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An economic analysis for integrated bi-objective biofuel supply chain design using support vector machine

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Abstract

Using second-generation biomass and biofuel deal with environmental pollution and CO_2 emissions. Therefore, this paper design an integrated multi-period bi-objective biofuel supply chain network using support vector machine (SVM) and economic analysis to reduce the cost of generating biofuels and CO_2 emissions. The economic analysis consists of three scenarios for supplying biomass. The SVM method specifies the potential place to build the bio-refinery. The next step solves the model with the augmented ε-constraint method. Finally, results show that biomass production and imports simultaneously reduce costs by 24.5% compared to the production scenario and 4.3% compared to the import scenario. According to the results obtained, despite the increase in cost, it reduces the amount of CO_2 emissions. So, the Pareto solution resulted from the augmented ε-constraint method for the problem is determined as one of the most effective techniques to help the decision-makers.

Keywords: bio-refinery, biomass, SVM, economical analysis, CO_2 emission.

1. Introduction

Nowadays, technology in the industrial and service sectors is rapidly advancing. The driving force behind these technologies is fossil fuel use. Therefore, in addition to their unique advantages, new technologies have disadvantages that have irreversible effects on the environment and endanger human health. These disadvantages include air pollution, global warming, climate change, food crisis, and so on. These disadvantages, if not reflected in the short term, will impose serious damages to the international community in the long term. For example, one of the most disastrous long-term effects of greenhouse gas emissions is the permeation of the ozone layer. For the reasons explained and to the end of fossil fuel resources shortly, researchers are considering replacing fossil fuels with renewable fuels (Babazadeh et al., 2017).

Politicians for increasing social welfare, environmental protection, and economic development have focused on renewable energies stem from water, wind, solar, geothermal heat, tides, and so forth (Azadeh et al. , 2013). Renewable fuels are subsets of renewable energies. Biomass is a type of renewable energy that produces biodiesel and bioethanol. The first-generation and the second-generation are two biomass categories. First-generation biomass is like corn, sugar cane, and sugar beet. Due to the use of first-generation biomass in human food, the use of this biomass category causes a food crisis (Ghaderi et al., 2018). For this reason, researchers recommend using second-generation biomass, such as Switchgrass, Jatropha, and Miscanthus. These plants not requiring water for growth, so they grow well in marginal lands (Zhang et al., 2013; Li and Hu, 2014).

Every year about 5.4 billion liters of bioethanol can be produced by establishing second-generation plants next to the food processing sectors. The second-generation biomass offers a significant perspective due to the extensive accessibility, abundance, and comparatively inexpensive biomass. The use of second-generation biomass is proving to be a substitute source of energy for a narrow range of nonrenewable energy and food crops. Second-generation biomass technology can help Iran to tackle air pollution in its big cities. The other advantages are an improvement in fuel security, mitigation of climate change, and development of the economy (Bharj, Singh and Kumar, 2020; Kazemi Shariat Panahi et al., 2020).

The above recommends the use of second-generation biomass. Besides, the characteristics of second-generation biomass are consistent with the conditions announced by the Iranian Ministry of Agriculture. These conditions convert 20% of the country's total lands as marginal lands like loss of 90% of the country's wetlands, drought, and dust. These factors illustrate the importance of evolution to cultivate these products to obtain biomasses. On the other hand, the lack of bio-refineries in Iran and neighboring countries raises the question of These conditions are their location and capacity, the mode of transportation, the amount of biomass cultivation and their location, the demand for biofuels, and the other alternatives that are needed. Therefore, to consider all of these factors together, it is necessary to go over their supply chain.

What has been extracted from the literature review shows that many studies have been done on the supply chain of biofuels. Decisions on the supply chain of biofuels directly affect social and environmental performance; therefore, optimizing this chain is important for the sustainability of the supply chain (Ghaderi et al., 2018). On the other hand, the European Commission has approved that by 2020, renewable fuels will replace 20% of fossil fuels. Along with the factors mentioned, the shortage of bio-refineries indicates the importance of achieving this perspective.

Biofuel supply chain models vary in terms of environmental and cost considerations, depending on their nature. The different objective functions demonstrate this different point of view (Bairamzadeh et al., 2015; Osmani and Zhang, 2017; Rabbani et al., 2018). Researchers have proposed different approaches to tackle biofuel supply chain problems and have, therefore, focused more on cost reduction and environmental issues. Mathematical planning and multi-criteria decision-making models proposed to tackle these types of problems. To select the cultivated lands or areas of the bio-refinery can use the mathematical modeling approach to solving the proposed fuel supply chain model and multi-criteria decision making(Babazadeh et al., 2017).

Also, neural network tools decision and predict as a new approach in addition to multi-criteria decision-making methods, with appropriate indicators and historical data (Hui and Choi, 2016).

Since governments pay high costs to reduce air pollution and the risks associated with the emission of fossil fuels, the costs imposed by this approach also accept the system, although part of the other costs due to lack of use from Biofuel deleted. Therefore, an economic scenario study of different approaches can further reduce these costs imposed on the system. The economic analysis of biofuel scenarios is essential for the proper design of the supply chain before modeling. Also, the use of neural networks to identify and select areas for the construction of a bio-refinery, based on historical data, gives high reliability in the accuracy of the results.

Therefore, based on the research gap of reviewing the literature and the content presented, the contributions of this paper are as follows:

- Appropriate economic analysis of biomass supply scenarios to Iranian conditions;

- Identifying potential bio-refinery locations using SVM with appropriate criteria and historical data;
- Multi-Period Bi-Objective modeling by considering bio-refinery capacity and added capacity, the biomass transfer rate between two points, and biomass cultivation capacity;
- Integrating SVM and economic analysis of modeling the bio-refinery supply chain.

This paper, to eliminate the research gap, provides an integrated model of biofuel supply chain network using SVM and economic analysis. The economic analysis consists of three scenarios that select the most economical ones. SVM identifies potential locations and ultimately provides a bi-objective supply chain model based on the results of the previous two steps. The results show that using the most economical scenario significantly reduces the cost of biomass production. It also offers Pareto solutions based on the existing conditions for solving the bi-objective deterministic model using the augmented ε-constraint method using GAMS software and CPLEX solver.

The remainder of this article is as follows: In Section 2, the literature review extracts the research gap. Section 3 provides the problem description of the supply chain of biofuels. Then the discussion of different scenarios and supply chain modeling is provided in Section 4 along with a numerical example. Finally, Section 5 summarizes the potential of the research pathway.

2. literature review

In the following, the approaches to manage Biofuel supply chain networks sufficiently discusses in the literature.

Biofuel Supply Chain

Due to supply chain uncertainty, Li and Hu (2014) developed a two-stage stochastic model to maximize annual profit. This model, in the first phase, address investment decisions, and in the second phase, investigate biomass and bio-fuels flows. Moreover, Osmani and Zhang (2017) presented a multi-objective and multi-period model under uncertainty for the production of second-generation biomass to increase economic and environmental performance. Finally, the augmented ε–constraint and Benders decomposition methods solve the model. Kim et al. (2011) suggested a supply chain model that considers the amount and location of biomass, candidate sites for processing and their capacity, and distribution of biomass and biofuels. The model to maximize the expected benefit with a two-stage mixed-integer stochastic model, consider the first stage for investment decisions, and the second stage for material flow decision. Marufuzzaman, Eksioglu, and (Eric) Huang (2014) presented a stochastic two-step model of the mixed-integer linear program. This model optimizes both cost and environmental issues. Ultimately, this model is solved using a hybrid model of Lagrangian relaxation and L-shaped.

Poudel et al. (2016) introduced a model in which several facilities with limited funding resources consider the supply chain of biofuels. This model determines the facilities in the chain that minimizes both costs of the supply chain and post-disaster situation. Due to the NP-hard nature of the problem, the generalized Benders decomposition algorithm solves it. Babazadeh et al. (2017) considered an environmental oriented model; firstly, they identified the appropriate locations for JCL cultivation with the Data Envelopment Analysis (DEA) method and then used a mathematical model to optimize the number, location and capacity of JCL cultivation centers, collection centers, bio-refineries, and distribution centers. In an another study, Golpira et al. (2015) modeled the Green Supply Chain Network as bi-objective Mixed-integer programming. The first objective is to minimize supply chain costs, and the second objective is to reduce CO_2 emissions. Conditional Value at risk used to counter the uncertainty of supply chain demand. The significant contribution of this study is to integrate statistical environmental parameters with the risk management approach.

To optimize three pillars of sustainability –economic, environmental, and social– and the uncertainty of input data, Bairamzadeh et al. (2015) presented a multi-objective mixed-integer model with a robust possibilistic approach. In this model, both strategic decisions, including the type of technology, biomass locations, and capacities, etc., and tactical decisions, including inventory levels, production rates, etc., have been considered. In another similar work, due to the epistemic uncertainty of the data and the economic, environmental, and social objectives, Ghaderi et al. (2018) proposed a multi-objective robust possibilistic programming model for the bioethanol supply chain. Moreover, the multi-objective possibilistic programming model provided by Babazadeh et al. (2017) for the second-generation supply chain, which reduces the cost and environmental effects in the objective function. This model has been developed to reduce the overall average and risk value. Finally, the lexicographic and augmented ε-constraint combination method solves the proposed model. Considering the relationship between supply chain performance and its sustainability, Jafarnejad and Aliabadi (2017) provided a two-objective model with environmental and social issues. In this model, some factors are considered such as uncertainty, limitation of access to facility resources, carbon monoxide emissions, and carbon dioxide, etc., are considered, they used the weighted sum method to solve this model.

To design and manage the biofuel supply chain, Roni et al. (2017) presented a multi-objective mixed-integer linear programming model. This model reduces CO_2 emissions from transport in addition to consideration of the social impact of these fuels. The augmented ε-constraint model is used to solve the model. Given that uncertainty in biomass removal can lead to instability in the supply of raw materials in the supply chain of biofuels, Nguyen and Chen (2018) presented a stochastic two-stage model with a supplier selection for the sustainability of raw material supply. This model in the first stage decides to choose the supplier, and in the second stage, it decides on the supply chain network. The proposed model has finally been solved with the enhanced and regularized L- shaped decomposition algorithm.

Solving Approaches

Mirkouei and Haapala (2014) used a Support Vector Machine method to select suppliers for improving the performance of the Biomass supply chain network. Finally, to implement the model of the Biomass supply chain network integrated the outcomes of this method with the model presented.

Sangaiah et al. (2019) focus on the liquefied natural gas supply chain. Therefore, this paper presents a mixed-integer linear programming model at a specific time horizon to minimize vendor costs. The model was first validated in small dimensions and then solved with Cuckoo Optimization Algorithm that provides high-quality solutions. Finally, a comparison is made between the total profit of the seller and the cost of the firm to find the optimal firm level.

Mostafaeipour et al. (2018) introduce a new hybrid approach to predicting air travel demand using 2011-2015 by the Islamic Republic of Iran Aviation Organization. For this purpose, using two measures of income and population, the artificial neural network is used to forecast demand. To improve the performance of an artificial neural network, it used evolutionary metaheuristic algorithms such as BAT and Firefly, which increased compatibility and efficiency with real data. The results show that the output of this method is up to 90%

compatible with real data.

In this paper, Goli, and Zare (2018), use artificial intelligence tools to forecast the demand for dairy products in Iran. These tools include Multi-Layer Perceptron, Adaptive-Neural-based Fuzzy Inference System and Support Vector Regression, which have been improved by the use of metaheuristic algorithms Particle Swarm Optimization, Genetic Algorithm, Invasive Weed Optimization, and Cultural Algorithm. First, researchers select appropriate criteria and then perform prediction to reduce the error. The results showed that inflation and population were the most effective factors in dairy consumption. Also, Particle Swarm Optimization has the best performance in index selection and Invasive Weed Optimization with the error of .008 and has the best coefficient of determination of 95% among metaheuristic algorithms.

Table 1 summarizes part of the literature review for extracting research gaps. As shown in Table 1, the most important research gap of this study is the integration between modeling, neural network, and economic analysis.

Table 1. Literature Review

	Objective Function			Type of Model					Solving Approaches					
Authors (year)	Cost	Environmental	Social	Stochacid	Uncertain	Certain	Multi-Objective	Multi-stage	Methahurictic	augmented ε-constraint	MCDM	Artificial Intelligence	modeling	Economical analysis
(Marufuzzaman et al., 2014)		*		*				*	*				*	
(Bairamzadeh et al., 2015)	*	*	*		*		*						*	
(Poudel et al., 2016)	*					*			*				*	
(Babazadeh et al., 2017)		*				*		*			*		*	
(Osmani and Zhang, 2017)	*	*			*				*	*			*	
(Mostafaeipour et al., 2018)									*			*		
(Ghaderi et al., 2018)	*	*	*		*		*						*	
(Goli and Zare, 2018)									*			*		
(Sangaiah et al., 2019)	*				*							*	*	
This article	*	*				*	*			*		*	*	*

3. Problem definition

This paper divide into three general phases. The first phase proposes three scenarios of biomass supply and selects the best scenario using economic analysis. The second phase extracts potential biomass sites using artificial neural network tools. The third phase presents the supply chain model using the results of the first and second phases and reports these results. The three phases are described in detail below:

Economic analysis

It is plausible that all small and large projects of all sizes, such as national, international, etc., require econometrics. In the case of private sector projects, the economic project does not necessarily attract the investors' satisfaction, but the project must at least meet investors' expectations. In the case of government projects, this can be different. Governments implement specific programs to raise funds and increase the attractiveness of projects because the role of governments is different from investors, investors are seeking more profit, and governments are attempting to increase the welfare and satisfaction of the community. Therefore, governments may have to pay extra for providing services and increasing community satisfaction.

Today, increasing air pollution and environmental problems have raised not only the problems of society, but also dramatically increased the costs of these problems, such as people's illness, environmental costs, and other costs. As stated before, one of the proposed solutions is the use of renewable fuels instead of fossil fuels. Also, the implementation of this system imposes high costs. Therefore, it is necessary first to choose the best scenario by analyzing the economic scenarios and considering the new added costs and eliminating previous costs. Since the government is obliged to implement the system, so the scenario doesn't need to be fully economic, since all scenarios may cost, but are selected from cost scenarios for the scenario with the lowest cost. The advantage of this analysis before the supply chain model may be a part of the high supply chain cost neglected due to the lack of consideration of the overall system implementation.

Bio-refinery site selection

One of the solutions to the success of a biofuel production project is the proper select the location of bio-refineries. Over the years, fossil fuel refineries have made in many areas, and many successes and failures have come about for governments, Successes such as reducing maintenance costs due to weather conditions or faults such as creating troubles for residents in those areas. Machine learning and the construction of the bio-refinery high reliability use these data and experiences for costs and problems that arise after that.

Supply chain

Finally, after identifying the economic scenario and the locations for bio-refinery construction, it is necessary to decide on the amount of biomass production, transportation, distribution, and other decisions. In addition to the goal of reducing related costs, this supply chain is seeking to reduce costs and negative environmental impacts. Therefore, this paper provided the supply chain model.

This method ensures that the value of the minimizing function never exceeds the optimal value obtained from the model's solution. This view is suitable for highly conservative and risk-averse decision-makers, and this ensures the highest safety and reliability of the response to the uncertainty of uncertain constraints. The reason for providing this model is its pessimistic advantage. This view is due to the advantage that makes the decision-maker in all possible positions place on the safety margin. Since the decision-maker in this model is government, the high costs imposed by this method assure the government that no other surplus cost will be imposed on the system, and will use its budget in other sectors. Therefore, from the state's viewpoint, this not only provides general satisfaction in this regard, but the government is also able to provide more welfare services to the community, which is highly reliable in allocating budget and bearing the costs of it. All in all, Fig 1 summarizes the steps in the paper.

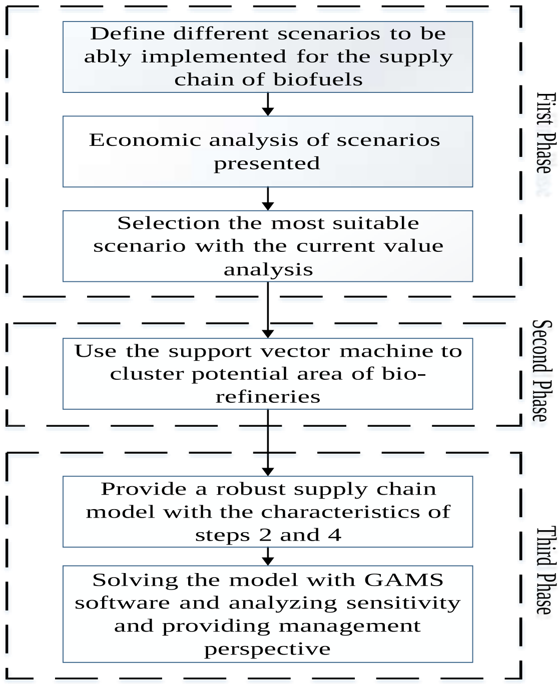

Figure 1. Summary of paper processes

4. Methodology

Economic analysis

In this economic analysis is the decision-maker of the government. In other words, this analysis has nothing to do with the investor and seeks to reduce the costs imposed on the government. Therefore, after identifying possible scenarios for establishing a supply chain for biofuels, proportional cash flow is created to the costs and benefits associated with the government. Fig 2 shows this cash flow.

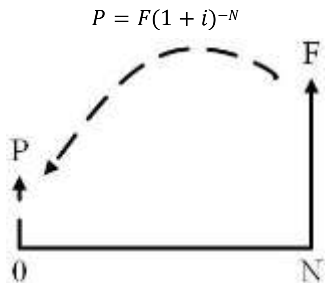

Figure 2. The relationship between present and future values

In this figure, P is the current value, F is the value of the future, N is years that the project implements, and i is the minimum attractive rate of return. Up or down signs of cash flow according to project output are profits or costs, respectively. So the current value of the following equation is calculated:

$$P = F\ (P|F.i\%.N) \tag{1}$$

$$(P|F.i\%.N) = (1+i)^{-N} \tag{2}$$

Relationship 2 derive from the tables of economic factors. If the calculated value of P is positive from the above relation, the economic plan, and otherwise, is a non-economic plan. If all schemes have negative P-value and decision-maker is obliged to select a scheme, a scheme that has the greatest P-value selected.

Support Vector Machine (SVM)

Vapnik (1998) introduced a support vector machine for pattern recognition. A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane, which categorizes new examples. In two-dimensional space, this hyperplane is a line dividing a plane into two parts wherein each class lay on either side.

Step 1. Optimization problem:

$$\min_{\omega.b.e} \zeta(\omega.b.e) = \frac{1}{2}\omega^T\omega + \gamma\frac{1}{2}\sum_{k=1}^{N} e_k^2 \quad (3)$$

s.t

$$y[\omega^T\varphi(x_k) + b] = 1 - e_k \qquad k = 1.\cdots.N \quad (4)$$

Step 2. Lagrangian

$$\zeta(\omega.b.e;\alpha) = \zeta(\omega.b.e) - \sum_{k=1}^{N} \alpha_k\{y_k[\omega^T\varphi(x_k) + b] - 1 + e_k\} \quad (5)$$

α_k is the Lagrangian coefficient and according to the conditions of Kuhn-Tucker:

Step 3. Optimal conditions:

$$\frac{\partial\zeta}{\partial\omega} = 0 \rightarrow \omega = \sum_{k=1}^{N} \alpha_k y_k \varphi(x_k) \quad (6)$$

$$\frac{\partial\zeta}{\partial b} = 0 \rightarrow \sum_{k=1}^{N} \alpha_k y_k = 0 \quad (7)$$

$$\frac{\partial\zeta}{\partial e_k} = 0 \rightarrow \alpha_k = \gamma e_k \qquad k = 1.\dots.N \quad (8)$$

$$\frac{\partial\zeta}{\partial\alpha_k} = 0 \rightarrow y_k[\omega^T(x_k) + b] - 1 + e_k = 0 \qquad k = 1.\dots.B \quad (9)$$

Step 4. A series of linear equations in LS-SVM instead of the quadratic problem in SVM:

$$\begin{bmatrix} I & 0 & 0 & -Z^T \\ 0 & 0 & 0 & -Y^T \\ 0 & 0 & \gamma^I & -I \\ Z & Y & I & 0 \end{bmatrix} \begin{bmatrix} \omega \\ b \\ e \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ I \end{bmatrix} \quad (10)$$

Where $Z = [(x_1)^T y_1. \dots . (x_N)^T y_N]$, $Y = [y_1. \dots . y_N]$, $\bar{I} = [1. \dots .1]$, $e = [e_1. \dots . e_N]$, $\alpha = [\alpha_1. \dots . \alpha_N]$, So the above relation is simplified as follows (Remove ω, e):

$$\begin{bmatrix} 0 & -Y' \\ Y & ZZ^T + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{11}$$

To the matrix applies Mercer's conditions where $\Omega = ZZ^T$:

$$\Omega_{kl} = y_k y_l (x_k)^T \varphi(x_l) = y_k y_l K(x_k. x_l) \tag{12}$$

$K(x_k. x_l)$ is a kernel function and, in linear conditions, this function is defined as $(x_k. x_l) = x_l^T x_k$

Mathematical formulation

This section introduces a bi-objective multi-period mixed-integer programming for the supply chain of biofuels. In the proposed model with environmental and cost objectives, choosing the location of the bio-refinery and its capacity, choosing the location of the biomass cultivation and its amount, and decides how much biofuel from each bio-refinery is sent to each source of demand also it decides about the amount of capacity and added capacity of bio-refinery. In general, the purpose of this article is to illustrate the integration of SVM and economic analysis in modeling the bio-refinery supply chain.

Before describing the model, the assumptions of this model are as follows:

- The bio-refinery capacity can be added at the time of need without considering the need for the hold period.
- The capacity and added capacity of the bio-refinery are in certain ranges and cannot exceed their minimums and maximums.
- There is no limitation on added capacity, and at the time of deciding to build bio-refinery, it is possible to increase the capacity as much as required.
- Depreciation and varieties of transport are not considered, and the average cost and emitted CO_2 are assumed.

Table 2 presents the notations for model determination.

Table 2. Notations for deterministic model.

Indices	
i	Set of potential biomass cultivation centers
j	Set of all potential bio-refineries
k	Set of demand market
t	The number of periods
Technical parameters	
φ	The conversion rate of biomass to fuel
M	The big number
F	The Fixed Cost of constructing a new bio-refinery
V	The Variable Cost of constructing a new bio-refinery
V'	The unit production cost
NC	Minimum Capacity required to construct a bio-refinery
XC	Maximum Capacity allowed for each refinery
CUL_i	The capacity of the cultivation center $i-th$
D_{kt}	The demand of the market $k-th$ in $t-th$ period

C_{ij}	The cost of sending any biomass unit with a truck from $i-th$ cultivation to $j-th$ bio-refinery
C'_{jkt}	The cost of sending any bio-diesel unit with a truck from $j-th$ bio-refinery to $k-th$ demand market in $t-th$ period
E_{ij}	The amount of CO_2 emitted from the cultivated land $i-th$ to bio-refinery $j-th$ per Ton
R_{jk}	The amount of CO_2 emitted from the bio-refinery $j-th$ to demand market $k-th$ per Ton
U_j	The amount of CO_2 emitted from the construction of the bio-refinery $j-th$
Decision variable	
cost	The total cost of the objective function
envir	The total CO_2 emitted of the objective function
add_{jt}	The added capacity of the bio-refinery $j-th$ in $t-th$ period
cap_{Jt}	The capacity of the bio-refinery constructed $J-th$
x_{ijt}	The amount of sent biomass from the cultivation $i-th$ to the bio-refinery $j-th$ in $t-th$ period
x'_{jkt}	The amount of sent bio-diesel from the bio-refinery $j-th$ to the demand market $k-th$ in $t-th$ period
y_{Jt}	If bio-refinery $J-th$ constructed 1, otherwise 0.

$$\min cost = \sum_i \sum_j \sum_t C_{ij} \times x_{ijt} + \sum_t \sum_{j \in J_1} (F \times y_{jt} + V \times cap_{Jt}) + \sum_j \sum_k \sum_t C'_{jkt} \times x'_{jkt} + \sum_j \sum_t V' \times add_{jt} \tag{13}$$

$$\min envir = \sum_i \sum_j \sum_t E_{ij} x_{ijt} + \sum_j \sum_t U_j y_{jt} + \sum_j \sum_k \sum_t R_{jk} x'_{jkt} \tag{14}$$

$$\sum_j x_{ijt} \leq CUL_i \qquad \forall i\,.\,t \tag{15}$$

$$\varphi \times \sum_i x_{ijt} = \sum_{p=1}^{t} cap_{jp} + \sum^{t} add_{jp} \qquad \forall j\,.\,t \tag{16}$$

$$\sum_j (cap_{jt} + add_{jt}) \geq \sum_k D_{kt} \qquad \forall t \tag{17}$$

$$cap_{jt} \geq NC - M \times (1 - y_{jt}) \qquad \forall j.t \tag{18}$$

$$cap_{jt} \leq XC \times y_{jt} \qquad \forall j.t \tag{19}$$

$$\sum_t y_{jt} \leq 1 \qquad \forall j \tag{20}$$

$$\sum_j x'_{jkt} = D_{kt} \qquad \forall k.t \tag{21}$$

$$\sum_k x'_{jkt} \leq \sum_{p=1}^{t} (cap_{jp} + add_{jp}) \qquad \forall j.t \tag{22}$$

$$add_{jt} \leq M \times \sum^{t} cap_{jp} \qquad \forall j.t \tag{23}$$

$$cost \geq 0 \tag{24}$$

$$envir \geq 0 \tag{25}$$

$$add_{jt} >= 0 \qquad \forall j.t \tag{26}$$

$$cap_{Jt} \geq 0 \qquad \forall j.t \tag{27}$$

$$x_{ijt} \geq 0 \qquad \forall i.j.t \tag{28}$$

$$x' \geq 0 \qquad \forall i.k.t \tag{29}$$

$$y_{Jt} \in \{0.1\} \qquad \forall j.t \tag{30}$$

Equation (13) is the first objective function of the proposed model that seeks to reduce the costs of transfer of biomass to bio-refinery, bio-refinery construction, and added capacity and the transfer of biofuel to the demand market. In this equation, the cost of biomass transportation also includes the costs of cultivation and production. Equation (14) is the second objective of the proposed model, which aims to reduce the whole environmental impacts of CO2 emissions in the bio-refinery construction, transportation of biomass to bio-refinery, and biofuel to the demand market. There are several constraints to optimize objective functions: Equation (15) controls that the amount of biomass that sends to the entire bio-refinery is not greater than the capacity of that cultivated land because of the capacity of each agricultural land is specific. Therefore, the amount of biomass that it sends should be as large as its capacity land. Equation (16) shows that the total biofuel produced in a bio-refinery must be as large as the total capacity created (capacity created is core capacity and added capacity at different times). Also, the conversion rate of biomass to biofuel shows that not all biomass converts to bio-fuel. Equation (17) balances the relationship between the market demand and the capacity of the biofuel. Therefore, the capacity created in each period must be greater than the total demand for that period because it is meet all demand. To build a bio-refinery should be noted that the capacity of the bio-refinery is limited and should not be less or more than a specified limit. Therefore, equation (18) controls that the capacity of the bio-refinery is not lower than the minimum permissible capacity, and in contrast, Equation (19) controls that the capacity of the bio-refinery does not exceed the maximum permitted. Equation (20) prevents a bio-refinery from being built more than once during the entire period under review. Equation (21) is similar to Equation (16) except for biofuel. Accordingly, the number of biofuels sent to the demand market must be equal to that market demand. Observing equal the market demand capacity is because the total market demand is met. Equation (22) shows that produced biofuels are equal to or greater than the capacity of bio-refineries. In other words, the amount of bio-fuel sent to the demand market maximizes the amount of biofuel produced. Equation (23) does not allow added capacity to be considered before the bio-refinery is constructed. In other words, there is no added capacity until there is no bio-refinery. Finally, Equations (24-30) represent the type of model variables.

5. Numerical Example

This numerical example is presented and solved in the following three sub-sections:

Economic analysis

This section presents three scenarios of biomass production and the best scenario use for implementing the supply chain model.

1. All biomass will be produced inside the country, and in case of a shortage, there is no need to produce biofuels.

2. All biomass will be produced abroad, and, if there is a shortage, there will be no need to produce biofuels.

3. Biomass will be produced both inside the country and imported from abroad.

The special conditions of Iran in the field of dust and government support for removing the source of dust, it is possible that consider a real assumption of non-payment of taxes. Another assumption that can be considered, such as Iran and Iraq, Iran can invest in cultivating and creating employment in Iraq and, in return, obtaining exemptions from the import of biomass.

Therefore, the scope of the determination of the costs and amounts considered in the data is presented to the regional conditions of Iran and Iraq. On average, a ton of biomass, regardless of its type, costs $ 100. Cash flows from three scenarios are based on the cost and benefits of a ton of biomass. Assuming that the cost per ton of biomass is $ 100 per ton of net cost, in other words, environmental costs, unemployment, etc., which are lowered following the implementation of the biomass plan, is included in the final cost of biomass production, the Cash flow is generated. If the initial cost of a biomass production project is $700 per ton, the cash flow of the first scenario over the next ten years will be as Fig 3.

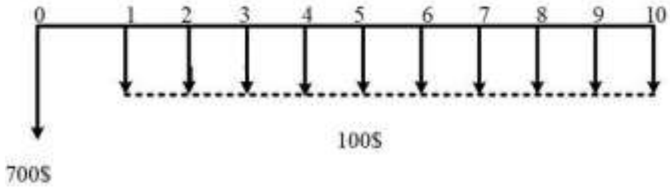

Figure 3. The cash flow of the first scenario

In the second scenario, imports to the country only impose import costs on the system. In contrast, the cost per ton of biomass is estimated at $ 160 per year. Therefore, the cash flow of this scenario is as Fig 4.

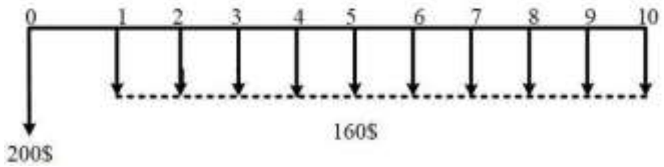

Figure 4. The cash flow of the second scenario

In the third scenario, the average cost of both domestic and foreign supply is considered. Since these costs are intended for 1 ton, the average cash flow will be as Fig 5.

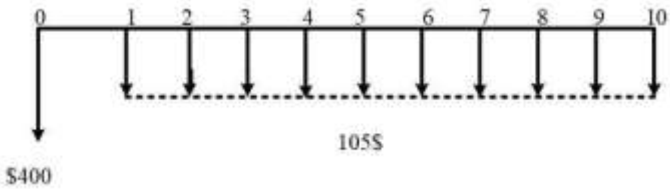

Figure 5. The cash flow of the third scenario

Since interest rates in Iran range from 15% to 23%, the average rate is 19% of the bank's interest rate as the minimum rate of return and the inflation rate in the last few years was, on average, 10%. Looking at the past inflation rate in Iran and given the current economic stability, it is realistic to keep this inflation rate in the next ten years.

Since there is a hypothesis that there is no tax on the research, so the current cash flow of the projects and the inflation of cash flows make the same result. Therefore, without regard to inflation, we calculate the present value of each of the three scenarios.

First scenario:

$$NPW(19\%) = 700 + 100((P|A.19\%.10) = 700 + 100 \times 4.3389 = 1133.89 \quad (31)$$

Second scenario:

$$NPW(19\%) = 200 + 160((P|A.19\%.10) = 200 + 160 \times 4.3389 = 894.224 \quad (32)$$

Third scenario:

$$NPW(19\%) = 400 + 105(P|A.19\%.10) = 400 + 105 \times 4.3389 = 855.5845 \quad (33)$$

Therefore, the third scenario is the most suitable scenario for reducing biomass production costs. In the next section, to increase the reliability of bio-refineries, their potential location is determined.

SVM

Choosing a potential location for a bio-refinery requires proper criteria that make this site more reliable when it comes to bio-refinery. These criteria include availability, centrality, and workforce. Availability and centrality are different. The availability of the refinery's location is in such a way that its access to the facilities and the road is suitable for production and distribution centers. The central point is that the bio-refinery in the place where it is built has its product market in its range. Therefore, there may be a lot of access to the demand market, but not central to that market. In the case of the workforce, it should be noted that the place to be selected has a well-trained and experienced workforce in place to attain the minimum labor costs.

The 15 existing locations that are candidates for the construction of a bio-refinery are in the SVM model, and we select their potential locations. Therefore, the output of this stage is the potential locations with high reliability for the construction of a bio-refinery. By normalizing the input data, the 15 locations listed in Table 3 are reported. Therefore, using the linear kernel function in SVM, with a precision of 60% of the table below, shows the final output of this method. In this table, the number 1 represents a good and potential location, while showing -1 a bad and non-selective location. Therefore, as it is known, places 1, 8, and 13 will be removed from the program and will be decided on the remaining 12 locations in the proposed model.

Table 3. Potential bio-refinery locations based on the SVM model

Locate	availability	centrality	workforce	Output
1	0.776611146	4.65803485	2.218551313	-1
2	0.124695176	1.347757157	0.989331253	1
3	0.097352687	1.196680457	0.975074048	1
4	0.08808766	0.642622743	0.92657435	1
5	0.364595653	1.771476905	0.97026048	1
6	0.101854693	1.160503462	0.928488833	1
7	0.361599551	1.704100294	0.956549666	1
8	0.216537727	1.335435916	0.951102909	-1
9	0.034241887	1.047727547	0.903207856	1
10	0.230510059	1.401925929	0.941419377	1
11	0.08808766	0.642622743	0.92657435	1
12	0.32524847	0.604177639	0.978697235	1
13	0.206010806	1.282933252	0.963991696	-1
14	0.123575898	1.246085642	0.984430878	1
15	0.201490652	1.546909986	0.972167299	1

Modeling

Finally, after the previous steps, this paper solves multi-period bi-objective biofuel supply chain programming using the augmented ε-constraint method with GAMS software and CPLEX solver. Table 4 shows the output of this method as a payoff table. In this table, the first column represents the total cost of the supply chain, and the second column represents the whole of the committed CO_2. Given the objective function of Table 4, the outputs of the variables are as follows.

Table 4. The payoff table of augmented ε-constraint

Rows	Cost	CO2
1	6.857309E+7	9.446398E+7
2	6.880946E+7	9.273635E+7
3	6.928463E+7	9.100871E+7
4	6.988550E+7	8.928108E+7
5	7.066310E+7	8.755344E+7
6	7.194770E+7	8.582581E+7
7	7.345998E+7	8.409817E+7
8	7.523998E+7	8.237054E+7
9	7.749769E+7	8.064290E+7
10	8.209169E+7	7.891527E+7
11	1.239344E+8	7.718763E+7

Figures 6 to 8 represent the x variable in the model. These figures show the output of rows 1, 6, and 11 of table 4. The variable x represents the rate of biomass transfer for different periods. In this figure, each column represents a period. Each color also represents the biomass from cultivated land to a bio-refinery. For example, blue indicates in figure 6, the amount of biomass sent from the first crop to the bio-refinery. The upward trend of these figures illustrates two points: Firstly, to reduce the cost of bio-refineries, bio-refinery is built at the lowest possible capacity, and then added-capacity is created. Secondly, this added capacity reflects the increasing demand in subsequent periods.

Figures 9 to 11 represent the x' variable in the model. These figures show the output of rows 1, 6, and 11 of table 4. The variable x' represents the bio-fuel transfer for different periods. In this figure, each column represents a period. Each color also represents the bio-fuel from bio-refinery to the demand market. For example, blue indicates in figure 9 is the amount of first bio-refinery sent to the first demand market. The upward trend in these figures is indicative of increased demand.

The sensitivity analysis of the model on costs is as follows. Tables 5 to 7 show a 10, 20, and 30 percent increase in cost, respectively. Tables 8 to 10 also show cost reductions of 10, 20, and 30 percent, respectively. These tables show the inverse relationship between costs and CO_2 emission rates. As prices increase in each table, the CO_2 emission decreases. The increased cost is due to the increased production of biomass and biofuel, and therefore more use of bio-fuels reduces CO_2 emissions. The inverse relationship between price and CO_2 also is found between different tables by increasing the costs by 20%, the cost increases, and the CO_2 emissions decrease. Similarly, with a 20% reduction in costs, costs decrease, and CO_2 emissions increase.

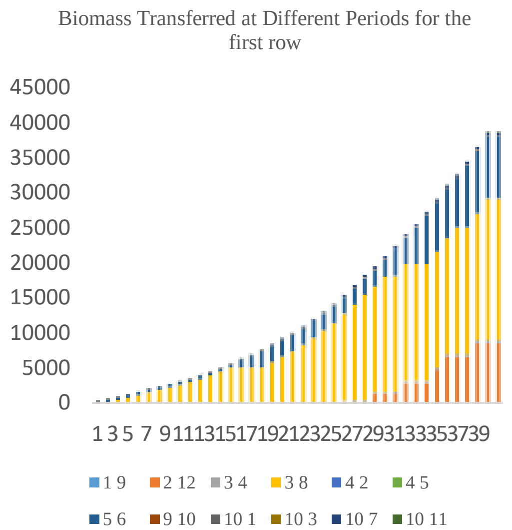

Figure 6. Biomass transferred at different periods for the first row

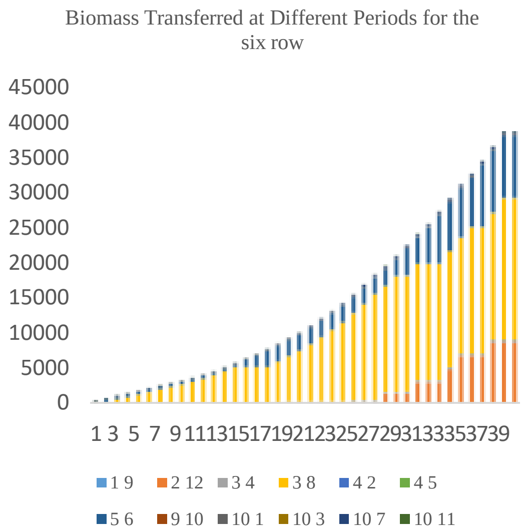

Figure 7. Biomass transferred at different periods for the six row

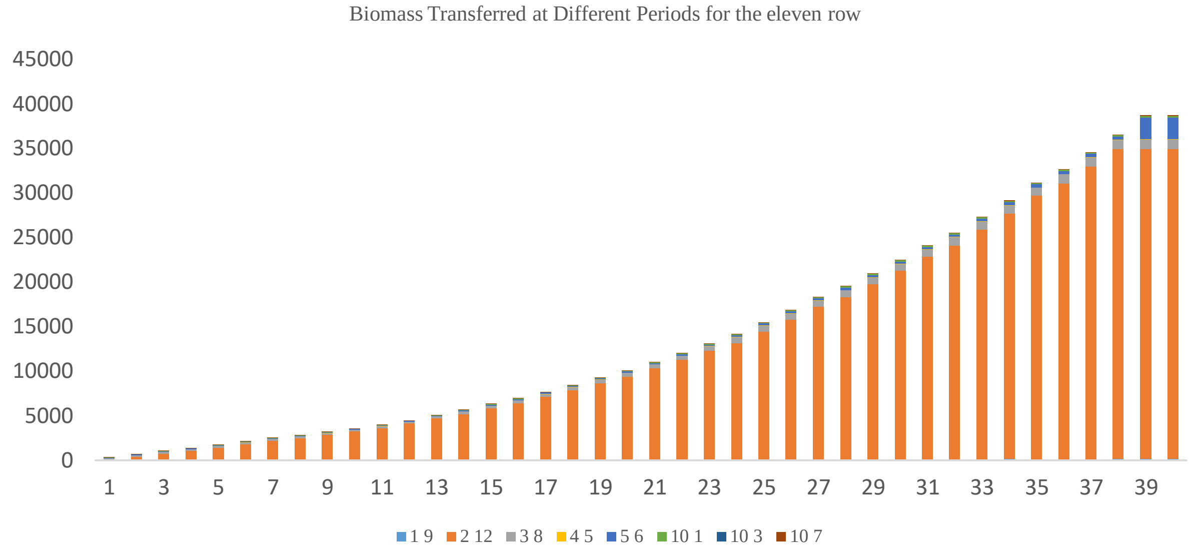

Figure 8. Biomass Transferred at Different Periods for the eleven row

6. Conclusion

In this paper, an optimal framework for biomass and biofuel production was presented. In this framework, different scenarios of biomass could be considered first, and the most suitable scenario was chosen. Subsequently, in areas where bio-refinery construction was possible, the SVM method and reliability criteria turned into potential locations for selecting a bio-refinery. Eventually, with the dual-mode model, costs for biofuels and CO2 emissions decreased throughout the production process. Therefore, it has been shown that in terms of different scenarios and increasing reliability, the costs of biomass production and conversion to biofuels can be significantly reduced. The problem is modeled using the average cost and CO_2 emissions, regardless of the type of transport. Modeling innovations are based on a combination of economic analysis and SVM. In other words, integrating economic and SVM analysis and considering mathematical modeling helps in bio-refinery and their added-capacity. As expected as biomass growth was expected due to increased demand in subsequent periods, biomass transfer rate, biofuel production rate and biofuel transmission increased in successive periods. In addition, due to the conflict between cost and CO 2, an increase in cost reduces the CO 2 that managers can make the right decision depending on condition of country. Based on the results presented, management insights are briefly described:

1. The importance of environmental issues may not account for the cost impact. Therefore, managers can decide to implement this approach according to the current situation.

2. Different scenarios have different results in terms of cost and environmental issues. Therefore, understanding the situation in the first perspective by managers can lead to proper decision making of scenarios.

3. As biomass cultivation leads to job creation, this should not be overlooked for managers.

4. Given Iran's rich oil reserves, its sale and purchase of bio-fuels can be on the agenda of managers.

Due to data uncertainty, this paper suggests using economic scenarios under its uncertainty and uncertainty models to solve the problem for future work. In addition, the type of transportation and use of other machine learning tools can be addressed in future work.

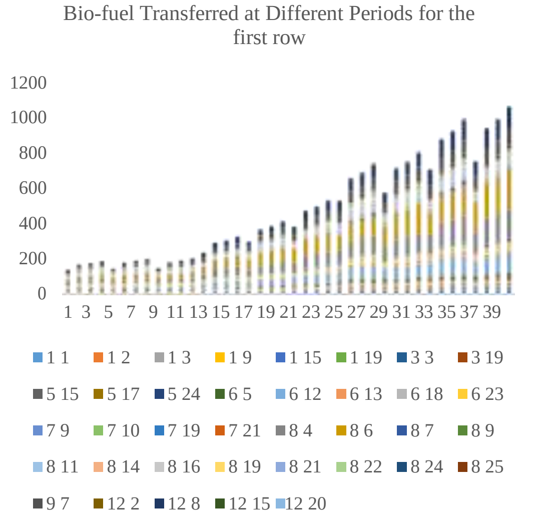

Figure 9. Bio-fuel transferred at different periods for the first row

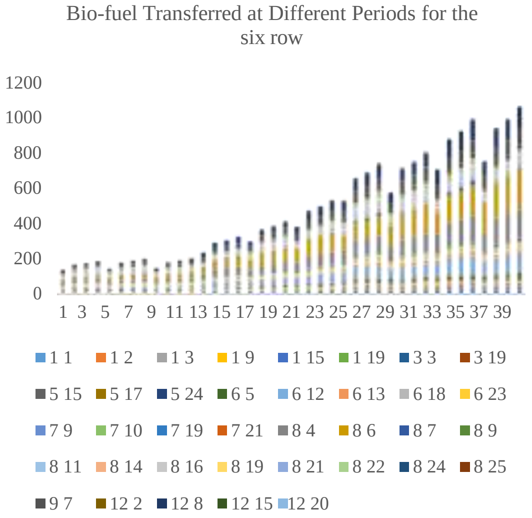

Figure 10. Bio-fuel transferred at different periods for the six row

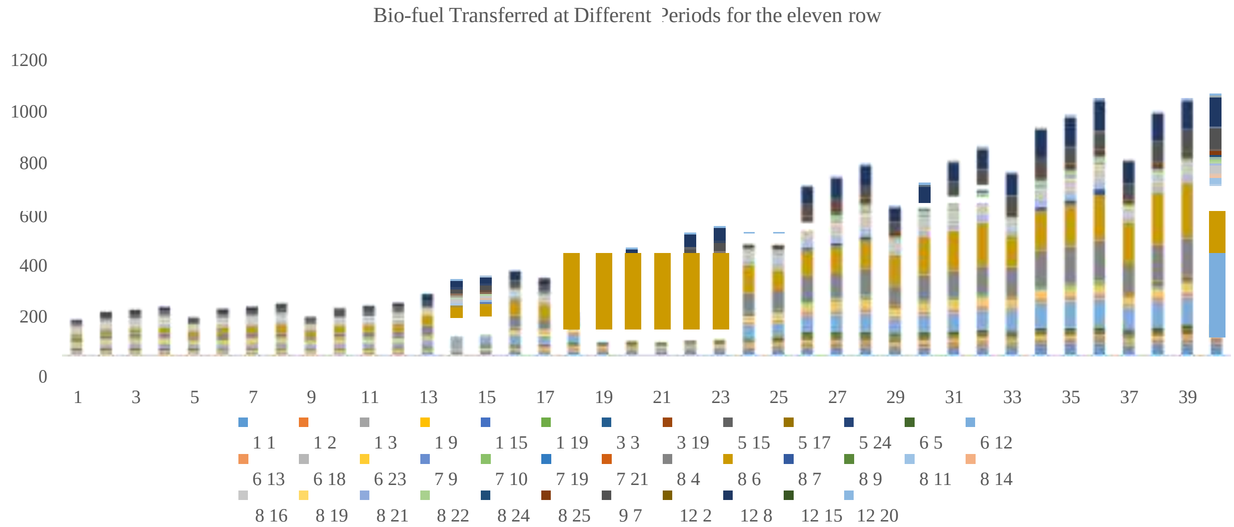

Figure 11. Bio-fuel Transferred at Different Periods for the eleven row

Table 5. The trade-off between two objectives under 10% cost incensement

Cost	CO_2
7.43E+07	9.43E+07
7.46E+07	9.26E+07
7.50E+07	9.09E+07
7.56E+07	8.92E+07
7.64E+07	8.75E+07
7.76E+07	8.58E+07
7.92E+07	8.40E+07
8.10E+07	8.23E+07
8.33E+07	8.06E+07
8.79E+07	7.89E+07
1.298464E+8	7.718756E+7

Table 6. The trade-off between two objectives under 20% cost incensement

Cost	CO_2
8.00E+07	9.42E+07
8.03E+07	9.25E+07
8.07E+07	9.08E+07
8.13E+07	8.91E+07
8.21E+07	8.74E+07
8.33E+07	8.57E+07
8.48E+07	8.40E+07
8.67E+07	8.23E+07
8.90E+07	8.06E+07
9.36E+07	7.89E+07
1.35E+08	7.72E+07

Table 7. The trade-off between two objectives under 30% cost incensement

Cost	CO_2
8.58E+07	9.41E+07
8.60E+07	9.24E+07
8.65E+07	9.07E+07
8.70E+07	8.90E+07
8.77E+07	8.73E+07
8.89E+07	8.56E+07
9.05E+07	8.39E+07
9.25E+07	8.23E+07
9.48E+07	8.06E+07
9.94E+07	7.89E+07
1.41E+08	7.72E+07

Table 8. The trade-off between two objectives under 10% cost reduction

Cost	CO_2
6.28E+07	9.46E+07
6.31E+07	9.29E+07
6.35E+07	9.11E+07
6.41E+07	8.94E+07
6.50E+07	8.76E+07
6.62E+07	8.59E+07
6.78E+07	8.42E+07
6.95E+07	8.24E+07
7.17E+07	8.07E+07
7.63E+07	7.89E+07
1.19E+08	7.72E+07

Table 9. The trade-off between two objectives under 20% cost reduction

Cost	CO_2
5.71E+07	9.48E+07
5.73E+07	9.30E+07
5.78E+07	9.13E+07
5.84E+07	8.95E+07
5.92E+07	8.78E+07
6.05E+07	8.60E+07
6.20E+07	8.42E+07
6.37E+07	8.25E+07
6.59E+07	8.07E+07
7.05E+07	7.89E+07
1.14E+08	7.72E+07

Table 10. The trade-off between two objectives under 30% cost reduction

Cost	CO_2
5.13E+07	9.49E+07
5.15E+07	9.31E+07
5.20E+07	9.14E+07
5.26E+07	8.96E+07
5.35E+07	8.78E+07
5.48E+07	8.60E+07
5.63E+07	8.43E+07
5.80E+07	8.25E+07
6.02E+07	8.07E+07
6.48E+07	7.90E+07
1.08E+08	7.72E+07

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