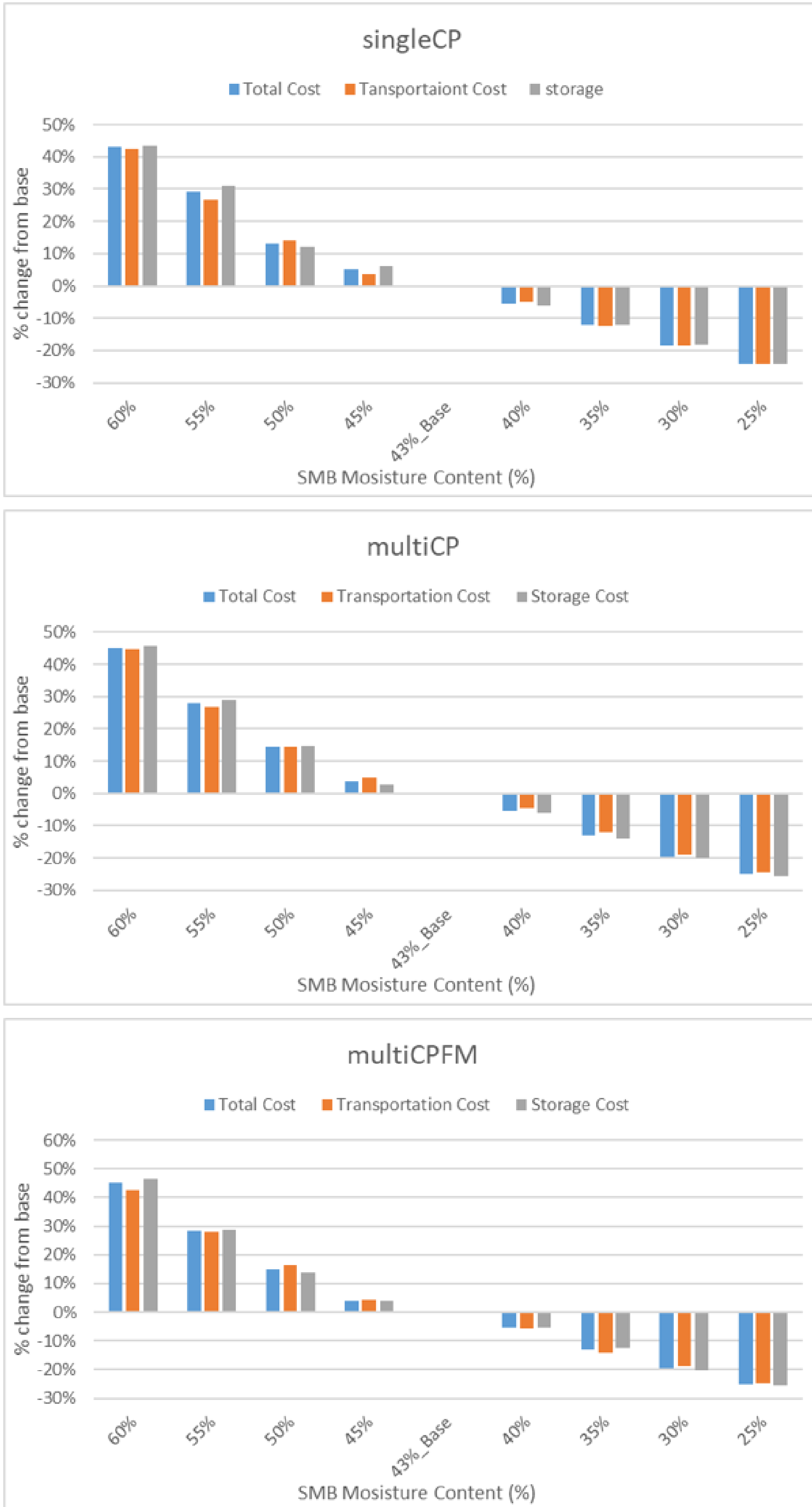


Figure 3.17: Percentage change in total costs under different moisture content in **singleCP**, **multiCP**, **multiCPFM** scenarios

Chapter 4

Conclusion and Future Work

4.1 Conclusion

As more countries and regions join in the development and promotion of the bioeconomy, challenges and new opportunities are faced by industries that contribute to the sustainable development of bioeconomy. One of the largest challenges is to discover novel uses of co-products, and to identify potential users of co-product, and to market co-products at the lowest costs. As most of the co-products from biobased production process are in non-discrete form and high in moisture content, it is expensive to store and to transport co-products from production sites to end users. Most research on co-products are currently at the pilot level or laboratory scale. There is a need for full scale research as the size of bioeconomy grows.

This thesis researched the supply chain network of a full scale SMB distribution system from a bioprocessing plant to agricultural land. The distribution of SMB requires storage sites and transportation by trucks. Therefore, the location of the storage system and service coverage area are important factors affecting SMB supply and logistic costs. MILP models were used to solve for optimal storage location and field areas that could receive SMB. The configuration of single and multiple storage systems along with different candidate sites (designated storage sites or on-farm storage) were investigated. These models were used to examine a case study involving a bioprocessing plant located in East Tennessee, corn field locations (SMB demand nodes), and transport distance based on existing infrastructure.

Different participation and application rates were also investigated. There is little information about farmers' willingness to adopt SMB as a soil amendment or if farmers perceive SMB to be a reliable substitute for commercial fertilizers and what application rate they would prefer. For participation rates, a random sampling algorithm was applied to generate a set of decision units that contain corn field as demand nodes. The total available corn area is much larger than the area that can be served by SMB currently produced by the bioprocessing facility. At a 5% participation rate, demand for SMB is still comparable to what the bioprocessing plant currently supplies. In another words, all SMB can be applied to fields even with very low participation rate. The SMB application rates were varied from 100% to 50% to reflect farmers' uncertainty about the effectiveness of SMB as a substitute for nitrogen.

Optimal network solutions including the location of storage sites, capacity, and field areas served based on a single random draw of the demand nodes suggest that participation rates will not affect the costs significantly until the participation rate is lower than 15%. Given the same participation and application rate, assumptions about the number of storage sites allowed and candidate locations plays an important role in the optimal network configuration and corresponding costs. As single storage site is the most expensive solution because the larger storage units cost more. However, single site transportation costs are comparable to other strategies, such as having multiple storage site locations. This single large storage location could be located at the bioprocessing plant or west of it, depending on demand. If multiple locations are considered, and only Farmers CoOP are included as candidate locations, then SMB storage costs will be lower. However, transportation costs could be slightly higher than the single storage solution because of constraints on location and a finite number of Farmers CoOP. The capacity of the storage sites could be as large as 7000 tons if candidate location constraint to be only in Farmers CoOPs. The option of storing SMB on-farm will decrease the costs of both transportation and storage. Given that the unit cost is the same setting up storage on-farm or in designated off-farm locations (such as, Farmers CoOPs), the storage cost decreased because more smaller capacity storage unites enter into solution and the cumulative capacity costs are less than the large capacity ones holding the same volume.

Although there is an abundance of corn produced in the study region, it should be noted that when participation rate is very low, SMB transportation costs can increase substantially. A lower application rates (or farmer's interest) could worsen the situation. The single storage site option remains a feasible alternative if the storage costs can be reduced. The most cost efficient strategy is to work with farmers to set up on-site storage systems. A Sample Average Approximation model with limited scenarios also suggests that this strategy, on average, can lower the costs by about 40% compared with only use designated locations as storage. If SMB is stored in designated location excluding on-farm storage option, Monte Carlo simulation results suggest that the transportation costs are skewed to the left when participation rate is high.

4.2 Future Work

The nature of SMB delivery and demand markets are topics that have not been well studied. However, farmers' interest will increase if conventional fertilizer prices increase,industrial-scale recycling of co-products from bio-based industries becomes economically profitable, and the importance of development of circular economy is well recognized. There are at least four potential productive avenues of future research.

4.2.1 Farmers' willingness to adopt SMB practice

SMB is a comparatively new soil amendment and fertilizer substitute to many field crop growers. The results of Chapter 3 indicate that participation rate (farmer demand) is a crucial driver of the SMB distribution costs. When the participation rate is high, transport and storage costs are low. Therefore, in order to successfully distribute SMB to farmers at a reasonable cost, it is important to understand farmers' willingness to use the material in lieu of or in conjunction with conventional fertilizer. If farmers do not want to adopt the practice, what might be the barriers?

A primary survey could be conducted to estimate farmer demand for SMB, focusing on understanding farmers' attitude, perceived benefits, and anticipated impediments and barriers related to the management and application of SMB. Understanding farmers' willingness to use SMB is essential for contract design and potential sharing of costs. However, cost is only one aspect in the farmers' decision making. There may be other concerns, such as social norms and learning ability, that may need to be addressed and understood to assist and encourage farmers' adoption of this new type of soil amendment. Experience can also be drawn from the use of manure fertilizer for crop production [14, 54, 5].

4.2.2 Machinery management

At least one proPush spreader will be needed to spread the current available amount of SMBs on fields. The coordination costs of using a few spreaders across numerous fields could be challenging. The current equipment cost for a proPush is about $42,000. The through put on applying SMB is low due to the machine loading and unloading time, which is about 5 acres per hours [33].

Machinery management and scheduling is part of a comprehensive logistic analysis. Given the large initial investment and limited number of machines available, how to improve spreading efficiency without interfering with other tillage activities remains an important question. This may affect operations on farm, and hence farmers' willingness to adopt.

4.2.3 Moisture content

A Techo-Economic Analysis (TEA) may be required if the bioprocessing plant considers lowering the moisture content of SMB. This type of analysis will assist decision makers in understand the costs and benefits of investing in drying equipment and importantly the cost recovery process. Further drying SMB will reduce storage, delivery, and perhaps field application costs. However, it is unclear how much this will cost the bioprocessing facility with respect to equipment purchasing and additional management costs.

4.2.4 SMB application in crops other than corn

University of Tennessee Biosystems Engineering and Soil Science (BESS) researchers are conducting experiments on SMB application with fescue production to understand long term soil benefits, machinery use, and optimal application rates, given different soil characteristics.

If SMB can be used in fescue production, this will increase the number of demand nodes and the field time of applying SMB by another 30 days because fescue fertilization is typically scheduled in June.

Applying SMB on perennial crop, such as fescue, maybe more attractive to farmers because they may perceive less direct soil and yield effects from the practice [54]. However, it is also important to help farmers understand the immediate and long term benefits of using organic materials, such as SMB, to promote its area-wide use.

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Vita

Lixia He Lambert was born of Xinsheng He and Jinyi Wang in October 1970 in Inner Mongolia China. She grew up in a small rural town in Inner Mongolia and moved to Wuhan, Hubei Province at the age of 12. Her father is a professor in Agricultural Economics and Rural Development, who profoundly influenced her desire to become an agricultural economist. She has a diploma in Fermentation Engineering and a M.S. in Agricultural Economics from Huazhong Agricultural University, China. In December 2004 she completed her PhD in Agricultural Economics from Purdue University. She worked for Alberta Ingenuity Center for Water Research based at University of Calgary from November 2004 to December 2006. After that She has been working as postdoc and research scientist in the Department of Agricultural and Resource Economics at University of Tennessee from 2007 to 2018. One of her work focus at University of Tennessee is large scale modeling on estimation of woody biomass availability and bioenergy facility location problems. Curious of new algorithms of solving large scale modeling, supply chain network design and optimization for agricultural and bioenergy industry, she applied and was accepted by the graduate program in the Department of Industry and System Engineering at University of Tennessee in 2015. In August 2018, she expects to complete her MS in Industrial Engineering.