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Sustainable site selection for biomass refineries: an analytic network process model for optimizing bioenergy production in Iran

Zeynab Pashmi [1], Maryam Chamehsara [2], Sara Parsi [3], Abooali Golzary [4,*]

[1] Department of Industrial Engineering, Mazandaran University of Science and Technology, Babol, Iran
[2] Department of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran
[3] Faculty of Management and Economics, Tarbiat Modares University, Tehran, Iran
[4] School of Environment, College of Engineering, University of Tehran, P.O. Box 14155-6135, Tehran, Iran
[*] Correspondence: Abooali Golzary email: abooaligolzary@ut.ac.ir

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Abstract

Biomass, with its abundant resources and versatility, is increasingly recognized as a sustainable alternative to fossil fuels for fuel and chemical production. However, establishing an efficient supply chain for microalgae-based biomass refineries poses challenges due to irregular production patterns and the dispersed distribution of resources. This study presents a framework for selecting an optimal location for a biomass refinery in Iran, chosen for its favorable conditions, including abundant sunlight, carbon dioxide, and saline water. Using a mathematical optimization model and network analysis, this framework evaluates potential refinery sites based on criteria such as infrastructure access, climate conditions, and algae growth suitability. Economic, environmental, social, and logistical indicators guide the decision-making process. The results identify Bushehr as the optimal location, primarily driven by transportation cost efficiency, which significantly impacts the overall supply chain costs. By optimizing transportation routes, this model not only reduces expenses but also maximizes the biomass energy potential, contributing to a more sustainable bioenergy infrastructure. The insights from this study support the transition toward sustainable energy production and offer a strategic approach to designing effective biomass refinery supply chains.

Keywords Biomass, refinery, supply chain optimization, microalgae, sustainability

1. Introduction

In recent decades, urbanization and industrial activities have led to a significant problem for humans known as "climate change," which scientists attribute to the increase in greenhouse gases [1]. In 2022, severe weather events such as droughts, heatwaves, massive wildfires, and destructive floods caused significant damage to agricultural products and infrastructure, increasing costs [2]. To address this issue, the continuous development of bioenergy processing technologies has accelerated the establishment of bio-refineries. This trend is expected to grow with fluctuations in fossil fuel prices and increasing global concerns about climate change [3].

Several technologies have been developed to adapt to different types of biomass, including anaerobic digestion to increase the value of waste materials, conversion into gas and thermal decomposition to adapt lignocellulosic biomass to low moisture, and hydrothermal liquefaction for liquefying wet biomass [4-8].

At the International Conference on Climate Change held in Mexico from November 29 to December 10, 2010, Iran was among the top 10 countries producing greenhouse gases, making the subject matter doubly important. Therefore, in line with the Paris Agreement (September 12, 2015, COP21, Paris), which commits Iran to reduce greenhouse gas emissions by 4% through the presentation of NDC (National Commitment Document), there is a need to prioritize actions towards reducing greenhouse gas emissions in Iran [9-11].

Biomass is a valuable source of renewable energy that can be converted into biofuels either directly or indirectly. Bio-oil production from biomass has been the subject of much research, and significant progress has been made in developing the necessary technology [12-15].

While algae-based biomass has great potential for biofuel production, limited research has been conducted in this area. Algae require sunlight, carbon dioxide, and nutrients to grow, and Iran's abundance of saltwater, sunlight, and ample land, along with high carbon dioxide emissions, make it an ideal location for algae cultivation [16-18]. By cultivating algae, atmospheric carbon dioxide can be removed, preventing air pollution. Additionally, algae can purify wastewater and remove heavy metals while providing an energy source that can be used to power factories, reducing the need for fossil fuels and the resulting air pollution. Compared to other energy crops, algae have high growth rates, produce large amounts of lipids, and require less water. Algae can grow in various weather conditions and locations, and with the use of specific reactors, high efficiency can be achieved [19-23].

In this article, we aim to identify the optimal location and suppliers for establishing a biofuel refinery among several potential sites. Selecting suitable locations for biomass refineries is a complex but critical task due to the irregular production and dispersed distribution of biomass resources. Numerous approaches have been developed for locating bio-refineries, including combining social and biophysical analyses to evaluate the feasibility of repurposing facilities like paper pulp mills for bio-refinery use. This study builds upon these methods, integrating multi-criteria decision-making techniques to address the unique economic, environmental, and logistical factors essential for sustainable biofuel production.[24], mixed-integer linear programming models for identifying economically viable bio-refinery sites [25, 26], and a computational intelligence framework for biomass supply chain design based on an artificial neural network approach [27].

In recent years, several articles and research studies have been conducted on selecting the optimal location and identifying suppliers in supply chain management [28, 29]. However, optimal location selection models in sustainable supply chains are not employed. Therefore, the use of linguistic variables in multi-criteria decision-making methods and linear programming models, can be considered a novel aspect of the proposed models. Additionally, this study highlights the inadequacy of decision-making factors in location selection, particularly in bio-refinery location selection, where economic, environmental, and social factors hold significant importance.

To address this issue, a multi-criteria decision-making (MADM) method was used to prioritize indicators and criteria, and a linear programming model was implemented using the SCIP methodology in GAMS software version 24.4.1 to select suppliers. The outputs of the linear programming model, including the purchase amount from each supplier and their weight, were used as inputs in the bioenergy refinery location-allocation. location-allocation. The refinery location-allocation problem was addressed using the Analytic Network Process (ANP) network-based multi-criteria decision-making method with Super Decisions software to identify the optimal location for the bio-refinery among the candidate nodes. Economic, environmental, and social indicators within the sustainable supply chain group were considered to enhance the supply chain, minimize transportation costs to the refinery, and maximize the potential of biomass energy supply. The combination of these methods can be considered a distinguishing aspect of this study.

2. Methodology

There have been numerous proposals for supplier selection methods in the literature, including Data Envelopment Analysis (DEA) [30], Analytic Hierarchy Process (AHP) [31], Fuzzy Analytic Hierarchy Process (FAHP) [32, 33], Analytic Network Process (ANP)[34], TOPSIS [35], Game Theory [36], and others. Quantitative mathematical programming models such as linear programming [37], mixed integer programming [31], and nonlinear mixed integer programming [38] have also been presented. Linear programming is a widely used and standard tool that is extensively used for scientific computations performed by computers. Its most common application is to solve general resource allocation problems for a set of activities under limited resources in an optimal manner. In this section, we describe the linear programming model used to select suppliers of raw materials for the bioenergy refinery, which are essentially algae cultivation laboratories, from among the candidate cities in Iran that meet the initial conditions. The objective of this model is to maximize the purchase value from each supplier while minimizing the costs (Figure 1).

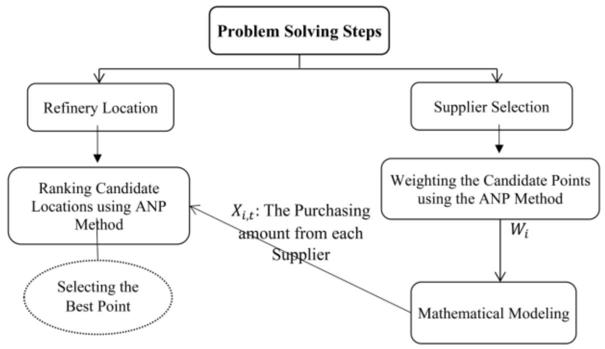

Figure 1 View of the general stages of the problem. This figure illustrates the general stages of the problem-solving process, including refinery location, supplier selection, mathematical modeling, and weighting candidate points using the ANP method.

Assumptions of the model:

- Variable $X_{i,t}$ represents the quantity purchased from each supplier as a real number.
- The cost of using any vehicle (whether it is fully utilized or not) must be paid.
- The company's budget is limited in each period.
- The time interval is discrete, and the demand is certain.
- All vehicles will be sourced from outside the organization.
- Each supplier has its own discount strategy.
- The total production capacity of suppliers exceeds the refinery's requirements, so there is no shortage.

- Algae, after the production process, are dried and stored. Therefore, storage costs are also considered.
- The time interval, including holidays, is 6 days.

Model constraints:

- Purchase capacity
- Company's budget capacity
- Vehicle capacity

The objective is to determine the quantity purchased from the proposed suppliers, considering their weights, in a way that minimizes the total supply chain cost.

Therefore, the model must balance the following costs:

- Holding costs
- Purchase costs
- Transportation costs

Symbols:

- $i \in N$: Potential available suppliers
- $t \in T$: Planned time interval

Parameters:

- W_i: Weight obtained for each supplier using the ANP method
- $V_{i,t}$: Minimum order quantity that supplier i can provide at time t
- $C_{i,t}$: Production capacity of supplier I at time t
- D_t: Company's demand at time t
- B_t: Company's budget for purchasing raw materials
- H: Unit holding cost
- k: Vehicle capacity
- $l_{i,t}$: Number of vehicles required for each supplier at time t
- m: Transportation cost per vehicle
- pc_t: Company's capacity for purchasing at time t
- $\mathrm{I_t}$: Average inventory at time t

Variables under investigation:

- $X_{i,t}$: Quantity purchased from each supplier
- $\mathrm{I_t}$: Average inventory at time t, dependent on the variable $X_{i,t}$
- $\mathrm{y_{i,t}}$: is equal to 1 if we purchase from supplier I at time t. The binary variable is equal to 1 I at time t and 0 otherwise.

Objective function:

1) $\mathrm{Max(TVP)} = \sum_{i=1}^{N}\left(\sum_{t=1}^{T} W_i * x_{i,t}\right)$

2) $\mathrm{Min(TCP)} = \sum_{i=1}^{N}(\sum_{t=1}^{T} p_i * x_{i,t}) + \mathrm{H}\sum_{t=1}^{T}(\sum_{i=1}^{N} x_{i,t}/2) + \sum_{t=1}^{T}(\sum_{i=1}^{N} l_{i,t} * m)$

Constraints:

St:

1) $\sum_{i=1}^{N}x_{i,t} = D_t$ t=1,2,..,T

2) $\sum_{i=1}^{N}\left(\sum_{t=1}^{T}x_{i,t}\right) \le pc_t$

3) $x_{i,t} \ge V_{i,t}$ $\quad i = 1, \dots, \mathrm{N} \quad t = 1, \dots, \mathrm{T}$

4) $\mathrm{y_{i,t}} = \begin{cases} 1 & x_{i,t} > 0 \quad \text{If we purchase from supplier i} \\ 0 & o.w \quad Otherwise \end{cases}$

5) $x_{i,t} \le C_{i,t}$ i=1,…,N t=1,…,T

6) $\sum_{i=1}^{N}(\sum_{t=1}^{T} p_i * x_{i,t}) \le B_t$

K is the vehicle capacity, where if the purchased load is less than the capacity, one truck is sufficient, and if the purchased load is greater than k and less than or equal to 2k, two trucks are needed, and so on.

7) $\begin{cases} 0 < x_{i,t} \le k & l = 1 \\ k < x_{i,t} \le 2k & l = 2 \\ \dots & \dots \\ (c-1)k < x_{i,t} \le ck & l = c \end{cases}$

8) $p_i = \begin{cases} 0 < x_{i,t} \le q_{i,1} & p_{i1} \\ q_{i,1} < x_{i,t} \le q_{i,2} & p_{i2} \\ q_{i,2} < x_{i,t} & p_{i3} \end{cases}$

9) $\mathrm{I_{t-1}} + \sum_{i=1}^{N} x_{i,t} \ge D_t$

10) $\mathrm{I_t} = \sum_{i=1}^{N} x_{i,t} - D_t + \mathrm{I_{t-1}}$ t=1,…,T

11) $\sum_{i=1}^{N} x_{i,t} \ge 0$ $\quad \forall i, \forall t$

Objective function 1 aims to maximize the total value of purchases from different suppliers, while objective function 2 seeks to minimize the costs associated with supplier selection. The first term in the objective function represents the cost of purchasing from suppliers over the entire planning horizon based on the specified unit purchase price. The second term represents the inventory holding cost based on the average inventory formula in the planning horizon. The third term represents the transportation cost considering the required number of vehicles and the rental cost per vehicle, denoted as "m".

Constraint 1 ensures that the company's demand requirements are met, indicating no shortage. Constraint 2 determines the purchasing capacity range of the company, and the supplier's product supply capacity in each period is reflected in constraint 3. Constraint 4 represents a binary variable that takes 1 if seaweed is purchased from supplier i at time t and 0 otherwise. Constraint 5 indicates that the purchase cannot exceed the production capacity of each supplier. The compatibility of the purchase cost with the company's budget is expressed in constraint 6. Constraint 7 specifies the required number of vehicles. The overall discount model is represented in constraint 8, which indicates the purchase price for a specified purchase volume, considering that different suppliers have different discount strategies. The sum of the average inventory from the previous period and the purchase amount in the current period ensures the demand for the current period, as evident in constraint 9. Constraint 10 represents inventory balance, and constraint 11 determines the variable model.

To solve the linear programming model, the SCIP methodology in the GAMS software, which utilizes the constraint generation approach, has been employed. In the following section, we will introduce a case study used in this research, followed by a discussion of the obtained results.

2.1 Description of the case study - phase 1

In this study, we have considered a supply chain network comprising five cities in Iran. The data on these cities, including their production capacity, purchasing capacity, minimum order quantity, and other relevant factors, were approximated and obtained from expert opinions. We selected these 5 cities as candidate points for supplier selection, considering the requirements for algae growth, such as proximity to saline water, proximity to a refinery for the supply of CO_2, and air temperature, with the optimal temperature range for algae growth being 28-18 degrees Celsius. To determine the weights of each point, we employed the Analytic Network Process (ANP) multi-criteria decision-making method and the Super Decision software. Each of these points has been incorporated into the linear programming model with their respective weights (Figures 2-4).

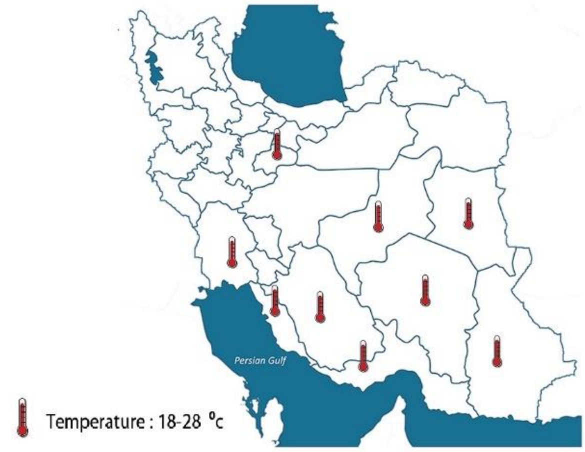

Figure 2 Area Temperature: 18-28°C. Figure 2 shows the temperature range (18-28°C) suitable for algae growth in the candidate cities, which is a critical factor for selecting optimal cultivation locations.

Figure 3 Coastal Cities in the South (Saline Water). Figure 3 highlights the coastal cities in southern Iran (e.g., Bandar Abbas, Bushehr, and Imam Khomeini Port) that have access to saline water, a key resource for algae cultivation.

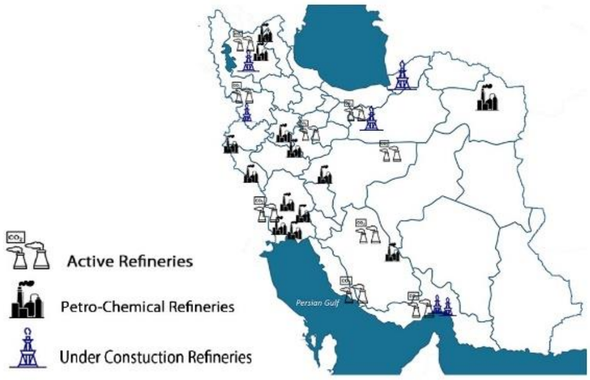

Figure 4 Cities with Suitable CO_2 levels. Figure 4 identifies cities with suitable CO_2 levels, which are essential for efficient algae growth and biofuel production.

2.2 Calculating the weights of supplier candidate points

The Analytic Network Process (ANP) is a decision analysis method that is more general than the Analytic Hierarchy Process (AHP) and can handle complex relationships between different decision levels in a network format. It takes into account interactions and feedback among criteria and alternatives [39].

Some decision indicators are quantitative, and it is possible that they have different units. In such cases, it is necessary to normalize these indicators or transform them into qualitative indicators within the range of 0-1. If the value of an option Ci falls within a range (Cil, Ciu), a value of 0 is assigned to the minimum value Cil, and a value of 1 is assigned to the maximum value Ciu. This property holds for positive indicators. However, if an indicator is negative, such as cost, a value of 0 is assigned to the maximum value, and 1 is assigned to the minimum value. Essentially, it is evaluated based on the level of desirability [40]. The cities of Bandar Abbas, Shiraz, Ahvaz, Bushehr, and Bandar Imam Khomeini have been selected as candidate points for supplier selection, considering the conditions mentioned above. The criteria for weighting include access to saline water, air temperature, proximity to petrochemical industries, startup costs, and availability of required human resources. The resulting matrix obtained by transforming qualitative and quantitative indicators into weighted qualitative indicators is shown below:(Figure 5).

$$
\begin{array}{r c}
 & \begin{array}{ccccc} \text{Proximity to the Saline Water} & \text{Temperatur} & \text{Proximity to the refinery} & \text{Setup cost} & \text{Access to Human Resource} \end{array} \\
\begin{array}{r} \textbf{Bandar Abbas} \\ \textbf{Ahvaz} \\ \textbf{Boushehr} \\ \textbf{Shiraz} \\ \textbf{Imam Khomeini port} \end{array} &
\begin{bmatrix}
0.955 & 0.865 & 0.955 & 0.5 & 0.5 \\
0.865 & 0.665 & 0.745 & 0.5 & 0.665 \\
0.955 & 0.865 & 0.955 & 0.5 & 0.5 \\
0.335 & 0.255 & 0.955 & 0.5 & 0.5 \\
0.955 & 0.59 & 0.955 & 0.045 & 0.045
\end{bmatrix}
\end{array}
$$

Figure 5 Transformation of qualitative and quantitative indicators into weighted qualitative indicators, consolidating data for analysis and decision-making.

If the weights of criteria depend on the weights of options, and the weights of options depend on the weights of criteria, the problem becomes more complex. It goes beyond a hierarchical structure, forming a network or non-linear system. In such cases, hierarchical rules and formulas cannot be used to calculate the weights of elements, and instead, network theory must be employed to calculate the weights of elements (Table 1).

2.3 Solution of the first stage model

This section described the numerical and verbal parameters used in the linear programming model for supplier selection. Then, the results of solving the model using GAMS software are presented (Tables 2-5).

Table 1 Applying network theory for complex decision-making in supplier selection among cities in Iran.

Cluse Nodes Labels		Goal	Criteria					Candidate Points				
		Supplier Selection	Temperature	Proximity to the Saline Water	proximity to Refinery	Human Resource	Setup Cost	Ahvaz	Imam Khomeini Port	Bandar Abbas	Bushehr	Shiraz
Goal	Supplier Selection	**0.3333**	0	0	0	0	0	0	0	0	0	0
Criteria	Temperature	**0.095**	0	0	0	0	0	0	0	0	0	0
	Proximity to the Saline Water	**0.034**	0	0	0	0	0	0	0	0	0	0
	proximity to Refinery	**0.02822**	0	0	0	0	0	0	0	0	0	0
	Human Recourse	**0.06763**	0.5	0.5	0.5	0.5	0.5	0	0	0	0	0
	Cost	**0.1083**	0	0	0	0	0	0	0	0	0	0
Candidate Points	Ahvaz	**0.23927**	0.062514	0.03853	0.017243	0.246568	0.09217	0	0	0	0	0
	Imam Khomeini Port	**0.18194**	0.03947	0.14576	0.120684	0.01899	0.243569	0	0	0	0	0
	Bandar Abbas	**0.37894**	0.018995	0.14576	0.12069	0.076801	0.05475	0	0	0	0	0
	Boushehr	**0.06169**	0.189947	0.14576	0.12069	0.080837	0.05475	0	0	0	0	0
	Shiraz	**0.13817**	0.018114	0.02417	0.12069	0.076801	0.05475	0	0	0	0	0

This table presents the application of network theory for supplier selection among candidate cities in Iran. The weights for each city (Shiraz, Bushehr, Bandar Abbas, Imam Khomeini Port, and Ahvaz) are calculated based on criteria such as setup cost, human resources, proximity to refinery, proximity to saline water, and temperature. The goal is to select the optimal supplier for algae biomass production.

Table 2 Weight Value Obtained for Each Supplier.

	1	2	3	4	5
W_i	0.239267	0.18194	0.378935	0.06169	0.138169

This table displays the weight values (Wi*Wi*) assigned to each supplier (1 to 5) using the Analytic Network Process (ANP) method. The weights are normalized and sum to 1, reflecting the relative importance of each supplier in the decision-making process.

Table 3 Numerical Parameters for Solving the Linear Programming Model.

	1	2	3	4	5	6
D_t	150	120	100	110	90	100
PC_t	1500	1800	1400	1700	1500	1300
B_t	55000	65000	55000	60000	50000	45000

This table provides the numerical parameters used in the linear programming model, including demand (Dt), purchasing capacity (PCt), and budget (Bt) for each time period (1 to 6). Units: Dt (tons), PCt (tons), Bt (USD).

Table 4 Numerical Parameters for Unit Price of Goods.

	1	2	3	4	5
P_1(I)	50	65	70	73	80
P_2(I)	45	60	65	68	75
P_3(I)	40	55	60	63	70

This table lists the unit price of goods ($Pq(i)$) for each supplier (1 to 5) across three price tiers ($P1(i)$, $P2(i)$, $P3(i)$). The prices are in USD per ton and vary based on the quantity purchased.

Table 5 Numerical Parameter for Supplier Production Capacity.

	1	2	3	4	5	6
1	65	73	67	65	70	67
2	57	62	58	60	62	61
3	46	50	52	50	50	48
4	71	70	70	73	71	67
5	67	70	65	67	70	65

This table shows the production capacity of each supplier (1 to 5) across six time periods (1 to 6). The values represent the maximum amount of biomass (in tons) that each supplier can produce in a given time period.

3. Results

To solve the multi-objective model of the supplier selection problem, the SCIP method in GAMS software version 24.4.1 was executed on a 64-bit machine with a processing power of 2.26 GHz. Tables 6-8 shows the results obtained from solving the model.

Table 6 Results Obtained from Model Solution.

Computational Time (M)	Z1	Z2
6.4737	154.290	32025

This table presents the results of the linear programming model, including the total cost ($Z2$), total purchase value ($Z1$), and computational time (in minutes). The model was solved using the SCIP methodology in GAMS software.

3.1 Sensitivity analysis

In sensitivity analysis, we examine the effects of changes in the parameters of a model on its final output. The reason for the importance of sensitivity analysis is that in the real world, model parameters (objective function coefficients, right-hand side values, technical coefficients, number of variables, number of constraints) vary, and these variations are related to environmental conditions.

This section aims to examine the sensitivity of the supplier selection model to changes in critical factors such as demand and purchase price. We plotted the changes in the objective functions separately based on purchased price demand and purchase price variations. The steeper the slope of the graph, the more the cost or purchasing value functions depend on the purchase price or demand item. Inaccurate purchase price predictions may undermine the calculated financial index and impede the reliability of the economic analysis.

3.2 Sensitivity analysis of the model to changes in the demand factor (Dt)

As with any location problem, sensitivity analysis concerning the demand factor requires attention. Tables 9-17 displays the values of the objective function, purchase amount, and the number of required vehicles for both an increase and decrease in the demand variable (Figure 6, Figure 7).

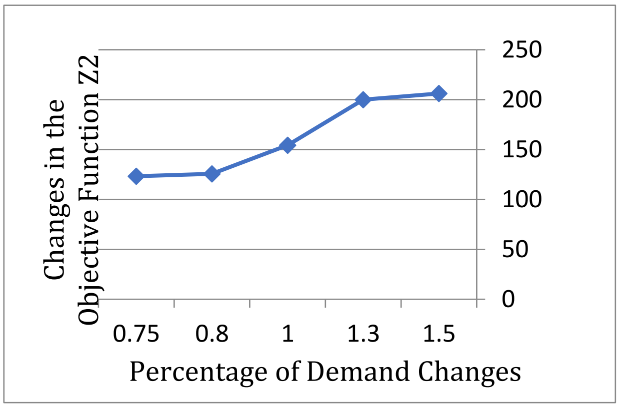

Figure 6 Sensitivity Analysis Chart of the Second Objective Function (Existing Costs) with respect to Changes in Demand. Figure 6 shows the sensitivity of the second objective function (total costs) to changes in demand. The steeper the slope, the more sensitive the costs are to demand fluctuations.

Table 7 Results of X.L (Purchase Amount from Each Supplier in 6 Time Periods).

	1	2	3	4	5	6
1	75.000	90.000	100.000	110.000	90.000	100.000
2	75.000	30.000				

This table shows the quantity of biomass purchased from each supplier (1 to 5) across six time periods (1 to 6). The values are in tons and represent the optimal purchase amounts determined by the model.

Table 8 Results of L.L (Number of Required Trucks in 6 Time Periods).

	1	2	3	4	5	6
1	1.000	1.000	1.000	1.000	1.000	1.000
2	1.000	1.000				

This table indicates the number of trucks required to transport the purchased biomass from each supplier (1 to 5) across six time periods (1 to 6). The values are based on the vehicle capacity and the quantity of biomass purchased.

Table 9 Results Obtained from Solving the Model with Changes in the Demand Variable.

Computational Time(M)	**Z1**	**Z2**	**D_t**
8.032	206.169	46767.5	**50% increase**
5.832	199.980	42820	**30% increase**
6.4737	154.290	32025	**Actual amount**
8.535	125.61	25990	**20% decrease**
8.985	123.281	27117.5	**25% decrease**

This table presents the results of the sensitivity analysis for changes in the demand variable (Dt). It shows the total cost ($Z2$), total purchase value ($Z1$), and computational time (in minutes) for different demand scenarios (50% increase, 30% increase, 20% decrease, and 25% decrease).

Table 10 Results Obtained X.L (Purchase Amount from Each Supplier in 6 Time Periods) with a 30% Increase in Demand Variable.

	1	2	3	4	5	6
1	80.000	84.000	100.000	110.000	117.000	130.000
2	85.000	72.000	30.000	33.000		
3	33.000					

This table shows the quantity of biomass purchased from each supplier (1 to 5) across six time periods (1 to 6) when the demand is increased by 30%. The values are in tons.

Table 11 Results obtained for L.L. (number of required trucks in 6 time periods) with a 30% increase in the demand variable.

	1	2	3	4	5	6
1	1.000	1.000	1.000	1.000	1.000	1.000
2	1.000	1.000	1.000			
3	1.000					

This table indicates the number of trucks required to transport the purchased biomass from each supplier (1 to 5) across six time periods (1 to 6) when the demand is increased by 30%.

Table 12 Results Obtained X.L (Purchase Amount from Each Supplier in 6 Time Periods) with a 20% Decrease in Demand Variable.

	1	2	3	4	5	6
1	80.000	90.000	80.000	88.000	72.000	80.000
2	40.000	6.000	30.000	33.000		

This table shows the quantity of biomass purchased from each supplier (1 to 5) across six time periods (1 to 6) when the demand is decreased by 20%. The values are in tons.

Table 13 Results Obtained L.L (Number of Trucks Required in 6 Time Periods) with a 20% Decrease in Demand Variable.

	1	2	3	4	5	6
1	1.000	1.000	1.000	1.000	1.000	1.000
2	1.000	1.000				

This table indicates the number of trucks required to transport the purchased biomass from each supplier (1 to 5) across six time periods (1 to 6) when the demand is decreased by 20%.

Table 14 Results Obtained X.L (Purchase Quantity from Each Supplier in 6 Time Periods) with a 50% Increase in Demand Variable.

	1	2	3	4	5	6
1	80.000	90.000	98.000	103.000	120.000	130.000
2	77.500	90.000	52.000	62.000	15.000	20.000

This table shows the purchase quantity (Xi,t) from each supplier (1 to 5) over six time periods (1 to 6) when the demand is increased by 50%. The values are in tons. Xi,t represents the quantity purchased from supplier i in time period t.

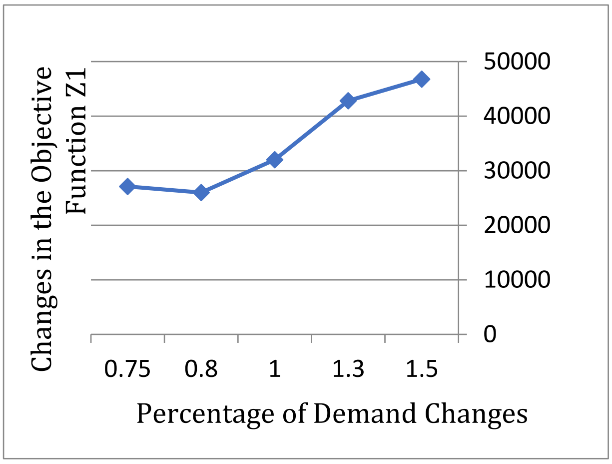

Figure 7 Sensitivity Analysis Chart of the First Objective Function (Purchase Value) with respect to Changes in Demand. Figure 6 shows the sensitivity of the first objective function (total purchase value) to changes in demand. The steeper the slope, the more sensitive the purchase value is to demand fluctuations.

Based on the two above graphs, the objective functions have a direct relationship with the demand, increasing with an increase in demand.

Sensitivity Analysis of the Model to concerning Changes in Purchase Price Factor (Pq(i)) (Tables 18-20).

As observed in the tables, the variables of purchase quantity, number of vehicles, and objective function Z1 remained unchanged with the variation in the purchase price. Only the objective function Z2, representing the costs, has been modified (Figure 8, Figure 9)

Table 15 Results Obtained L.L (Number of Trucks Required in 6 Time Periods) with a 50% Increase in Demand Variable.

	1	2	3	4	5	6
1	1.000	1.000	1.000	1.000	1.000	1.000
2	1.000	1.000	1.000	1.000	1.000	1.000

This table indicates the number of trucks required to transport the purchased biomass from each supplier (1 to 5) across six time periods (1 to 6) when the demand is increased by 50%.

Table 16 Results Obtained X.L (Purchase Amount from Each Supplier in 6 Time Periods) with a 25% Decrease in Demand Variable.

	1	2	3	4	5	6
1	80.000	90.000	75.000	82.000	67.000	75.000
2	32.500	27.000				

This table shows the quantity of biomass purchased from each supplier (1 to 5) across six time periods (1 to 6) when the demand is decreased by 25%. The values are in tons.

Table 17 Results Obtained L.L (Number of Trucks Required in 6 Time Periods) with a 25% Decrease in Demand Variable.

	1	2	3	4	5	6
1	1.000	1.000	1.000	1.000	1.000	1.000
2	1.000	1.000				

This table indicates the number of trucks required to transport the purchased biomass from each supplier (1 to 5) across six time periods (1 to 6) when the demand is decreased by 25%.

Table 18 Results Obtained from Solving the Model with Changes in Purchase Price Variable.

Computational Time(M)	**Z1**	**Z2**	**P_q(i)**
6.476	154.29	5.45337	**50% increase**
5.79	154.29	36450	**20% increase**
6.225	154.29	24480	**20% decrease**
5.03	154.29	5.15712	**50% decrease**

This table presents the results of the sensitivity analysis for changes in the purchase price variable ($Pq(i)$). It shows the total cost ($Z2$), total purchase value ($Z1$), and computational time (in minutes) for different purchase price scenarios (50% increase, 20% increase, 20% decrease, and 50% decrease).

Table 19 Results Obtained from X.L (Purchase Amount from Each Supplier in 6 Time Periods) with 50% and 20% Increase in Purchase Price Variable.

	1	2	3	4	5	6
1	75.000	90.000	100.000	110.000	90.000	100.000
2	75.000	30.000				

This table shows the quantity of biomass purchased from each supplier (1 to 5) across six time periods (1 to 6) when the purchase price is increased by 50% and 20%. The values are in tons.

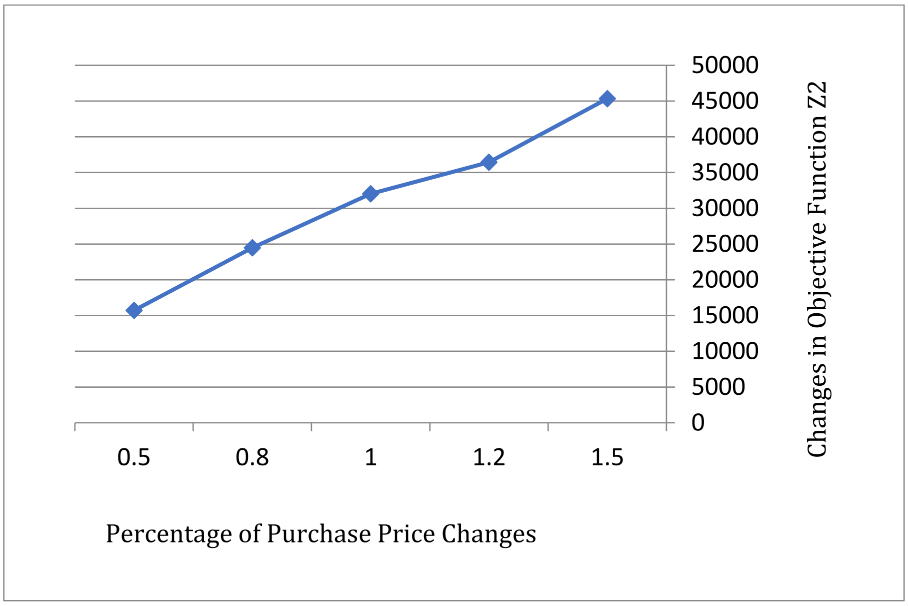

Figure 8 Sensitivity analysis chart of the second objective function (existing costs) with respect to changes in purchase price. Figure 8 shows the sensitivity of the second objective function (total costs) to changes in purchase price. The steeper the slope, the more sensitive the costs are to price fluctuations.

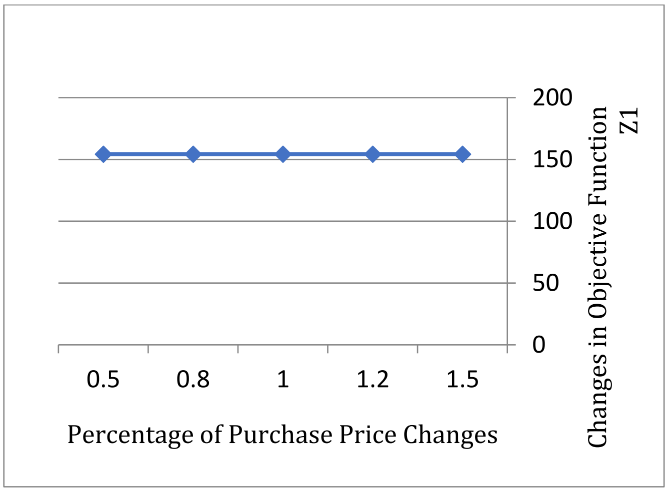

Figure 9 Sensitivity analysis chart of the first objective function (purchase value) with respect to changes in purchase price. Figure 9 shows the sensitivity of the first objective function (total purchase value) to changes in purchase price. The steeper the slope, the more sensitive the purchase value is to price fluctuations.

Table 20 Results obtained for L.L (number of required trucks in 6 time periods) with a 50% and 20% increase in the purchase price variable.

	1	2	3	4	5	6
1	1.000	1.000	1.000	1.000	1.000	1.000
2	1.000	1.000				

This table indicates the number of trucks required to transport the purchased biomass from each supplier (1 to 5) across six time periods (1 to 6) when the purchase price is increased by 50% and 20%.

The sensitivity analysis highlights the significant impact of demand variations on both objective functions (Z1 and Z2), with increased demand directly correlating with higher purchasing quantities, vehicle requirements, and overall costs. This strong dependency on demand fluctuations underscores the importance of accurate forecasting to manage resource allocation effectively. Adapting supplier and transportation arrangements to these fluctuations can help optimize costs and align supply chain operations with real-world demand conditions.

In contrast, changes in purchase price primarily affect the cost-related objective function (Z2 without altering purchasing quantities or logistics requirements. This resilience to price volatility demonstrates the model's operational stability, though it also signals the need for strategic supplier management. Establishing competitive and flexible supplier contracts, possibly with volume-based pricing or discount options, can mitigate the impact of rising costs, thus enhancing overall supply chain efficiency.

Overall, the sensitivity analysis suggests that while demand forecasting and logistical flexibility are critical for maintaining operational efficiency, proactive cost management through supplier negotiations can sustain cost-effectiveness. By balancing these strategies, supply chain managers can ensure a more adaptable and resilient biofuel refinery network capable of responding to market dynamics and supporting sustainability goals.

3.3 Description of case study -phase 2

This section develops a sustainable supply chain network to select the best location for establishing a biogas refinery. The network includes cities, each evaluated based on decision criteria in three economic, environmental, social, and critical domains. The scoring of each option is done approximately, considering the actual conditions. Finally, the option with the highest calculated weight is selected (Table 21, Table 22).

The pairwise comparison scoring method, similar to the previous case study, is based on the desirability scale ranging from 0 to 1. According to the output of the GAMS software, it can be observed that the options of Bushehr and Bandar Abbas have the highest scores and are selected as suitable suppliers (Figure 10) (Table 23).

As indicated in Table 23, Bushehr, with the highest obtained weight, is selected as the preferred location for establishing the refinery (Figure 11).

Table 21 Decision Criteria.

Criteria	Sub-criteria Code	Sub-Criteria	References
Economic	X_1	Purchase cost	[41]
	X2	Transportation cost	[41, 42]
Social	X_3	Job Creation	[43, 44]
	X_4	Social Acceptability	[44-46]
	X_5	Social Benefits	[47-49]
	X_6	Human Development Index	[47]
Environmental	X_7	Air pollution	[47]
	X_8	Noise pollution	[47]
	X9	Land usage rate	[47]
Critical	X_{10}	Abundant availability of water resources	[47]

This table lists the decision criteria used for selecting the optimal location for the biorefinery. The criteria are divided into economic, social, environmental, and critical domains, with sub-criteria such as purchase cost, transportation cost, job creation, and air pollution.

Table 22 Determination of Candidate Points.

Candidate Points	**Abadian**	**Boushehr**	**Mahshahr**	**Bandar Abbas**	**Imam Khomeini Port**	**Lavan Island**	**Asabuyeh**	**Ahvaz**	**Shira**	**Chabanar**
Y1	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10

This table identifies the candidate points (cities) considered for establishing the biorefinery. Each city is evaluated based on decision criteria such as access to water resources, proximity to saline water, and social benefits.

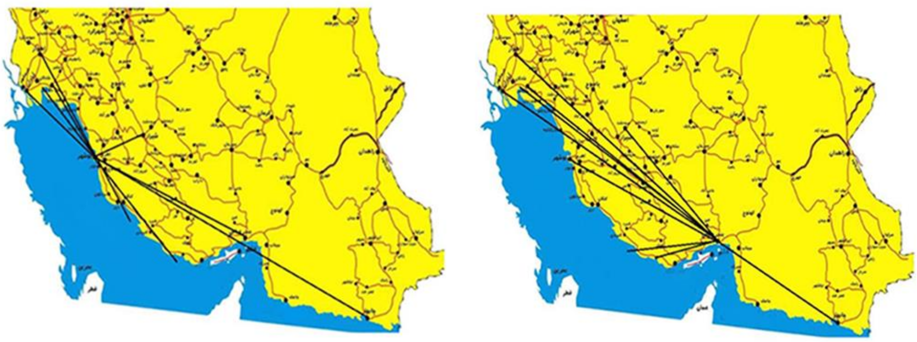

Figure 10 Transportation route from suppliers to candidate points. This figure illustrates the transportation routes from suppliers to candidate points for establishing the biorefinery. The routes are optimized to minimize transportation costs and maximize efficiency.

Table 23 Pairwise Comparison Scoring Results for Supplier Selection.

	Abadan	**Boushehr**	Mahshahr	Bandar Abbas	Imam Khomeini Port	Lavan Island	Asalouyeh	Ahvaz	Shiraz	Chabahar
Weight	0.046304	0.0200712	0.102835	0.176561	0.08212	0.041563	0.142742	0.034527	0.020498	0.152138

This table presents the pairwise comparison scoring results for supplier selection. The weights assigned to each candidate city (e.g., Bushehr, Bandar Abbas) are based on their performance across the decision criteria. Bushehr has the highest weight and is selected as the optimal location.

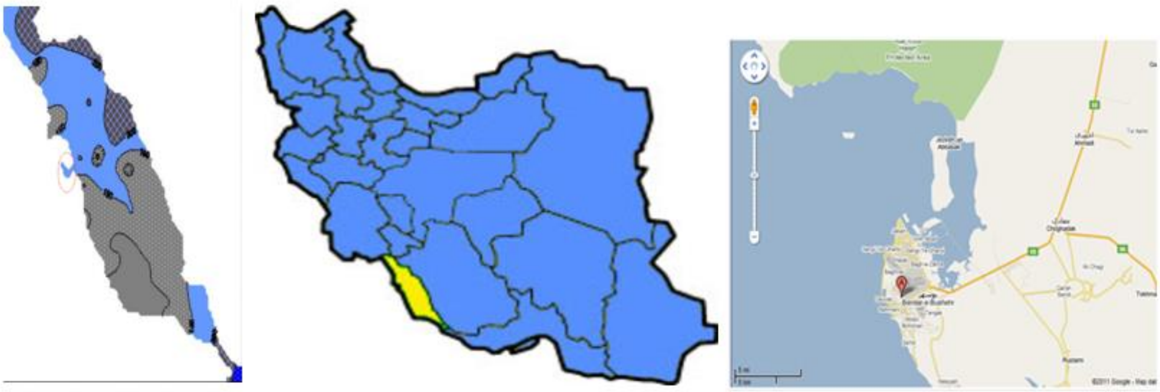

Figure 11 The selected point: Bushehr city. This figure highlights Bushehr as the selected optimal location for establishing the biorefinery. Bushehr scored the highest based on economic, environmental, and social criteria.

This case study effectively demonstrates a multi-criteria decision-making approach for selecting the optimal location for a biogas refinery. By assessing 10 cities based on economic, environmental, social, and critical criteria, the model provides a structured method for evaluating each option's feasibility. The pairwise comparison scoring method, applied within the GAMS software, enables a precise weighting of factors, resulting in a well-rounded analysis that accounts for real-world conditions.

The final results, as shown in Table 23, reveal that Bushehr has the highest weight among candidate cities, with Bandar Abbas also scoring highly. These findings highlight the model's emphasis on balancing costs, social benefits, environmental impacts, and critical factors, such as water resource availability. Bushehr's selection as the preferred site underscores its advantageous position across multiple criteria, making it an optimal location for sustainable biogas refinery operations.

In conclusion, this structured evaluation approach provides valuable insights into sustainable supply chain planning for bioenergy projects. By integrating various decision criteria, this model offers a replicable framework for similar location-based projects, ensuring that site selection aligns with broader economic, social, and environmental sustainability goals.

4. Conclusions and perspectives

With the global shift towards carbon neutrality and renewable energy by 2050, the need for sustainable energy solutions is more pressing than ever. By 2100, projections suggest that nearly all global energy will come from clean sources. This study addresses this global priority by developing a sustainable site selection model for biomass energy production, focusing on optimal refinery location. Utilizing the Analytic Network Process (ANP) as a multi-criteria decision-making method, we assessed ten candidate locations across Iran, ultimately identifying Bushehr County as the most suitable site. This selection reflects a robust evaluation based on economic, environmental, social, and critical criteria, making Bushehr an optimal choice for a biomass refinery in terms of cost efficiency, logistical convenience, and environmental viability.

4.1 Phase one: insights into supplier selection

In the first phase, our approach integrated linear programming with Multi-Attribute Decision-Making (MADM) techniques to prioritize suppliers based on demand, budget, capacity, and calculated ANP weights. The incorporation of linguistic variables added depth to ecological and logistical considerations, enhancing the model's applicability to real-world supply chains. The results provided valuable insights into supplier rankings and optimal purchasing volumes, contributing to a realistic and practical model that bridges theoretical analysis with operational reliability. This hybrid approach allows for more adaptive decision-making that can respond to market dynamics and environmental conditions effectively.

4.2 Phase two: refinery location model results

In the second phase, the study developed a refinery location model by applying a structured framework that combines economic, environmental, social, and critical indicators. This phase involved evaluating ten candidate locations, with Bushehr achieving the highest score of 0.200712. This choice reflects its economic and logistical advantages, including minimal transportation costs and optimal supply chain efficiency. The model's success in prioritizing Bushehr not only demonstrates the robustness of the ANP-based approach but also provides a replicable, scalable framework applicable to similar bioenergy projects worldwide. Additionally, the emphasis on sustainability indicators ensures that the selected site aligns with broader environmental and social objectives.

In summary, this research introduces a comprehensive, practical model for sustainable biomass refinery site selection, supporting renewable energy goals and providing a replicable decision-making framework. Future research could explore additional variables, such as dynamic pricing and demand changes, to enhance the model's adaptability to evolving market conditions and geographic contexts. This study's approach thus contributes significantly to the field of sustainable energy planning, offering a versatile tool for countries aiming to reduce reliance on fossil fuels and progress toward a cleaner energy future.

Author Contributions

Zeynab Pashmi: Involved in the conceptualization and methodology of the project, acquisition of data, as well as the analysis and interpretation of the findings. She also played a key role in writing the original draft. **Maryam Chamehsara**: Contributed to the conceptualization and methodology, interpreting the gathered information, and also supervised the research process. **Sara Parsi**: Focused on the conceptualization and methodology, reviewing and analyzing the information, as well as interpreting the results. **Abooali Golzary**: Contributed to the project's conceptualization and methodology, played a role in sourcing resources, validating the information, and interpreting the findings. Additionally, he supervised the research process. All authors are in agreement with the final version of the manuscript.

Data Availability Statement

Data will be made available on request.

Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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