A Data-Driven Mixed-Integer Linear Programming Optimization Model for a Biofuel Supply Chain Network

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Abstract

This paper focuses on a Data-Driven Mixed-Integer Linear Programming Optimization Model for a Biofuel Supply Chain Network. The research project is an adaptation of the IISE Logistics and Supply Chain Division Case Competition 2024. The case presents a bioethanol company in Texas that is designing a supply chain consisting of suppliers, hubs, and biorefineries to facilitate the conversion of raw materials into biofuels. The team further refined the case study with the addition of more decision variables, parameters, and a more detail analysis of county-specific demands. A comprehensive literature review of similar scholarly work has been provided to contextualize the nature of supply chain linear programming problems. A model with an objective function and a set of constraints has been formulated to optimize the supply chain network, using data from various sources, such as Google API. An optimal solution was calculated, providing insights into hub and plant operations, transportation and logistics, financial performance, and scenario testing.

Keywords: Supply Chain Management, Mixed-Integer Linear Programming, Operations Research, Optimization, Biomass Logistics, Logistics Optimization, Hub and Spoke Model

1 Introduction

Currently around 73% of the United States energy is derived from fossil fuels [1]. Carbon emissions and limiting inventory is a very big concern in contemporary society for this industry. The introduction of the bio-fuel industry was created to solve this concern in emissions and limiting resources by utilizing biological products as a possible fuel replacement. Currently this industry struggles in their production efficiency and supply chain to truly benefit our societal needs. This project aims to solve a piece of the problem by providing solutions to improving the supply chain issue of this industry. A bioethanol company in Texas is designing a supply chain of suppliers, hubs, and biorefineries to facilitate the conversion of raw materials into bio-fuels. Raw materials are transported from suppliers of Texas counties to hubs using trucks. Hubs are responsible for consolidating and pre-processing biomass while maintaining product quality; no material storage is allowed after processing is complete. The preprocessed biomass is transported from hubs to bio-refineries using trains. As shown in Figure 1, a potential network of hubs, biomass sources, and biorefineries has been mapped to help the company identify the best routes while reducing overall transportation and delivery costs. All additional cost information related to investments and capacities is available through feasibility studies conducted by government agencies. The company aims to minimize investment and transportation costs by optimizing flow patterns and determining the optimal number of hubs and biorefineries required to meet demand.

2 Literature Review

A comprehensive literature review of similar scholarly work was conducted to enhance our understanding of the problem. In Jeong et al.'s paper [2], the researchers presented an optimized biodiesel supply chain model using mixed-integer linear programming (MILP). The paper aimed to balance transportation resources and capacity construction by developing a feasible supply chain model capable of minimizing costs. Prior to formulating the model, a spatial analysis was conducted to evaluate geographical constraints such as resource availability, demand, and the distances between feedstock supply and biofuel facilities. Previous literature reviews have shown that decreasing the number of facilities increases capacity per plant, reduces construction costs, and increases overall transportation

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distance. Three echelons (biodiesel production, oilseed availability, and oilseed demand) were selected to develop the objective function of minimizing the summation of transportation costs, biodiesel production costs, and plant construction costs, subject to the constraints. The research was applied to the NGP Region of Montana, resulting in the introduction of two new plants and increased capacity in an existing plant. Different variants of the solution were provided, depending on the spectrum of resource availability and feasibility of selection. Similarly, Sharifzadeh et al.'s paper focused on the economic viability of biofuel technologies due to the dispersity of resources geographically [3]. Researchers developed a mixed-piecewise integer linear program subject to constraints such as potential locations, biomass resource availability, cost of upgrading existing centers, deployment of mobile centers, and many more. Results indicate optimality is met through a combination of upgraded centers and centralized pyrolyzes. Depending on scenario and feasibility of solution, other alternatives such as mobile centers can be deployed to increase efficiency and flexibility.

Additional literature has also been collected pertaining to the MILP capabilities to solve the biofuel supply chain problems. In Ge et al's formulations [4], this study addresses the high costs and logistical challenges in the biofuel supply chain by implementing 12 conversion pathways for biofuel production to minimize overall supply chain cost. A MILP model was used to incorporate factors such as biomass types, transportation modes, biorefinery locations, and conversion pathways. The optimized model reduced biofuel unit cost by 14.6% with further analysis identifying biorefinery construction costs and biofuel throughput as the major drivers to the design. An additional study focuses on optimization with biomass in the poultry areas [5], this study optimizes the design of a biomass supply chain that converts poultry to biogas (in similar concept to our case study). The study utilizes a MILP model that integrates geographic information systems (GIS) and analytic hierarchy process (AHP) to optimize facility locations and transportation flows. The main goal of this study is to maximize profit and minimize transportation distance. The overall outcome of this optimized model is a major reduction in cost which achieved a payback period of 4.56 years and an increase in energy generation. Analysis has presented that major economic drivers in this problem are the biomass purchasing costs and the maximum transportation distances that had the largest factors.

Within biomass production, most models are deterministic, often using mixed-integer linear programming (MILP) [6]. Cobuloglu and Buyuktahtakin developed an MILP model for switchgrass-based biofuel production, focusing on land allocation, establishment, biomass production, and transportation [7]. Their objective was to maximize total economic value by optimizing biomass sales revenue, the economic value of soil erosion prevention, and savings from reduced greenhouse gas emissions. They designed a triple scenario experiment over a 10-year planning horizon for a project in Hugoton, Kansas, revealing that government incentivization could make marginal land utilization for switchgrass cultivation more profitable. Sensitivity analysis highlighted the importance of strategic budget allocation and land use.In conventional supply chain literature, most studies take an individualistic scope, with simulation research focusing on facility location planning and optimization papers primarily examining routing problems [8]. Melo et al. studied the feasibility of integrating these elements into a single model [9]. Integrated problems can be categorized into Location, Inventory, and Routing, leading to studies on Location-Routing Problems (LRP) and Inventory-Routing Problems (IRP). The first LRP was studied by Min et al. [10], and later research has expanded on integrating supply chain elements. Liu et al. included additional supply chain components in IRPs [[11], [12]]. Simulation-Optimization (S-O) frameworks can be divided into simulation-based optimization, simulation optimization, and optimization-based simulation. These frameworks simplify problems by reducing complexities and improving analytical effectiveness. Surrogate modeling, used in inventory optimization, is an example of such simplification [[13], [14]]. S-O frameworks also allow recursion between optimization and simulation models, analyzing stopping criteria [15]. Integrated modeling and S-O frameworks represent a shift in supply chain research, with S-O gaining prominence while integrated models approach saturation.

3 Model Formulation

All objects highlighted in red are additional to the model presented in the case. These will be included in the optimization model after the base model is solved for.

Indices and Sets

- i: Index for suppliers (counties), $i = 1, 2, \ldots, 254$

- j: Index for hubs, $j = 1, 2, \ldots, 33$
- k: Index for biorefineries, $k = 1, 2, \ldots, 167$
- c: Index for counties (demand points), $c = 1, 2, \ldots, 254$ (same range as suppliers)

Parameters

1. **Supply and Costs**
   - S_i: Supply of biomass from supplier i (Mg)
   - C_{ij}: Transportation cost per Mg from supplier i to hub j (USD)
   - T_{jk}: Transportation cost per Mg from hub j to biorefinery k (USD)
   - L_j: Cost of opening hub j (USD)
   - M_k: Cost of opening biorefinery k(USD)
   - U: Cost of loading/unloading a train (USD)
   - V: Cost of loading/unloading truck 1 (USD)
   - T: Cost of loading/unloading truck 2 (USD)
   - G_{kc}: Transportation cost per Mg from biorefinery k to county c (USD)
   - D_{penalty}: Penalty cost for unmet demand (USD per liter)
   - r_b: Selling price of bioethanol(USD per liter)
   - r_e: Selling price of electricity per MWh (USD)
   - f_p: Fuel price factor for transportation cost adjustment
   - ρ_{bio}: Bioethanol density (Mg per liter)
2. **Capacities**
   - Q_j: Preprocessing capacity of hub j (Mg)
   - R_k: Conversion capacity of biorefinery k (liters)
   - E: Maximum Electricity Generation Potential of biorefinery (MWh)
   - TR_t: Capacity of a train (Mg)
   - CK_{t1}: Capacity of a truck 1 (Mg)
   - CK_{t2}: Capacity of a truck 2 (Mg)
3. **Demands and Yields**
   - d_c: Bioethanol demand at county c (liters)
   - Y_k: Conversion yield for biorefinery k (liters per Mg)
   - Y_e: Electricity generation yield for biorefinery (MWh per Mg)

Decision Variables

1. **Flows and Allocations**
   - x_{ij}: Flow of biomass from supplier i to hub j (Mg)
   - y_{jk}: Flow of biomass from hub j to biorefinery k (Mg)
   - z_{kc}: Flow of bioethanol from biorefinery k to county c (liters)
2. **Facility Operations**
   - $z_j \in \{0, 1\}$: Binary variable indicating whether hub j is opened (1 if yes, 0 otherwise)

- $w_k \in \{0, 1\}$: Binary variable indicating whether biorefinery k is opened (1 if yes, 0 otherwise)

3. **Transportation**
   - $n_{jk} \in \mathbb{Z}_{\geq 0}$: Number of trains needed to move biomass from hub j to biorefinery k
   - $m_{ij} \in \mathbb{Z}_{\geq 0}$: Number of trucks needed to move biomass from supplier i to hub j
   - $p_{kc} \in \mathbb{Z}_{\geq 0}$: Number of trucks needed to move biofuel from plant k to county c
4. **Other**
   - $d_{c,\text{unmet}}$: Amount of unmet bioethanol demand at county c (liters)
   - e_k: Amount of electricity co-generated at biorefinery k (MWh)

Objective Function

$$\text{Maximize} \quad Z = \left(\sum_k r_b Y_k \sum_j y_{jk} + \sum_k r_e e_k \right) - \left(\sum_j L_j z_j + \sum_k M_k w_k + \sum_{i,j} C_{ij} f_p x_{ij} + \sum_{j,k} T_{jk} y_{jk} + \sum_{j,k} U n_{jk} \right) \tag{1}$$

$$- \left(\sum_{i,j} V m_{ij} + \sum_c D_{\text{penalty}} d_{c,\text{unmet}} + \sum_{k,c} G_{kc} f_p z_{kc} \rho_{bio} + \sum_{k,c} T p_{kc} \right) \tag{2}$$

Constraints

1. **Supply and Demand Constraints**

$$\sum_j x_{ij} \leq S_i \qquad \forall i \quad \text{(Supply Constraints)} \tag{3}$$

$$\sum_c z_{kc} + d_{\text{unmet}} \geq d_c \qquad \forall c \quad \text{(Demand Satisfaction at County Level)} \tag{4}$$

2. **Facility Capacity Constraints**

$$\sum_i x_{ij} \leq Q_j z_j \qquad \forall j \quad \text{(Hub Capacity Constraints)} \tag{5}$$

$$\sum_j y_{jk} \leq \sum_t \frac{R_k}{Y_k} w_k \qquad \forall k \quad \text{(Biorefinery Capacity Constraints)} \tag{6}$$

$$\tag{7}$$

3. **Flow Conservation Constraints**

$$\sum_i x_{ij} = \sum_k y_{jk} \qquad \forall j \quad \text{(Flow Conservation at Hubs)} \tag{8}$$

$$\sum_c z_{kc} = Y_k \sum_j y_{jk} \qquad \forall k \quad \text{(Flow Conservation at Biorefineries to Counties)} \tag{9}$$

4. **Transportation Constraints**

$$n_{jk} \geq \frac{y_{jk}}{TR_t} \qquad \forall j \quad \text{(Train Capacity Constraints)} \tag{10}$$

$$m_{ij} \geq \frac{x_{ij}}{CK_{t1}} \qquad \forall i, j \quad \text{(Truck Capacity Constraints)} \tag{11}$$

$$p_{kc} \geq \frac{z_{pc}}{CK_{t2}} \rho_{bio} \qquad \forall k, c \quad \text{(Truck Capacity Constraints)} \tag{12}$$

5. **Electricity Generation Constraints**

$$e_k = y_{jk} R_k \qquad \forall k \quad \text{(Electricity Generation Constraints)} \tag{13}$$

$$e_k \leq E \qquad \forall k \quad \text{(Electricity Potential Constraints)} \tag{14}$$

6. **Binary and Non-Negativity Constraints**

$$z_j, w_k \in \{0, 1\} \qquad \forall j, k \qquad \text{(Binary Constraints)} \tag{15}$$

$$x_{ij} \geq 0, \quad y_{jk} \geq 0, \quad z_{kc} \geq 0, \quad n_{jk} \in \mathbb{Z}_{\geq 0},$$
$$m_{ij} \in \mathbb{Z}_{\geq 0}, \quad p_{kc} \in \mathbb{Z}_{\geq 0}, \quad d_{\text{unmet}} \geq 0, \quad e_k \geq 0 \quad \forall i, j, k, c \quad \text{(Non-Negativity and Integer Constraints)} \tag{16}$$

4 Experimental Design

Data Sources

The model relied on a combination of given and additional datasets to comprehensively represent the bioethanol supply chain network. The given datasets included:

- **Plant/Hub Locations, Investment, and Capacity**: Provided base details for potential hub and plant operations from IISE Logistics and Supply Chain Division Case Competition 2024 [16]
- **Truck Distance and Costs from Counties to Hubs**: Distances between suppliers and hubs and the incurred transportation cost were provided as part of these datasets
- **Supply per County**: Detailed the biomass availability in different regions.
- **Railroad Distance from Hub to Plant and Transportation Costs/Capacity**: Represented rail transport data for supply chain optimization.

Additional datasets were researched and included to enrich the model:

- **Individual County Demand**: County level population data was collected from the World Population Review [17] and the demand was spread to represent localized bioethanol needs.
- **Distances and Transportation Costs from Plants to Counties**: Gathered using GoogleMaps API [18] to simulate real-world transport routes. The Costs were calculated using a linear regression model on the distance cost matrix of the routes from the suppliers to the hubs
- **Gas Prices by County**: AAA data [19] provided fuel prices which were used as a multiplication factor to a portion of the road transportation costs.
- **Land Price Index**: Data from the U.S. Census Bureau [20] was used to obtain land prices and adjust hub and plant investment costs based on this index and tiered capacity.
- **Electricity Generation Capacity and Selling Price**: Electricity prices were incorporated using live data from ERCOT [21] to estimate revenue from electricity generation. The generation capacity was replicated from existing biofuel plants as published by PayneCrest [22]
- **County level information**: ARCGIS [23] and TxDOT [24] data was incorporated for accurate map locations and county metadata.
- **Loading Prices and Capacities of Trucks and Trains**: Referenced studies (Roni et al. [25], Grisso et al. [26], Mahmudi et al. [27], and Greenbrier [28] & Trailers of Texas [29]) provided parameters for vehicle costs and capacities. DOT-407 was selected for preprocessed biomass, DOT-406 was selected for processed bioethanol, and DOT-117 railcars were selected for partially processed biomass with all costs and capacities being adjusted accordingly.

Scenario Testing

To evaluate the robustness and adaptability of the model, 10 different scenarios were analyzed:

1. **Low Hub/Plant Capacity**: Simulated restricted operational capacity to understand bottlenecks.
2. **High Railcar Capacity**: Examined improved rail transport efficiency.
3. **High Penalty Costs**: Incentivized demand fulfillment by increasing penalties for unmet demand.
4. **High Electricity Revenue**: Modeled scenarios where electricity selling prices increased to account for renewable energy credits
5. **Subsidized Bioethanol Price**: Simulated the impact of government incentives on bioethanol pricing.
6. **High and Low Transportation Costs**: Analyzed the impact of fuel price fluctuations on the network.
7. **High and Low Demand**: Evaluated the effect of varying bioethanol demand.
8. **Optimal Baseline**: Assessed the default scenario to establish a reference.

Each scenario assumed all variables remained constant except the parameter being altered, enabling the identification of specific sensitivities within the network.

Visualization

Geospatial visualizations were generated to provide actionable insights:

- **Hubs and Plants**: Open hubs and plants were mapped on a Texas base map. Marker sizes were scaled according to their tiered capacities.
- **Truck and Train Routes**: Transportation routes between supply chain nodes were overlaid on the map, with color-coded paths indicating the mode of transport.

These visualizations aided in identifying optimal locations for hubs and plants while highlighting transportation efficiency across the network.

5 Results

Hub and Plant Operations

The optimization results indicate the strategic placement of hubs and plants to ensure an efficient and cost-effective bioethanol supply chain across Texas. The key findings are:

- **Hubs:**
  - **11 hubs** were selected out of a potential **33** locations based on demand, proximity, and capacity constraints.
  - The selected hubs are tiered by capacity:
    * **Small hubs** (75,000 Mg capacity): Efficient for regions with moderate demand or limited supply access.
    * **Medium hubs** (300,000 Mg capacity): Support larger operations in regions with higher demand.
    * **Large hubs** (600,000 Mg capacity): Positioned in strategic locations to handle maximum capacity and reduce bottlenecks.
- **Plants:**
  - **24 plants** were selected from a potential **167** options, focusing on those closest to the demand centers and transportation infrastructure.
  - All selected plants are **small-tier** plants (38,015,926 Mg capacity), indicating that the bioethanol demand can be met without requiring larger plants in the current scenario.

Figure 1 shows all the Texas Counties and Potential Locations of Hubs and Plants as given in the dataset. The suggested hubs and plants to open as per size are shown in Figure 2, which illustrates the geographic distribution of open hubs (blue) and plants (green) across Texas, with marker sizes proportional to their capacity tiers.

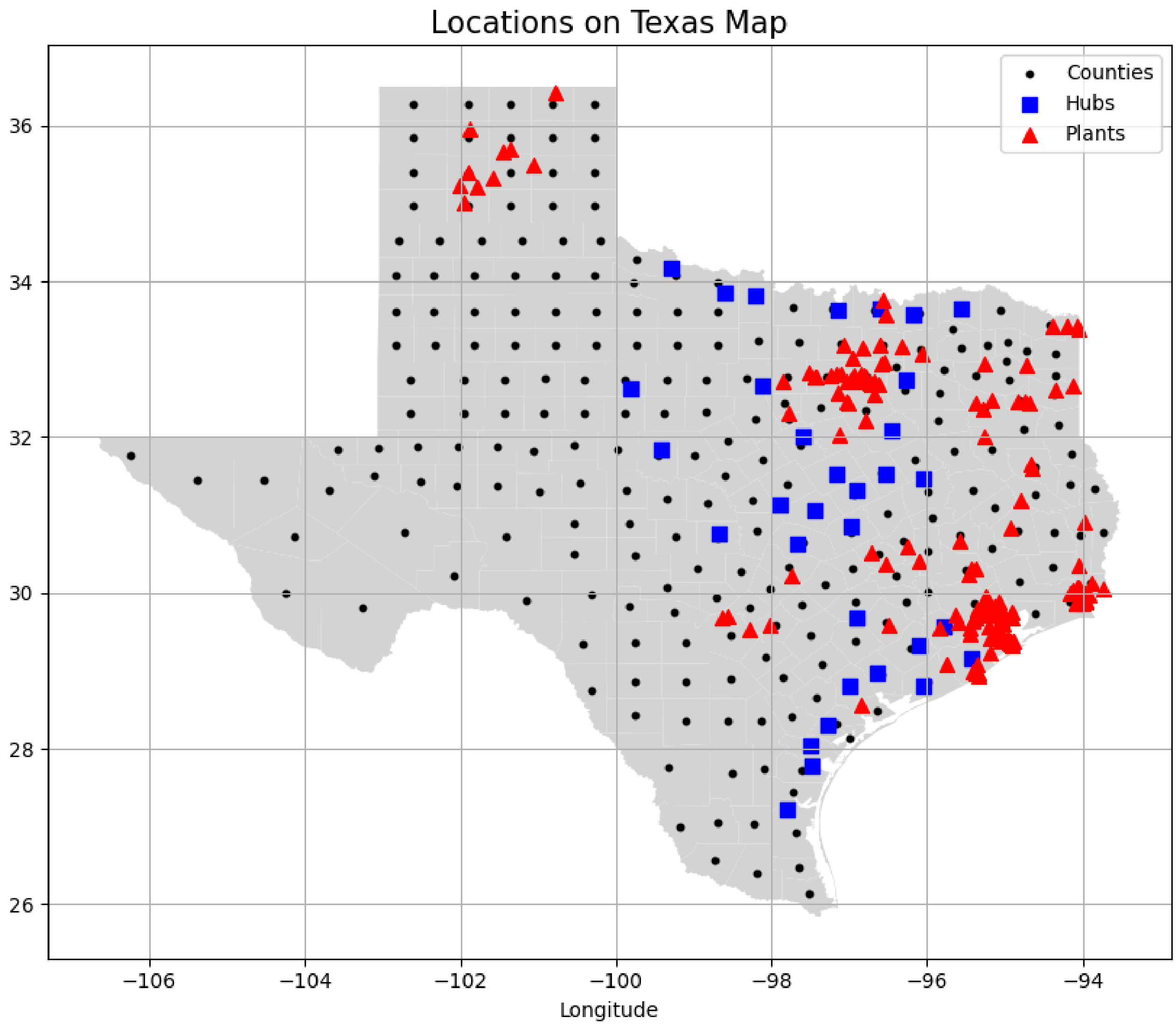

Figure 1: Map representing locations of suppliers and potential locations for hubs and plants in the state of Texas

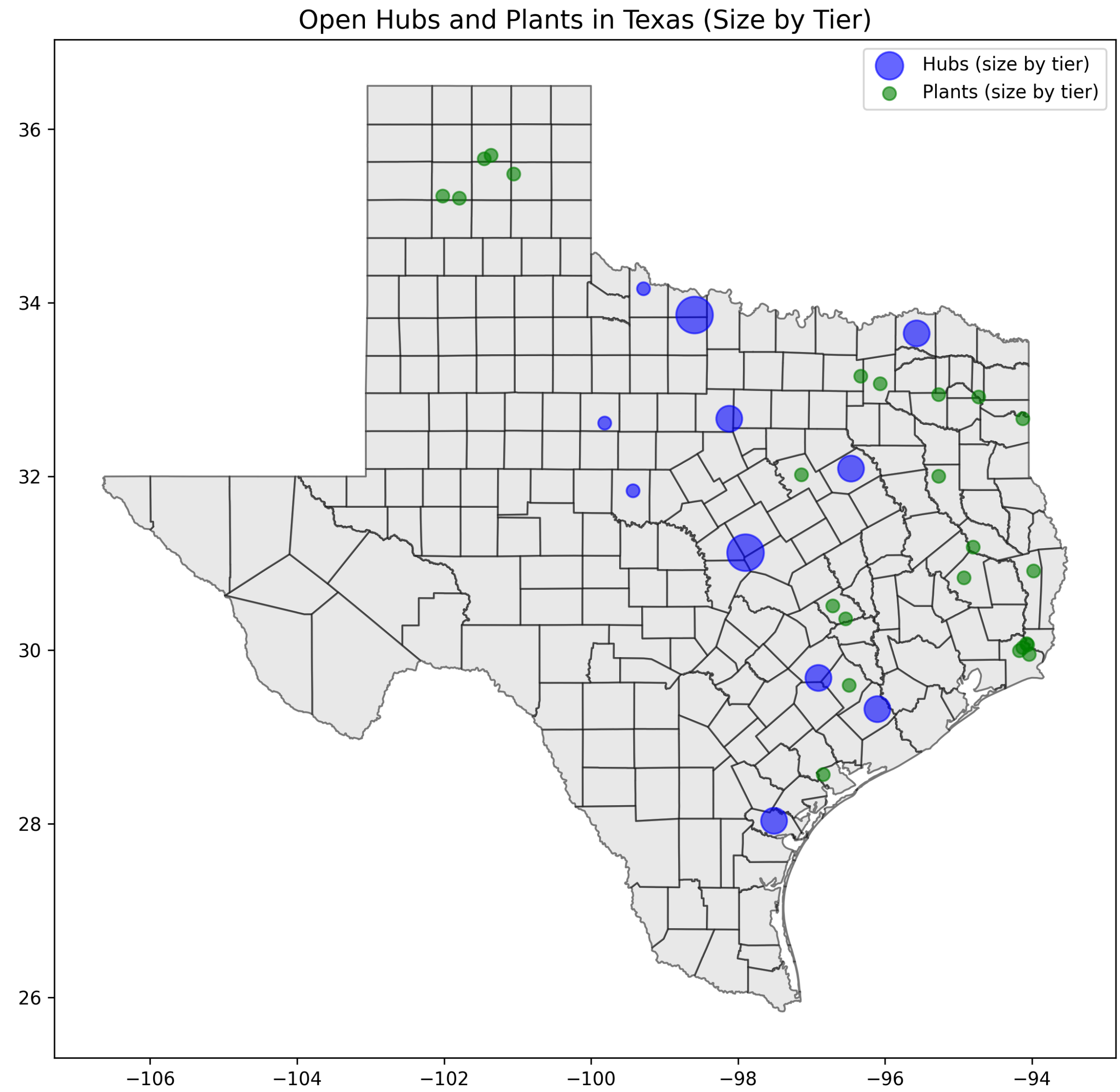

Figure 2: Geogrpahical Distribution of Open Hubs and Plants in Texas (Size by Tier)

Transportation and Logistics

- **Transportation Requirements:**
  - **Trucks:**
    - **128,136 trucks** were required to transport biomass from suppliers to hubs.
    - **20,939 trucks** delivered bioethanol from plants to demand counties.
  - **Trains:**
    - **360 trains** facilitated biomass transport from hubs to plants, emphasizing the critical role of rail transport.
- **Transportation Costs:**

  - The largest cost component is the **road transportation cost (suppliers to hubs)** at **$87.82M**.
  - The **rail transportation cost (hubs to plants)** is **$31.37M**.
  - The **road transportation cost (plants to counties)** is lower at **$21.17M**, reflecting the strategic placement of plants near demand centers.

Table 1: Optimal Solution Parameter Results

Decision Variable	**Value**
Total Demand	728,383,400 L
Total Supply	3,053,378 Mg
Number of Hubs	11 (potential 33)
Number of Plants	24 (potential 167)
Unmet Demand	21,383,285.71 L
Total Electricity Generated	1,439,903.25 MWh
Number of Trucks (Supplier to Hub)	128,136
Number of Trucks (Plant to County)	20,939
Number of Trains	360

Financial Performance

- **Revenue:**
  - Total revenue from bioethanol and electricity sales: **$404.30M**.
  - Bioethanol contributed **84%**, while electricity accounted for **16%**.
- **Costs:**
  - Total costs: **$284.63M**, comprising transportation, loading, and investment costs, as well as unmet demand penalties.
- **Profit:**
  - The overall profit was **$119.67M**, indicating the model's ability to balance revenue generation and cost optimization effectively.

Table 2: Optimal Solution Financial Results

Objective Function Term	**Amount ($)**
Revenue from Bioethanol	339,360,054.86
Revenue from Electricity	64,939,636.58
Total Revenue	**404,299,691.44**
Unmet Demand Penalty Cost	(10,691,642.86)
Hub Investment Cost	(35,796,279.22)
Plant Investment Cost	(45,991,675.11)
Road Transportation Cost (Supplier to Hub)	(87,820,047.23)
Rail Transportation Cost (Hub to Plant)	(31,372,258.13)
Road Transportation Cost (Plant to County)	(21,173,420.67)
Truck Loading Cost (Supplier to Hub)	(18,351,637.92)
Train Loading Cost (Hub to Plant)	(30,765,600.00)
Truck Loading Cost (Plant to County)	(2,662,503.57)
Total Costs	**(284,625,064.73)**
Total Profit (Revenue - Cost)	**119,674,626.71**

Scenario Testing

The model was tested across **10 scenarios**, altering specific parameters such as hub/plant capacity, transportation costs, penalty costs, demand levels, and bioethanol/electricity prices. Key observations include:

- Increasing electricity selling prices significantly improved profitability, highlighting the value of electricity as a byproduct especially with further incentivization through renewable energy credits and other programs.
- Higher penalty costs incentivized demand fulfillment but increased costs for unmet demand.
- Subsidized bioethanol prices showed a positive impact on revenue and profit margins.

Table 3: Different Instances & Their Results

Instance	Instance Type	Objective Value ($)	Optimality Gap (%)	Solution Time (s)
1	Low Hub/Plant Capacity	104,626,951.26	0.95	189
2	High Railcar	120,613,479.78	2.00	95
3	High Penalty Cost	98,614,433.18	1.99	217
4	High Electricity Revenue	184,401,457.40	0.99	36
5	Subsidized Bioethanol Price	170,243,099.03	1.04	131
6	High Transportation Cost	92,914,658.47	1.00	125
7	Low Transportation Cost	147,577,464.03	0.83	28
8	High Demand	-30,572,893.32	2.73	165
9	Low Demand	137,100,496.95	0.59	164
10	Optimal Solution	119,674,626.72	0.60	1,647

6 Conclusions and Future Research Directions

The optimization model developed for the biofuel supply chain network in Texas demonstrates significant potential in enhancing operational efficiency and economic viability. The findings highlight its potential to improve operational efficiency and economic viability for biofuel production and distribution. Key takeaways emphasize the model's capability, flexibility, and refinement:

1. **Optimization Efficiency**: The model successfully minimized transportation and investment costs while maximizing revenue from bioethanol and electricity generation. This demonstrates the model's ability to identify the most cost-effective locations and configurations for hubs and biorefineries.
2. **Scenario Flexibility**: By incorporating more costs in parameters, such as penalty costs for unmet demand and bioethanol price subsidies, the model showcased its adaptability. This addition to the model further refined the output, additionally the inclusion of counties futher realized more flexibility for the model to find optimal routings and investments.
3. **Revenue Drivers**: Bioethanol production emerged as the primary source of revenue as presented by our model. Additionally, electricity generation provided supplementary revenue, offering a valuable secondary income stream that enhanced overall profitability, particularly in scenarios with elevated electricity prices.
4. **Unmet Demand Challenges**: While the model optimized network operations, it highlighted persistent unmet demand, underscoring the need for further refinement in capacity planning and transportation logistics. This is most likely due to how our supply is structured, and as a result further refinement into the incoming resources for suppliers could greatly improve the optimality and accuracy of our model.

Across different instances, the model demonstrated adaptability, with objective values ranging from -$30.57 million in high-demand scenarios to $184.4 million when electricity revenue was maximized. The optimal solution achieved a total profit of $119.67 million with an optimality gap of 0.60% in 1,647 seconds. The network configuration selected

11 hubs (33% of the available options) and 24 plants (14% of the available options), effectively balancing investment costs and supply chain efficiency.

The total cost of $284.63 million was primarily attributed to transportation expenses ($140.37 million across road and rail), facility investments ($81.79 million), and loading operations ($51.78 million). Scenarios with high electricity revenue and subsidized bioethanol prices produced the highest objective values, underscoring the importance of policy incentives and diversified revenue streams. However, scenarios with high transportation costs and fluctuating demand significantly reduced profitability, highlighting the need for improved capacity planning and logistical efficiency.

Overall, these results showcase the model's potential to optimize bioethanol supply chains while identifying areas for further refinement, such as minimizing unmet demand and enhancing cost management in transportation and facility operations.This model serves as a steppingstone toward developing a more robust and accurate framework that can further optimize the bioethanol supply chain and address related supply chain challenges. Areas for improvement include:

1. **Model Enhancements**:
   - Introduce stochastic variables to address uncertainties in supply, demand, and transportation costs. For example the variation of biomass cost dependent on which side of the state it is being bought from.
   - Expand the range of conversion technologies to include chemical and biological methods, offering a broader set of operational configurations.
2. **Geographical and Resource Integration**:
   - Expand the model to multi-state or national networks to evaluate scalability and address region-specific logistical constraints.
   - Implement variables for feedstock sourcing based on regional biomass availability and associated costs.
3. **Environmental Objectives**:
   - Add greenhouse gas emission constraints at the county or state level to ensure compliance with sustainability standards.
   - Incorporate in-depth energy consumption data to provide a more accurate representation of environmental impacts.
   - Include waste limitation set by count or state governments to realistically enforce production limitations on each facility.
4. **Logistics and Decision Variables**:
   - Develop dynamic routing capabilities for real-time adjustments based on traffic patterns, weather, or resource availability.
5. **Economic and Policy Analysis**:
   - Explore the effects of green energy incentives, such as tax benefits or subsidies, to promote the adoption of biofuel technologies.
   - Examine the impact of penalties on fossil fuels to provide actionable insights for policymakers.

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8 Member Contributions

Literature Review

Ahmad, Ethan, and Atharva (2-3 Papers Per Member)

Mathematical Model

Atharva

Experimental Design and Gurobi Modeling

1. Data Collection and Parameter Generation/Modification - Atharva
2. Gurobi Modeling - Ahmad and Atharva
3. ARC Consulting - Ethan

Report

1. Motivation and Introduction - Ahmad, Ethan, and Atharva
2. Model Formulation - Atharva
3. Experimental Design - Ahmad
4. Results - Ahmad (Results Table) & Atharva (Content, Model, & Explanation)
5. Conclusions and Future Research - Ethan
6. Report Writing - All Members Contributed Equally

Presentation

All Members Contributed Equally

A Details of Open Hubs and Plants

Table 4: Details of Open Hubs and Plants

Open Hubs Details					
Hub	**County Name**	**Latitude**	**Longitude**	**Tier**	**Capacity**
17952	Coleman	31.83528	-99.42767	Small	75,000
17945	Wilbarger	34.16258	-99.28511	Small	75,000
17466	Jones	32.61514	-99.81358	Small	75,000
18042	Fayette	29.67922	-96.90505	Medium	300,000
17934	Palo Pinto	32.66522	-98.11879	Medium	300,000
17359	Wharton	29.31990	-96.10283	Medium	300,000
17201	Lamar	33.64844	-95.56841	Medium	300,000
17592	Navarro	32.09099	-96.46175	Medium	300,000
18127	San Patricio	28.03355	-97.50889	Medium	300,000
18303	Coryell	31.12247	-97.89691	Large	600,000
17620	Wichita	33.85992	-98.59059	Large	600,000
Open Plants Details					
Plant	**County Name**	**Latitude**	**Longitude**	**Tier**	**Capacity**
10062	Gray	35.483894	-101.051743	Small	38,015,926
10059	Hutchinson	35.699722	-101.360000	Small	38,015,926
10060	Hutchinson	35.659157	-101.452660	Small	38,015,926
9133	Marion	32.665000	-94.123330	Small	38,015,926
9142	Morris	32.915556	-94.724167	Small	38,015,926
9132	Jasper	30.911400	-93.976700	Small	38,015,926
10056	Potter	35.230000	-102.017500	Small	38,015,926
10058	Potter	35.205437	-101.791649	Small	38,015,926
10066	Calhoun	28.566421	-96.839191	Small	38,015,926
9131	Cherokee	32.002200	-95.268000	Small	38,015,926
9085	Angelina	31.186014	-94.798904	Small	38,015,926
9107	Hill	32.019382	-97.135938	Small	38,015,926
9140	Polk	30.832680	-94.923690	Small	38,015,926
9174	Jefferson	29.950000	-94.036389	Small	38,015,926
9057	Jefferson	29.993334	-94.169167	Small	38,015,926
9054	Jefferson	30.028925	-94.124053	Small	38,015,926
9056	Orange	30.073997	-94.071716	Small	38,015,926
9053	Orange	30.060556	-94.058611	Small	38,015,926
9060	Burleson	30.508894	-96.709831	Small	38,015,926
9184	Burleson	30.360014	-96.534439	Small	38,015,926
9204	Wood	32.943279	-95.268888	Small	38,015,926
9040	Colorado	29.594168	-96.486668	Small	38,015,926
9105	Hunt	33.068050	-96.063988	Small	38,015,926
9088	Hunt	33.154957	-96.328903	Small	38,015,926