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Research Article

Optimal Location of Biogas Plants in Supply Chains under Carbon Effects: Insight from a Case Study on Animal Manure in North Dakota

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Faced with increasing concerns over the negative environmental impact due to human and industrial activities, biomass industry practitioners and policy makers have great interest in green supply chains to reduce carbon emissions from supply chain activities. There are many studies which model the biomass supply chain and its environmental impact. However, animal waste sourced biogas supply chain has not received much attention in the literature. Biogas from animal manure not only provides energy efficiency, but also minimizes carbon emissions compared to existing biomass products. Therefore, this study proposes a mixed integer linear program that minimizes total supply costs and carbon emissions from an animal waste sourced biogas supply chain while it also incorporates carbon price in the model to see the impact of a carbon policy on tactical and strategic supply chain decisions. To validate the model proposed, a case study of North Dakota is adopted where there is a high potential for a biogas plant to be developed. The results of our optimization experiment indicate that supply chain performance in terms of both costs and emissions is very sensitive to a carbon pricing mechanism.

1. Introduction

Biomethane is formed in nature by the biological degradation of biodegradable organic material such as biowaste, sludge, manure, and agroresidues under anaerobic conditions. The main components of biogas are methane and carbon dioxide which can be captured and used to generate energy in the form of heat and electricity. They can also be used as vehicle fuel in either a compressed or liquefied form and as power for fuel cell vehicles [1]. According to US Energy Information Administration (EIA), biogas could displace about 5 % and 56% of natural gas consumption in the electric power and transportation sectors, respectively. There were 242 operating anaerobic digestions (ADS) on livestock farms in the US in 2016, producing about 981 million kilowatt-hours (kWh) of energy [2]. There is growing interest in installing ADSs converting daily manure of beef cattle, cows, hogs and poultry, and other animals to biogas due to both its economic and environmental benefit. Biogas produced from ADSs is considered methane neutral process because it has potential to capture methane that escapes into the atmosphere.

Required by the RFS2, developing a financially feasible and environmentally sustainable bioenergy supply chain across diverse feedstock harvesting, collection, storage, production, and transportation is challenging [3]. Strategic, tactical, and operational level decisions related to location, capacity, logistic issues, transportation networks, feed stock acquisition, and distribution of biomass or biofuel must be made for efficient and effective optimal network configuration [4, 5]. Traditional supply chain network design has focused on cost efficiency, but recent regulatory mandates require federal, states, and local authorities to expand their objectives beyond just economic metrics. Now, environmental performance consideration, such as carbon reduction and waste minimization, needs to be part of the project [6].

It is recognized that renewable energy is already playing a great role in reducing emissions in the energy sector in the US and many other countries. Fossil fuel-fired power plants are the largest source of emissions accounting for 31 percent of US greenhouse gas emissions. Interest in imposing a carbon tax on carbon emissions seems to be on the rise in the US, among decision makers [7], in order to increase the cost of energy produced from fossil fuels [3]. A national carbon tax of $40 per metric ton is expected to be raised at a rate of 5.6 percent per year and about $2.5 trillion in revenue would be yield over a 10-year period. It would also cut US emissions by 8 percent by 2021, as well as hike gasoline and electricity prices [8].

Motivated by the evolving regulatory climate change pressures in the United States, this paper develops an optimization model and consider the strategic decisions of the number and location of biogas plants, as well as the tactical optimization of its capacity and the biogas production in order to explore how the bioenergy industry can manage its supply chain under the two carbon regulatory schemes, including carbon pricing and carbon trading mechanisms, which are two popular environmental regulatory policy schemes that have been widely implemented in different nations [9, 10]. This study provides not only practical implications associated with the modeling effort but also research implications including discussion of additional outcomes and further development. A new approach in the biogas supply chain system is also required to face ever-changing energy markets because uncertainties in climate change calculation continue to pose some of the most challenging aspects in designing sustainable bioenergy supply chains [11]. In this regard, Mixed Integer Linear Programming (MILP) is an effective optimization tool, which captures the impact of different scenarios of emission price and caps on the biogas supply chain and provides optimal strategies in designing and planning for practitioners and policy makers. The proposed biogas supply chain model contributes to the sustainable biogas plant location modeling literature through helping organizations, policymakers, and scholars evaluate the tactical and operational biogas supply chain planning.

The remainder of the paper is organized as follows: Section 2 reviews the literature on carbon regulatory schemes and biomass supply chains; Section 3 presents the problem statement and optimization model that is proposed in this research; Section 4 describes a case study; Section 5 presents the results and the discussion of research findings and potential implications for policy makers. The paper concludes by providing a summary with future research directions in Section 6.

2. Carbon Regulation in the US and Biomass Supply Chain

It is recognized that renewable energy is already playing a great role in reducing emissions in the energy sector in the US and many other countries. Fossil fuel-fired power plants are the largest source of emissions accounting for 31 percent of US greenhouse gas emissions. Interest in imposing a carbon tax on carbon emissions seems to be on the rise in the US, among decision makers [7], in order to increase the cost of energy produced from fossil fuels [3]. A national carbon tax of $40 per metric ton is expected to be raised at a rate of 5.6 percent per year and about $2.5 trillion in revenue would be yield over a 10-year period. It would also cut US emissions by 8 percent by 2021, as well as hike gasoline and electricity prices [12].

There are significant efforts to design carbon tax and carbon cap-and-trade programs to mitigate climate change in other countries. The carbon trading scheme, also known as a cap-and-trade mechanism, is one of the significant policies for carbon emission mitigation [9]. It sets a fixed maximum level of carbon emissions, a cap, to achieve a reduction in emissions. Firms generating more emissions than the allocated allowance either pay a fine or purchase emissions allowance off the market from those firms which generated less than their allocated allowance [10]. Government regulations, community norms, and consumer expectations have all caused organizations to expand their focus beyond the economic aspect of supply chains [13].

In the last decades, researchers have been interested in deciding the location of biomass facility [6, 14–18]. Many efforts have been made to quantitatively consider biomass supply chain network design and management practices [14–18]. The objective considered takes into account economic and environmental aspects. The economic aspect identifies the cost-effective manner that minimizes the total supply chain costs regarding the number, capacity and location of biorefinery facilities, and flow of biomass [19] or maximizes the net profit [20].

On the other hand, improved life cycle performance is required to achieve sustainable biofuel supply chains that integrate environmental aspects. One of the challenges would be how to minimize the carbon footprint to maintain a low environmental impact. Recently, a number of authors have presented research on supply chain optimization of biomass that considers financial objectives as well as the environmental impact [21–23]. Different aspects such as potential GHG savings and impact of carbon tax and carbon trading on economic and environmental performance were also analyzed [24]. It was found that implementing a carbon emissions scheme was cost-effective that minimizes GHG emissions by promoting competitive advantage in biofuel technologies [25]. However, most of these studies focused on the biomass to biofuel supply chain.

Determining the optimal biogas plant location is a challenging task. Several studies related to biogas plants addressed some importance factors that influence the location decisions that includes but not limited to the current situation, potential biogas production, and biogas utilization [26–28], strategic and tactical decision level in biogas industry's supply chain management [4, 29], or the sustainable biogas plant location planning [30]. Mixed integer programming (MIP) and MILP are used extensively in the existing body of literature for strategic or tactical planning of biogas supply chains [15, 16, 31]. However, spatial distribution of supply and demand has a great influence on the design of biogas supply network [32] and optimal facility location highly affects the transportation cost. Therefore, another commonly used approach to the biofuel supply chain problem is application of geographic information system (GIS) based models, which can help to determine the most appropriate facility location in a specific area [1].

We address the problem of facility location in biogas supply chain that use animal manure from dairy farms, simultaneously deciding the optimal capacity of the plant at each location and the amount of animal manure to be transported from the daily farms to the biogas plant and the amount of carbon emissions from the biogas supply chain including acquisition, transportation, and production. Most of the previous studies formulated effective green supply chain design, while modeling efforts related to green supply chain design, which consider animal waste under a carbon policy strategy, are not well established in the literature. Considering these facts and research gaps, this study develops a MILP model to determine the optimal configuration of animal waste-based biogas supply chain along with the associated operational decisions that minimizes its economic and environmental performance under carbon policies.

Several factors are considered in the model: location of the manure resource, land use suitability for potential biogas plant location, practical constraints on our ability to harness it, and economic and environmental considerations with several restrictions [11]. We used this optimization model to solve a problem with real data from North Dakota in USA by integrating with GIS for spatial and network analysis.

3. Problem Statement and Mathematical Model

A mathematical model for biogas supply chain design under carbon policy is developed using a MILP. Biomass in the form of animal manure is considered as feedstock in the model. This biomass will then be shipped to energy conversion plants for anaerobic digestions (ADs), where the biomass is converted into biogas. Geography and distance can be important factors because biomass to energy schemes are highly geographically dependent due to the fact that manure supply and biogas demand are often widely dispersed. Thus, finding suitable locations for biogas plants, which minimize transportation distances and total supply chain costs, as well as associated carbon emissions is a key issue for sustainable biogas production. One way to serve multiple farms or ranches is to develop centralized or regional ADs, in which case it is important to decide optimal capacity of ADs and locations. The proposed model also considers the carbon pricing and trading scheme. Therefore, the biogas project either incurs costs if the carbon cap that is assigned is lower than the carbon emissions or gains revenues by selling excess carbon credits. The following supply chain inputs, decisions, and assumptions are made for the model.

Inputs

(i) The annual amount of cattle manure and annual natural gas demand. Only natural gas consumption by the electric power sector in North Dakota in 2016 is loaded into the model, because natural gas consumption by vehicle fuel is unknown [33]. Upstream leg of the supply chain is considered and downstream actors are not considered as the output from the plant is injected directly into the natural gas pipeline [29].

(ii) The distance between each node in the supply chain is determined by GIS.

(iii) Costs for acquiring animal manure, transporting it, and producing biogas.

(iv) Carbon price and cap.

(v) GHG emissions associated with acquiring manure, transporting manure and biogas, and producing biogas.

Decisions

(i) Locations of biogas plants.

(ii) Capacity levels for the biogas plants.

(iii) Amount of biomass to be transported from the feedstock region to the biogas plant.

(iv) Biogas production volume of each plant.

(v) Amount of carbon emissions for the entire supply chain including acquisition, transportation, and production.

Assumptions

(i) A refinery will not be shut down once it opens.

(ii) Truck is the only mode for transporting manure and biogas.

All notation used in the model formulation is summarized in Table 1 and a complete model formulation is presented in (1)-(15). The function Z_1 represents the total supply chain cost that includes the acquisition costs, investment costs including lifetime operation and maintenance costs, production costs, transportation costs of manure, penalty cost for shortage of biogas, and carbon credit generated from methane offset.

$$\begin{aligned}\min Z_1 = &\sum_{i\epsilon I}\sum_{j\epsilon J} c_i^{aq} X_{ij} + \sum_{k\epsilon K}\sum_{j\epsilon J}\left(c_j^k + \mathrm{v}c_j^{om}\right) Z_j^k \\ &+ \sum_{k\epsilon K}\sum_{j\epsilon J} Q_j^k c_j^{pr} \\ &+ \sum_{i\epsilon I}\sum_{j\epsilon J}\left(c_{ij}^t * d_{ij} * 2\right) + c^{lu}\right) X_{ij} \\ &+ \sum_{k\epsilon K}\sum_{j\epsilon J}\lambda\left(Q_j^k - m^d\right) - \sum_{j\epsilon J}\left(e_j^{moff}\alpha\right)\end{aligned} \tag{1}$$

where the transportation costs of manure are quantity, travel distance, and truck capacity dependent; therefore, (2) indicates the transport cost per ton mile.

$$c_{ij}^t = \frac{C^{tl}}{C^{hc}} \tag{2}$$

The objective function Z_2 represents the overall supply chain carbon emissions from acquisition, production, and transportation.

$$\min Z_2 = \sum_{i\epsilon I}\sum_{j\epsilon J} e_i^{aq} X_{ij} + \sum_{j\epsilon J}\sum_{k\epsilon K} e_j^{pr} p^k Z_j^k + \sum_{i\epsilon I}\sum_{j\epsilon J} e^{tr}\left(d_{ij}X_{ij}\right) \quad (3)$$

Given Z_1 and Z_2, the minimization of the overall supply chain cost when operating under a carbon pricing scheme or carbon trading scheme can be formulated in (4) and (5), respectively [10]:

$$\text{Carbon pricing scheme: Minimize } Z_1 + \alpha Z_2 \quad (4)$$

$$\text{Carbon trading scheme: Minimize } Z_1 + \alpha\left(Z_2 - CO_2^{cap}\right) \quad (5)$$

Equation (4) charges a carbon price of α corresponding to the amount of emissions generated in a carbon pricing situation. By adding a carbon cap in (5), in a carbon trading environment, a plant which generates more emissions than its allocated allowance ($Z_2 > CO_2^{cap}$) can purchase additional allowance or permits off the market at a price of α. Plants generating fewer emissions than the allowed emission allowance ($Z_2 < CO_2^{cap}$) can sell their surplus to those who may be exceeding their allocated limits. In the latter case, ($Z_2 < CO_2^{cap}$) would be a negative number turning carbon trading into a source of income that might help reduce the overall supply chain costs.

$$\textbf{s.t.} \quad \sum_{j\epsilon J} X_{ij} \le a_i\beta, \quad \forall \text{i} \quad (6)$$

$$\sum_{i\epsilon I} \theta X_{ij} = \sum_{k\epsilon K} Q_j^k \quad \forall \text{j} \quad (7)$$

$$\sum_{i\epsilon I} X_{ij} \le \sum_{k\epsilon K} p^k Z_j^k, \quad \forall \text{j} \quad (8)$$

$$\sum_{k\epsilon K} Z_j^k \le 1, \quad \forall \text{j} \quad (9)$$

$$Q_j^k \le p^k S_j^k \quad \forall \text{j, k} \quad (10)$$

$$\sum_{j\epsilon J}\sum_{k\epsilon K} Q_j^k = m^d \quad (11)$$

$$\sum_{i\epsilon I}\sum_{j\epsilon J} e_i^{aq} X_{ij} + \sum_{j\epsilon J}\sum_{k\epsilon K} e_j^{pr} p^k Z_j^k + \sum_{i\epsilon I}\sum_{j\epsilon J} e^{tr}\left(d_{ij}X_{ij}\right) = CO_2^{ce} \quad (12)$$

$$X_{ij} \ge 0, \quad \forall \text{i, j} \quad (13)$$

$$Q_j^k \ge 0, \quad \forall \text{j, k} \quad (14)$$

$$Z_j^k = \{0, 1\}, \quad \forall \text{j, k} \quad (15)$$

Table 1: Notations used in model development.

Sets	
I	set of ranch, indexed by (i= 1,2,. . .,I)
J	set of potential biogas plant location, indexed by (j= 1,2,. . .J)
K	set of biogas plant capacity level, indexed by (k=1,2,. . .,K)
Parameters	
a_i	maximum available animal manure
c_j^{aq}	average acquisition cost of cattle manure
c_j^{pr}	unit cost of biogas production at plant j (\$/m^3)
c_{ij}^t	transport cost per ton-mile from cattle farm i to plant j
c^{tl}	tons per truck load
c^{hc}	truck hauling cost per loaded mile
β	average wet or dry content of manure (%)
c^{lu}	truck loading and unloading cost of (\$/tons) manure
c_j^k	investment cost of the plant at location j with plant capacity level k
c_j^{om}	annual operational and maintenance cost of the plant at location j with plant capacity level k
v	lifetime of biogas plant (years)
λ	penalty cost for unmet demand
d_{ij}	road distance (miles) between ranch i and plant j
CO_2^{cap}	maximum amount (tons) of carbon dioxide that can be emitted
p^k	annual production capacity for biogas plant size k
e_i^{aq}	CO_2 factor (CO_2-eq. ton/dry ton) for animal manure acquisition
e^{tr}	CO_2 factor (CO_2-eq. ton-mile/truckload) for transportation
e_j^{pr}	CO_2 factor (CO_2-eq. m^3/dry ton) for biogas production
e_j^k	amount (tons) of CO_2 at location j with plant capacity level k
e_j^{moff}	amount of offset methane at location j
α	average expected cost of carbon price in \$/ton CO_2
θ	conversion efficiency to produce biogas from cattle manure (m^3/dry ton)
m^d	annual natural gas demand
Decision Variables	
X_{ij}	amount of cattle manure transported to plant j from cattle farm i
Q_j^k	amount of biogas converted in plant j at size k
Z_j^k	1 if biogas plant with size k is built, 0 otherwise
S_j^k	size of a biogas plant, if any, to be built at site k
CO_2^{ce}	amount of CO_2 that is emitted in supply chain

The objective functions in (4) and (5) are subject to the constraints (6) to (15). Constraints (6) limit the amount of animal manure procured to the amount that is available annually in each manure producing location. Constraints (7) are flow conservation constraints at the biogas plants, which state that the amount of converted animal manure equals the biogas produced by relating it to conversion rates at plants. Constraints (8) are logical constraints, stating that there is no flow through biogas plants unless one is open. Constraints (9) ensure that a maximum of one size can be chosen for each plant. Constraints (10) ensure that the amount of biomass that can be processed at a biogas plant is limited by the plant capacity. Constraints (11) allow biogas produced at each plant which is equal to the biogas demand. Constraints (12) calculate the carbon dioxide emissions across the whole supply chain. Constraints (13)-(15) enforce nonnegativity and binary restrictions on the decision variables.

4. A Case Study: Potential Biogas Production in North Dakota

North Dakota (ND) has few anaerobic digestion facilities, although it is a significant livestock producer (ND is ranked 16^{th} in the United States in cattle). Currently ND has only four operational biogas systems, and they involve water resource recovery and landfill. However, it is expected that there will be more than 39 new biogas plants based on ND's available resources. Upon the biogas installment, there could be enough electricity to generate 52.7 million kWh of power from biogas based natural gas enough to fuel 7,651 vehicles [34].

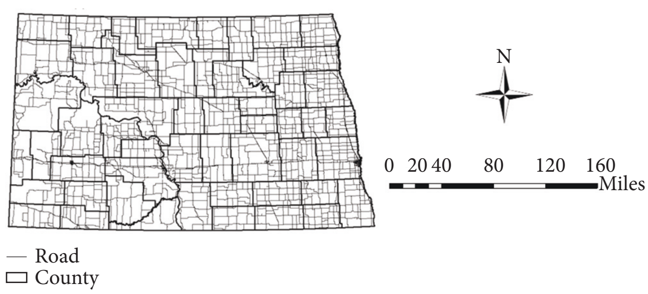
4.1. Cattle Manure Resource. A diverse set of animal waste feedstock resources are available in North Dakota for biogas production. Cattle waste is considered in this study due to its high potential for cattle manure production. Cattle are not uniformly distributed in the state; therefore cattle manure production amounts vary among regions. All cattle feedlots and inventories are collected through the ND State Feedlot Database from the Dickinson Research Extension Center [35]. Annual cattle manure is estimated by converting 1 head of cattle = 0.025 tons of manure/day [36] and multiplying by 365 and percentage of average wet or dry content of manure. This study considers the moisture content of manure and its effect on the biogas supply chain decisions. According to an expert in agricultural engineering at North Dakota State University, the moisture content of manure comprises a large portion of biomass (e.g., 30-85% on a wet basis, moisture content of cattle manure is 85%) and is a significant factor, especially for planning plant capacity and transportation. Figure 1(b) shows the geographic distribution of the cattle feedlots and quantity of solid cattle manure for each feedlot. The annual amount of cattle manure and locations has been generated using GIS. A cattle manure acquisition cost of \$10/ton is used [37].

4.2. Potential Biogas Plants. Twenty-two potential biogas sites were identified by performing a land use suitability analysis, considering the various factors and criteria in Figure 1(c). Table 2 presents the social, geographic, and land use criteria that were used to identify their potentially suitable sites for ADSs in ND. The default values of the criteria are based on literatures, as well as some assumptions. All criteria employ GIS analysis, such as creating buffer from lines (road, railway, and gas grid) or point feature (urban), and clipping polygons (park and water area). Social factors include public areas that are defined as urban, geographic factor such as water (river and aquifer surface area), Bureau of Land Management (BLM), forest service, national park, and wildlife, and land use factor such as road and railway, gas grid, and well and rig [8, 38]. The criteria for wells and rigs are assumed because no studies have been found that studied suitability analysis of biogas plant within an oil producing area. This assumption can be reconsidered later by consulting considering expert opinion or actual survey.

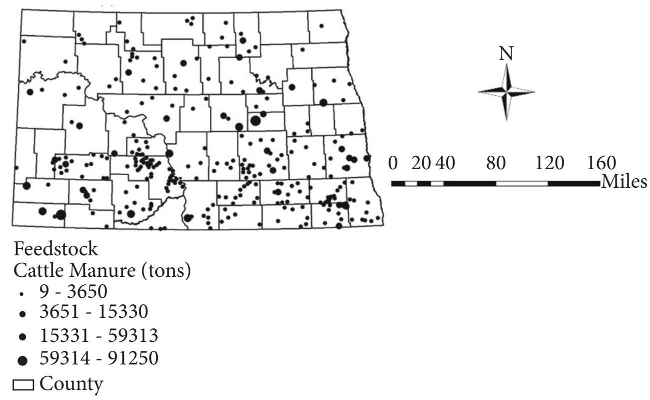
This study considers that each plant could have one of four sizes, according to the amount of cattle manure processed and amount of natural gas produced. The four types of biogas plant are named very small, medium, large, and very large [30]. In our model, we assumed that the four types of plant have different values for the initial investment and maintenance cost. The initial investment cost and life time maintenance cost of a biogas plant are subject to economies of scale. This work considered that annual operation and maintenance costs of a biogas plant represents on average 2% of the investment cost. Operation and maintenance costs were calculated for a plant with a life time of 20 years [30]. The biogas production cost of \$4 per m^3 is used [39] with conversion efficiency of $23 m^3$/ton [40].

4.3. Transportation Data. In this study, road transportation networks, including local, rural, urban, and highway, are used to estimate the cost of transporting cattle manure (see Figure 1(a)). The shortest path based on Dijkstra's algorithm between each node is generated using the O-D cost matrix application in ArcGIS. The hauling cost per loaded mile for cattle manure is \$4/mile, the cost of loading and unloading a truck is \$5/ton, and tons per truck load is 25 tons. Therefore, transport cost per ton mile is \$4 per mile/25 tons according to Oklahoma State University [37].

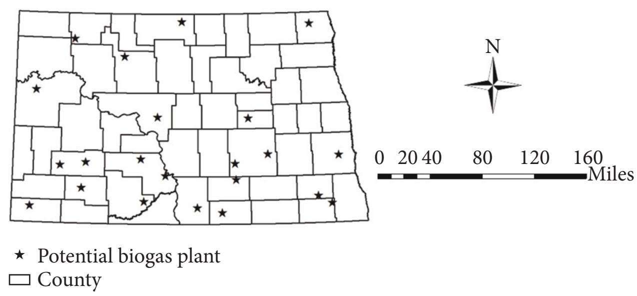
4.4. Environmental Impact Assessment. In terms of environmental impact analysis, the emission rate associated with biogas production, including feedstock acquisition, transportation, and production, is obtained from existing literature. The final CO_2-eq value is found to be 0.008ton CO_2-eq/ton of manure for acquisition [41], 0.002 ton CO_2-eq/ ton manure for transportation [42], and 0.08 ton CO_2-eq/ m^3 for biogas production [42]. The main components of biogas are carbon dioxide and methane; specifically, biogas is 60 to 70 percent methane and 30 to 40 percent carbon dioxide (CO_2) with a low amount of other gases including nitrogen, hydrogen, and hydrogen sulphide. The following calculations were developed based on study from our sources and the rules of arithmetic. According to Abdeshahian et al. [40], a 1 ton of manure will produce 23 m^3 of biogas. Therefore, (15) converts this figure to amount of CH_4 produced per ton of manure using the EPA's estimate that 60% of the biogas from anaerobic digestion is methane [43]. Then, calculate the equivalent amount of CO_2 by assuming that 1 ton of methane is equivalent to 21 tons of carbon dioxide. Thus, multiplying the tons of methane produced per ton of manure



(a) North Dakota counties and road



(b) Feedstock area of cattle manure



(c) Potential biogas plant locations

Figure 1: Geographic distribution of animal manure feedstock resource and potential biogas plants in North Dakota.

Table 2: Factor and criteria to select candidate biogas plant.

Factor	Criteria
Roads and railway	To exclude area which contain or are less than 200m away from major, county and rail network
Water (river and aquifer surface)	To exclude area which contain or are less than 150m away from water line
Bureau of Land Management (BLM)	To exclude area which contain or are less than 1km away from BLM surface land
Gas grid	To include area within 2km of gas pipeline
Forest service	To exclude area which contain or are less than 200m away from
Tribal land	To exclude area which contain or are less than 200m away from
National park	To exclude area which contain or are less than 200m away from
Wildlife	To exclude area which contain or are less than 150m away from wildlife area
Wells and rigs	To exclude area which contain or are less than 200m away from oil well and rig
Urban	To exclude area which contain or are less than 2km away

by twenty-one should provide a reasonable estimate of the amount of carbon dioxide equivalent gas (methane offset, e_j^{moff}). Captured methane qualifies as a carbon offset, which can be a source of carbon credits ($e_j^{moff}\alpha$).

$$e_j^{moff} = 0.6 \times \frac{23\ m^3}{1\ ton\ of\ manure} \times \frac{21\ tons\ of\ CO_2}{1\ ton\ CH_4} \times tons\ of\ manure\ converted\ into\ biogas \tag{16}$$

The carbon price (α) used in this case study is \$40/ton of carbon-equivalent emissions [12]. Environmental Protection Agency (EPA) indicated that 45% reduction in CO2 emissions from the 2005 level by 2030 will be achieved in North Dakota by replacing power plants with nonemitting generation resources. Using this rule, we set the initial carbon cap as 21 million metric tons of carbon emissions.

5. Results and Discussion

From Table 3, the cost-only and emission-only optimization scenarios without considering carbon price show what happens at the two extremes. From the analysis, it shows that the cost-only optimization (Z_1) and emissions-only optimization (Z_2) are two conflicting objectives. When cost-only optimization model is solved, a minimum supply chain cost of \$310,015,893 occurs which is \$60,25,757 less than when compared to the emission-only optimization. The reverse

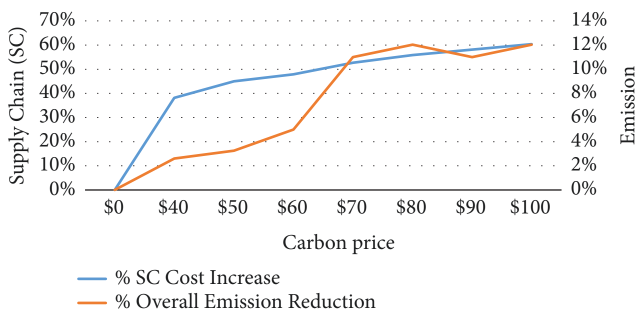


Figure 2: Cost increase and emission reduction performance.

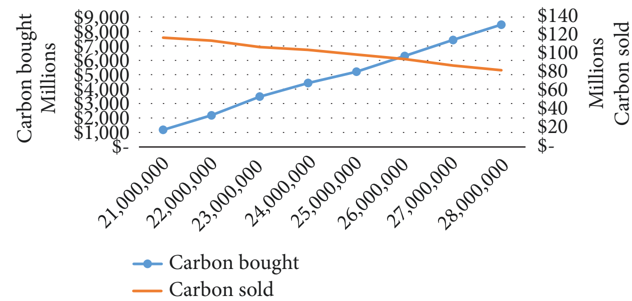


Figure 3: Carbon bought and sold with carbon cap variations.

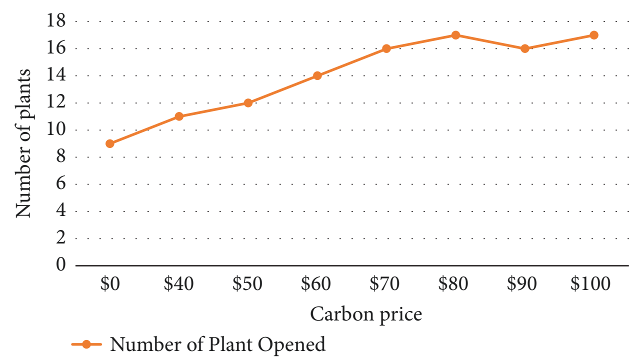


Figure 4: Number of plants opened with carbon price variations.

situation occurs in the emission-only optimization scenario where the minimum carbon emission of 2,245,564 tons emits at the maximum cost is incurred. The results clearly indicate that, without a carbon pricing mechanism in place, the supply chain could be less costly to manage. We also observe the number of total ADs opened and their size and amount of biogas produced for each optimization scenario. Table 4 shows that the number of ADs opened increases in the emission-only optimization, which may stem from the fact that the model assigns more ADs to minimize the emissions. Also, the average size of ADs eventually decreases for emission-only optimization as the assigned demand decrease; therefore less product is allocated to the ADs.

Figure 2 illustrates the supply chain cost and emission reduction performance over the range of the carbon prices when a carbon trading scheme is in place. The y-axis values in figure 2 represent the supply chain cost percentage increase and emission percentage reduction at each carbon price when compared to the $0 price. This perspective allows for evaluating the schemes' effectiveness over a range of carbon prices. Figure 2 shows that the supply chain cost increases steadily and relatively linearly, as the carbon price increases. However, the curve eventually flattens since, given the supply chain structure, there exist no more operational changes which impact emissions. As can be seen there is a rapid decrease in carbon emissions that occurs at the very low carbon prices of $0-$40 per ton. Interestingly, after this point, a slight emission reduction occurs until carbon prices reach $60 per ton. The next significant improvement in emission reductions occurs at a carbon price of over $60 per ton and continues to improve until carbon prices reach $80 per ton. Increasing the carbon price provides strong motivation to reduce emission level, and, as a result, reduces system costs by the sale of offset emission credits.

Figure 3 shows the cost of carbon purchased and sold at different levels of carbon cap. At a higher cap, the firm will sell less carbon and purchase more carbon. This indicates that a change in the carbon cap will have a greater impact on the amount of carbon sold and purchased. One primary and broad-based policy question is to determine the carbon price at which the maximum environmental performance can be achieved, without substantial negative impacts on the economy and competitive position of the biogas industry. Therefore, from this analysis the price range of $60-$70 appears to be the most effective and efficient option in terms of emissions generation and cost escalation in our model. Within this range, a dollar increase in supply chain costs has the greatest positive impact on carbon pollution reduction.

Table 5 reports capacities of the plants and amounts of biogas production in each county when carbon prices vary. The results suggest that Bowman and Foster are the counties in which the largest plant is constructed at carbon price of $0. On the other hand, when carbon price increased by $40, Stutsman may be the county with the largest plant. Under cap and trade, the number of biogas plants is only determined by the carbon price. For a fixed carbon cap, the number of biogas plants and their relative sizes are highly dependent on carbon prices. As seen in Figures 4 and 5, the number of biogas plants opened increases in order to minimize the carbon emission due to transportation. Also, the average size of the biogas plants will eventually decrease as less cattle manure is allocated to each biogas plant.

Figure 6 shows the geographical location of biogas plants in ND for the different carbon effect. The locations of biogas plants and their different optimal capacity levels are presented. As previously mentioned, having no carbon regulatory scheme in place (i.e., a carbon price of $0) results in 9 biogas plants being opened as the base scenario. Introducing a carbon price at the current national level of $40 per ton results in more biogas plants being opened. When carbon price increases to $100, the model opens 17 biogas plants in ND. An increase in the number of plants allows a reduction in transportation and emission costs, thus putting greater emphasis on more efficient and environmentally friendly transport and location decisions. It seems that the model

Table 3: Numerical results for the optimizations.

	Cost-only optimization (Z_1)		Emission-only optimization (Z_2)	
	Total SC costs ($)	Total Emissions (tons)	Total SC costs ($)	Total Emissions (tons)
Transportation	12,859,893	647,880	9,124,530	405,444
Acquisition	8,000,000	584,000	7,160,000	522,680
Production	1,656,000	1,472,000	1,482,120	1,317,440
Investment	287,500,000	-	352,500,000	-
Total	310,015,893	2,703,880	370,266,650	2,245,564

Table 4: Number of ADs opened and their relative size variation.

	Cost-only optimization (Z_1)	Emission-only optimization (Z_2)
Number of ADs	9	20
Total ADs Size (ton)	690,000	716,000
Average ADs Size (ton)	76,666	35,800

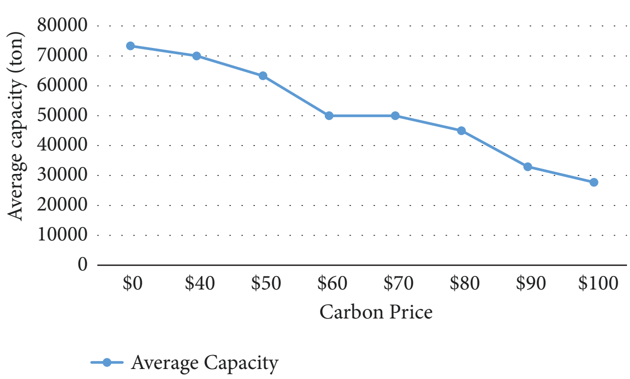


Figure 5: Average size of plants with carbon price variations.

locates biogas plant near the county that produces the largest amount of cattle manure. It can be concluded from the results that the location sites and plant capacities are highly dependent on per unit transportation cost for manure.

5.1. Sensitivity Analysis. In our model, we perform sensitivity analysis to identify the factors that are significant to the biogas supply chain, especially focusing on cost of biogas by comparing current carbon adjusted cost of natural gas. Thus, we measure cost of biogas delivered by dividing total supply chain cost by total amount of biogas produced in North Dakota as shown in Figure 7. This analysis also shows to determine the indifference point of carbon price at which unit cost of biogas and natural gas becomes equal. The cost of natural gas was calculated under carbon tax that is provided by Hafstead and Picciano [44]. The level of carbon price is varied from $0/ton of carbon-equivalent emission to $100/ton of carbon-equivalent emissions. Figure 7 indicates that the carbon price significantly impacts on the unit cost of biogas. Low level of carbon price results in lower cost of biogas and high level of carbon price results in higher cost of biogas. However, as carbon price increases the cost of biogas becomes higher than the cost of natural gas. The indifference point is achieved once carbon price exceeds $160/ton of carbon-equivalent emissions means that biogas production at current carbon price up to $159/ton is beneficial. This may stem from the penalty generated from the plants which emitted more emissions than its allocated carbon emission allowance.

In order to understand the increase in the cost of biogas as carbon price increases, we used break-even analysis to see the relationship between carbon price and the conversion efficiency, as well as natural gas demand and cattle manure acquisition cost. Figure 8 presents the break-even point for natural gas for different values of carbon price and rate of biogas production. The current conversion rate from animal manure to biogas production is relatively low; one ton of manure produces only 23 m^3 of biogas. In the baseline case, the conversion efficiency of biogas was 23 m^3 per ton of manure. The conversion efficiency rate increases up to 188 m^3 per ton of manure from baseline, because it was the maximum conversion efficiency level that would have impact on number of biogas plant and capacity level. It was assumed that there is no cost with improvement of conversion efficiency. When conversion efficiency is fixed, the cost of biogas increases as carbon price increases. When carbon price remains the same, the cost of biogas decreases as the conversion efficiency increases, meaning that the cost of biogas is higher with less efficient technology is employed and a higher carbon price is applied. The increase in the cost of biogas (as the conversion rate increases) is mainly due to the increase in transportation distance and processing costs. Technological improvement of biogas conversion is necessary in order to locate fewer biogas plants that process cattle manure and serve the demand area. Increasing the number of biogas plants will decrease the cost of transportation and the cost of processing additional manure while reducing carbon emissions as carbon price increases. From the analysis results, there is a tradeoff between carbon emission and the supply chain costs.

The change in the cost of biogas at different levels of demand and carbon prices was also investigated; see Figure 9.

Table 5: Total manure processing and biogas production in each county at carbon price of $0 and carbon price of $40.

County	Carbon price	Total manure capacity (t/y)	Biogas production (m^3/y)
Bowman	$0	100,000	2,300,000
	$40	70,000	1,610,000
Stutsman	$0	70,000	1,610,000
	$40	140,000	3,220,000
Sargent	$0	-	-
	$40	70,000	1,610,000
Foster	$0	100,000	2,300,000
	$40	100,000	2,300,000
Stark,Morton,McLean, Emmons, Cass, Hettinger	$0	70,000	1,610,000
	$40	70,000	1,610,000

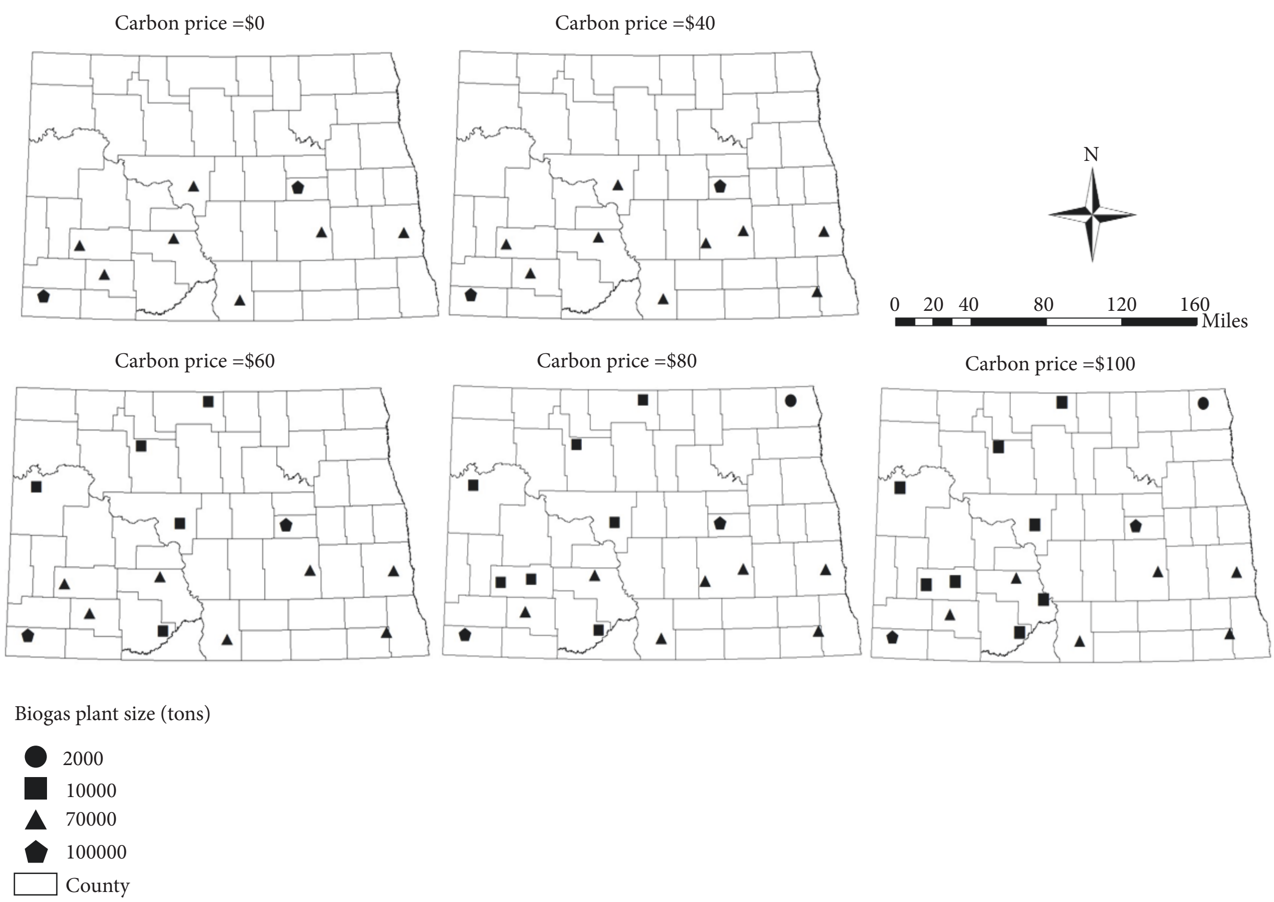


Figure 6: Impact of carbon price on biogas plant locations and sizes.

This result presents the impact that an increase of manure supply and carbon price on cost of biogas. These experiments were inspired by the natural gas consumption trend in the United State in that natural gas consumption is expected to increase about 11% by 2040 from the 2016 level of natural gas consumption [45]. Results show that when demand is fixed, the cost of biogas increases as carbon prices increase. It was found that the cost of biogas increases at the highest demand and at the highest carbon price. For example, the cost of biogas increases from $1.42 to $1.89 at carbon price of $0

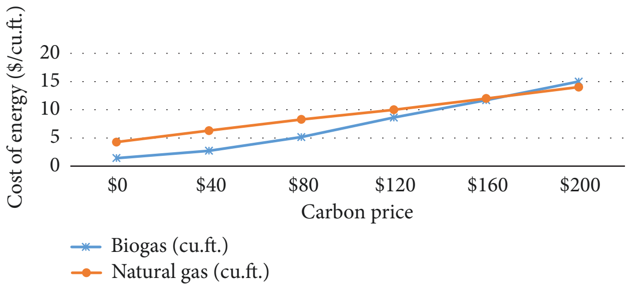


FIGURE 7: Impact of carbon price on energy cost using biogas and natural gas.

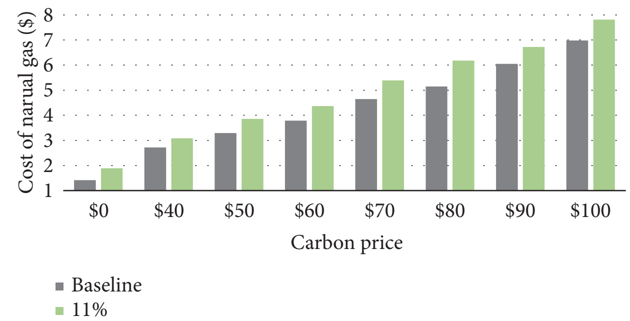


FIGURE 9: Analyzing the impact of demand variation and carbon price on cost of biogas.

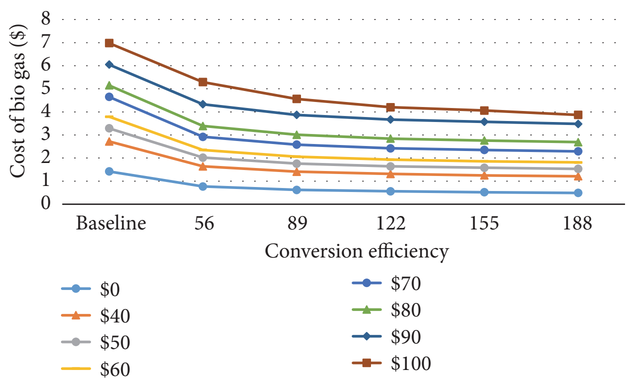


FIGURE 8: Cost of biogas by carbon price and conversion efficiency (m^3/ton).

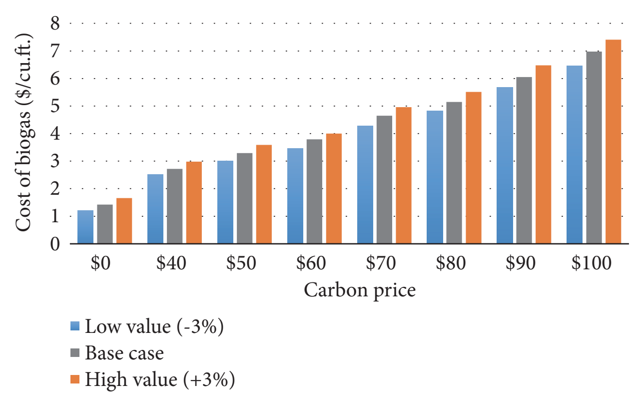


FIGURE 10: Impact of manure acquisition cost and carbon price on cost of biogas.

and $6.98 to $7.81 at carbon price of $100. These results may stem from long-haul shipments that occur in high demand and locating small number of biogas plants.

In Figure 10, the impact of manure acquisition cost on unit cost of biogas was analyzed by increasing or decreasing unit cost of manure acquisition by 3% [46] as well as the relationship between carbon price and cost of manure acquisition. The results show that the cost of biogas is highly dependent on manure acquisition cost. Without carbon price being added, the unit cost of biogas is decreased by 1.8% and increased by 2.5% from base case scenario. It is also found that the unit cost of biogas increases linearly as carbon price increases. The finding indicates that overall supply chain cost of biomass related to biomass acquisition will be reduced with improved collecting and process technology. Also, short-term biomass prices are driven by the cost of the raw material, while long-term bioenergy prices are driven by fossil fuel prices. Large scale animal manure supply is also affected by an initial cost of raw material and fertilizer price. Thus, the unit cost of cattle manure acquisition is highly sensitive to fertilizer price.

This study further evaluates the impact of critical parameters on system design and cost. The effects of wet and dry content of manure are analyzed with two carbon price scenarios by assigning weight for each type of manure. The result of sensitivity analysis of wet versus dry manure content is presented in Table 6. The results indicate that wet and dry content of manure and carbon price have significant impacts on the total supply chain costs, carbon credit, and cost of biogas. Wet manure AD is a bit more expensive than dry ADs in terms of acquisition, transportation, and production. Cow manure is about 85% dry basis which resulted in more supply availability that reduces the overall supply chain cost. There is a dramatic change in the number of biogas plants while the average capacity of plants remains the same. The biogas plant size of 70,000 tons remains optimal when the carbon price increase $0 to current level of carbon price.

6. Summary and Conclusion

Siting biogas plant that processes animal manure is a relatively unexplored field from a renewable energy supply chain point of view. In this study, we address greening the biomass supply chain for animal manure through consideration of the carbon effect along the SC and carbon strategy to provide tactical and strategic SC decisions.

This study contributes to the current literature in several ways. It proposes a mathematical model for design and management of a biomass to biogas supply chain, including anaerobic digestion as a source of renewable energy production. This study also contributes to the related body of knowledge by considering mainly waste biomass in the

Table 6: Impact of wet versus dry manure content.

Types of manure	Wet basis		Dry basis	
Scenario	Carbon price at $0	Carbon price at $40	Carbon price at $0	Carbon price at $40
Total cost (in $m)	464.5	579.2	45.5	348.1
Acquisition cost (in $m)	7.7	7.7	1.0	0.7
Investment cost (in $m)	385.0	385.0	35.0	52.5
Production cost (in $m)	70.8	70.8	9.2	1.8
Transport cost (in $m)	0.9	0.8	0.3	0.3
Emission cost (in $m)	-	114.9	-	61.0
Carbon credit (in $m)	-	8925.8	-	231.8
Cost of biogas ($/cu.ft.)	0.88	1.07	9.02	10.58
Number of plants	11	11	2	3
Average capacity (tons)	70,000	70,000	70,000	70,000

supply chain design model, while most of the studies focus on energy crops as a source of biomass. Therefore, waste management issues are handled by incorporating carbon policy into the bioenergy facility location problem with due consideration accorded to both monetary and environmental factors.

To validate the proposed model, computational experiments were performed on a case study using North Dakota, which is one of the significant cattle manure producers in the US. The experimental analysis shows that the biogas industry tends to reduce their carbon emissions significantly with introduction of a carbon price by locating less biogas plant to minimize the emissions from transportation and production. From sensitivity analysis, cost of biogas, size of biogas plant, and location were very responsive to different carbon prices, advanced conversion technological efficiencies, types of manure, and manure acquisition cost. This model can help supply chain practitioners devise and implement a strategy based on future expectations of a carbon policy. This model was developed mainly to determine the impact of carbon policies on biogas plant location problem. For future work, developing dedicated transportation mode, tradeoff between logistics costs of manure loss and collection of manure and the cost of transport that address vertical and horizontal relationship in supply chain management would be key area to improve the comprehensive nature of the model [47]. The proposed model can also be further improved by modeling animal waste with other biomass commodities (wood, industrial waste, crops, etc.) or using a multiple objective optimization of supply chain costs and social impact with a more comprehensive life cycle assessment.

Data Availability

The data used to support the findings of this study are included within the article and datasets from previously reported studies have been cited.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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