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Designing a Location-Allocation and Optimal Capacity Determination Model for Supply Chain Components under Uncertainty

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ABSTRACT

This research aims to design an optimal and adaptive supply chain network for sea cage aquaculture in southern Iran. It implements the optimal location and capacity of production, processing and distribution facilities in 11 coastal nodes to create a balance in economic efficiency, social justice and environmental sustainability. A scenario-based multi-objective mixed integer linear programming model has been developed in Python using PuLP. Three objective functions minimize the total cost, maximize socio-spatial weighted employment in underdeveloped areas, and minimize energy emission of production and transportation. A robust minmax optimization approach investigates demand uncertainty as well as cost in optimistic, normal and pessimistic scenarios. The ϵ constraint method has created a Pareto frontier for trade-off analysis. Purely economic optimization has concentrated capacity in relatively developed areas such as Qeshm and has ultimately led to geographical imbalance (CV=49%). Accordingly, Pareto analysis has proposed point P3 as the most sustainable solution. In this solution, which has led to a 52% increase in employment in underdeveloped areas, regional equity has also improved significantly. At this point, CV has reduced capacity to 20% and ultimately 70% of employment is guaranteed in coastal areas. Integrated multi-objective planning can create a suitable framework for resilient industrial development as well as spatial equity in southern Iran in the supply chain under study.

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INTRODUCTION

The aquaculture supply chain is an important part of the production processes related to this product, which plays a decisive role in the costs associated with this sector (Adebayo et al., 2025, Engle et al., 2025). This supply chain, which is related to aquaculture in sea cages, includes various stages of feed, packaging, distribution and final delivery to the market (Rowan, 2023). Each of these issues has multiple pressures, ranging from climate change to issues related to input price fluctuations to disease outbreaks, which can affect the supply and demand of products (Asche et al., 2018). Considering these issues, the formation and development of adaptive and optimal supply chain networks can lead to sustainable growth in this industry (Vlachos & Malindretos, 2023). Sustainable growth in the supply chain of these products is of great importance because it can ultimately lead to food security as well as stability in the supply and demand of products (Fu et al., 2026; Prastyabudi and Solvang, 2026).

One of the major challenges in the aquaculture supply chain is related to the identification and measurement of sources of uncertainty (Vlachos & Malindretos, 2018; Sinisaz-Shahshahani et al., 2026). In marine cage aquaculture, uncertainty comes in different forms – stochastic variables like water temperature and fish growth rates, unknown future states such as market volatility or policy changes, and competitor reactions. Managing these conditions calls for robust programming, stochastic optimization, scenario analysis, and even machine learning to anticipate complex behavioural patterns (Gladju et al., 2022).

Uncertainty in marine cage aquaculture takes many forms. In this context, many variables such as water temperature, fish growth rate, unknown future conditions such as market fluctuations, as well as policy changes and competitor reactions can have significant effects on its types and forms (Nguyen et al., 2025; Ibrahim et al., 2026). Therefore, managing these areas requires the creation of strong planning as well as stochastic optimization and scenario analysis to create a system for predicting complex behavioral patterns. (Sievers et al., 2022; Islam, 2005).

To enhance food security, the development of marine cage aquaculture can be considered as a national strategy that is used in the field of exports and reducing pressure on wild fish stocks. To achieve a sustainable and efficient system, a proper supply chain is required to follow the appropriate location with effective decisions. A major challenge in this regard is the geographical dispersion of potential locations, which raises the need to balance cost reduction and job creation in coastal areas, taking into account environmental constraints. In this context, creating the wrong network at the initial stages leads to high costs and project failure.

Aquaculture supply chain sectors are highly vulnerable to conditions such as economic and environmental uncertainty. Indicators such as demand fluctuations, input cost fluctuations, and climate risks can influence long-term decision-making in the field of production location. This study attempts to examine and present a mathematical model that can ultimately provide facility location and capacity allocation under uncertainty scenarios for southern Iran.

MATERIALS AND METHODS

This study attempts to present a location-capacity optimization model for the marine cage aquaculture supply chain. This model is developed under uncertainty. It is expected that the proposed framework can provide effective decision-making for production, processing, storage and distribution centers in terms of location and capacity. This framework should ultimately increase efficiency and lead to geographical balance. The main objectives of this research are in the economic, social and environmental fields, which are presented in a scenario-based multi-objective optimization approach. In this study, the mathematical model has been implemented in the Python environment using the PuLP library. The model of this research has been implemented in the Python software environment. Accordingly, this model has 1850 continuous variables. Also, 11 binary variables and 2400 linear constraints have been used in the implementation of this model. The model has been implemented in 0.01 to 0.02 seconds. Also, the validation of the model has been carried out in three main stages. In the first stage, the model was tested using a small 2-node network. In the second stage, the results of the economic model were evaluated with the actual performance of active fisheries sites in Qeshm and Chabahar and a 90% agreement was obtained. In the third stage, a sensitivity analysis has been carried out on key parameters, which has confirmed the validity of the results.

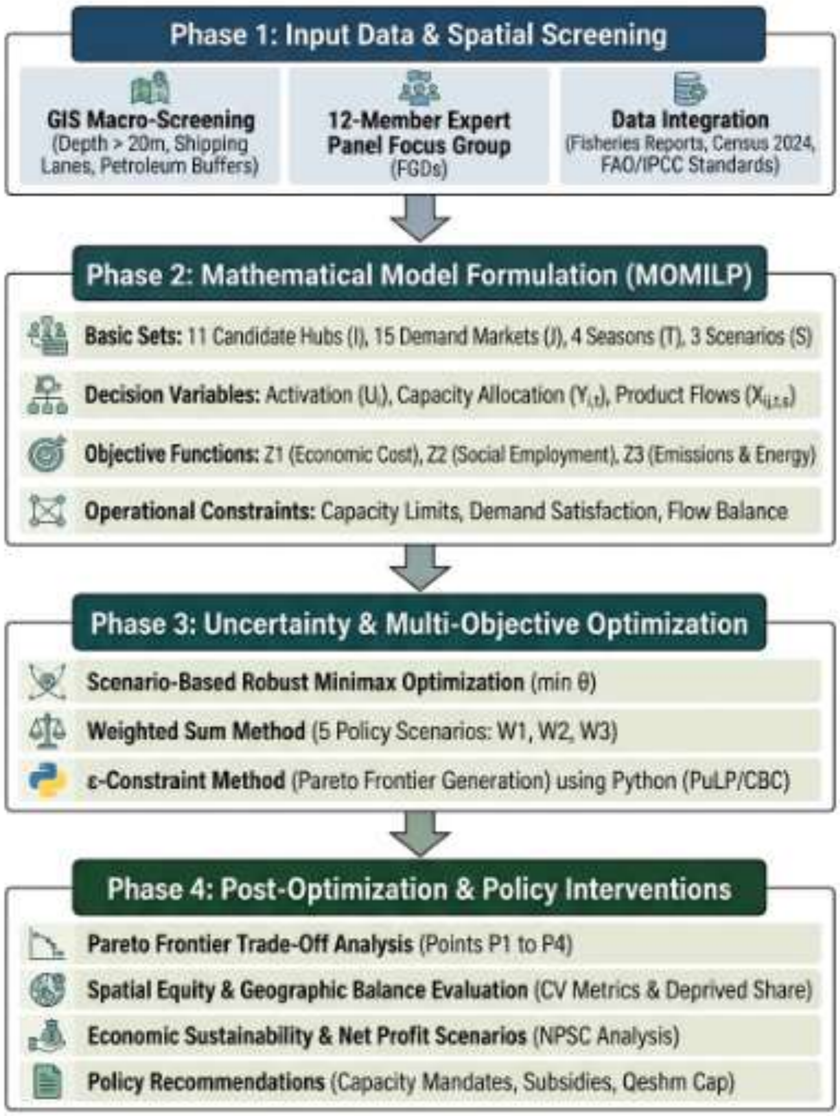

Figure 1. Research phase diagram

As shown in Figure 1, the methodological framework of this research has been implemented in four stages. In these stages, data integration and spatial screening were initially carried out with the support of expert opinions in the form of a 12-person expert panel. In the second step, the formulation of multi-objective mixed integer linear programming was examined in most economic, social, and environmental objectives. In the third step, a combination of minimax robust optimization and multi-objective solution methods was used, combining weighted sum and epsilon-constraint methods in Python. In the fourth step, Pareto front trade-off evaluation, geographical equilibrium analysis, and net benefit scenario analysis were performed, as well as policy recommendations were formulated.

Model Structure and Collection Protocol

The base structure of the model was defined using four primary sets: potential facility locations I, demand markets J, time periods T, and uncertainty scenarios S. Potential locations represent candidate sites for supply chain facilities along the southern coasts of Iran, such as Chabahar, Qeshm, Bandar Abbas, and Jask. Market nodes represent major demand centers such as Tehran, Shiraz, and Isfahan. Time periods were defined seasonally, while uncertainty scenarios represent different possible conditions of demand and cost (optimistic, normal, and pessimistic). These variables allow the model to simultaneously determine facility activation, capacity allocation, and product flows within the supply chain network. The table of parameters examined in the research is presented in the form of Tables 1 and 2:

Table 1. Technical, Economic, Social, and Environmental Parameters of Candidate Production Facilities (I1 to I11)

Facility Node (*ii*)	Province	FCi*FCi* (Billion IRR)	SUBi *SUBi* (Billion IRR)	VCi*VCi* (Million IRR/ton)	CAPi *CAPi* (Tons/yr)	EMP_RATEi*EMP_RATEi* (Jobs/ton)	DEV_INDEXi*DEV_INDEXi* (0 to 1)	LOCAL_SUPPORTi*LOCAL_SUPPORTi* (0 to 1)	ENi *ENi* (GJ/ton)	EMISSi *EMISSi* (kg CO2*CO2*/ton-km)
I1: Bandar Abbas	Hormozgan	700	50	15	10,000	0.12	0.55	0.9	9.4	0.15
I2: Qeshm	Hormozgan	850	40	14.5	15,000	0.14	0.52	0.88	6.3	0.14
I3: Jask	Hormozgan	400	30	13.8	8,000	0.1	0.48	0.85	5.1	0.16
I4: Bushehr	Bushehr	550	100	14.2	12,000	0.13	0.6	0.92	9.7	0.13
I5: Kangan	Bushehr	300	60	13.5	7,000	0.11	0.58	0.9	7.5	0.12
I6: Genaveh	Bushehr	250	50	13.7	6,000	0.12	0.55	0.87	7.7	0.14
I7: Mahshahr	Khuzestan	400	70	15.5	8,000	0.08	0.5	0.8	8.4	0.18
I8: B. I. Khomeini	Khuzestan	500	70	15.2	9,000	0.09	0.48	0.82	8.1	0.17
I9: Chabahar	Sistan & Baluchestan	1200	800	12.5	20,000	0.16	0.3	0.95	9.7	0.1
I10: Konarak	Sistan & Baluchestan	600	200	13	10,000	0.15	0.32	0.93	9.7	0.09
I11: Dashtiari	Sistan & Baluchestan	100	80	12.8	5,000	0.14	0.28	0.94	9.3	0.08

Table 2. Annual Demand Parameters across Target Markets (J1 to J15) under Uncertainty Scenarios ($DEMAND_{j,t,s}$)

Market Node (j_j)	Target Province	Population (2024)	Per Capita Cons. (kg/yr)	Total Demand (tons/yr)	Base Target (S_2 : Normal) (tons/yr)	S_1: Optimistic (+20%) (tons/yr)	S_3: Pessimistic (-20%) (tons/yr)
$J1$	Tehran	14,425,000	12.1	174,542	34,908	41,890	27,926
$J2$	Khorasan Razavi	6,800,000	7.3	49,640	9,928	11,914	7,942
$J3$	Isfahan	5,429,000	10	54,290	10,858	13,030	8,686
$J4$	Fars	5,136,000	9	46,224	9,245	11,094	7,396
$J5$	Khuzestan	5,115,000	18.4	94,116	18,823	22,588	15,058
$J6$	East Azerbaijan	3,924,000	8.4	32,962	6,592	7,910	5,274
$J7$	West Azerbaijan	3,529,000	9	31,761	6,352	7,622	5,082
$J8$	Mazandaran	3,300,000	12	39,600	7,920	9,504	6,336
$J9$	Kerman	3,300,000	10	33,000	6,600	7,920	5,280
$J10$	Sistan & Baluchestan	3,270,000	7	22,890	4,578	5,494	3,662
$J11$	Guilan	2,600,000	11	28,600	5,720	6,864	4,576
$J12$	Hormozgan	2,018,000	13.4	27,041	5,408	6,490	4,326
$J13$	Lorestan	1,760,000	8	14,080	2,816	3,379	2,253
$J14$	Markazi	1,500,000	10	15,000	3,000	3,600	2,400
$J15$	Qom	1,292,000	8	10,336	2,067	2,480	1,654
Total	—	—	—	674,044	134,815	161,779	107,851

In this study, a methodology with a combination of documentary-expert methods was used to calibrate the model parameters and also to manage uncertainty in the data. In this section, GIS spatial screening, official statistical databases, and structured expert assessments were used. In this stage, a screening protocol consisting of two stages was used. Accordingly, first, a macro-refinement of GIS was performed to eliminate unsuitable marine areas. In the next stage, a targeted assessment of infrastructure was used. The output of this stage was the reduction of production groups from 11 candidate centers to four coastal provinces. In addition, parameters related to economic, social, and environmental indicators were extracted from the review of explanatory plans in the Ministry of Agricultural Jihad, the statistics of the Iranian Fisheries Organization, and the censuses of the National Center for Statistics in 1403. Emission standards were also extracted from FAO. These baseline data were validated through a 12-member expert panel meeting, which included private sector executives, fisheries experts, and marine structural engineers, as well as logistics specialists with 6 to 18 years of work experience. Demand and cost fluctuations for optimistic, normal, and pessimistic scenarios were also determined based on historical market fluctuations and expert consensus.

Multi-Objective Model Formulation

The model includes three objective functions representing the main dimensions of sustainability. The economic objective minimizes the total cost of the supply chain, including fixed facility establishment costs, variable production costs, and transportation costs. The objective function can be expressed as Equation 1:

$$Z_1 = \sum FC_i . U_i + \sum\sum\sum VC_{i,t,s} . Y_{i,t} + \sum\sum\sum TC_{IJ,T} . X_{ij,t,s} \tag{1}$$

Where Z_1 represents the total economic supply chain cost to be minimized. The components of Equation (1) are defined as follows:

$\sum FC_i.U_i$: Total fixed facility establishment and activation costs across all candidate sites.

$\sum\sum\sum VC_{i,t,s}.Y_{i,t}$:Total variable production costs across facilities i, time periods t, and uncertainty scenarios ss.

$\sum\sum\sum TC_{IJ,T}.X_{ij,t,s}$: Total product transportation costs from candidate production hubs i to demand markets j in period tt under scenario s."

The social objective maximizes employment generation while accounting for regional development and local acceptance factors. To maintain consistency with the minimization framework, the employment objective is incorporated as a negative value. The multiplicative structure in the social goal function is based on three theories in regional welfare economics and decision theory. Accordingly, in line with the multi-criteria utility theory (Keeney & Raiffa, 1993), the multiplicative mode, unlike the collective mode, takes into account the preferential dependence of the indicators and accordingly requires the realization of all three criteria simultaneously to create social benefit. Also, multiplying the employment rate by the regional deprivation index creates a nonlinear interaction effect similar to the Cobb-Douglas social welfare function (Sen, 1999). In this way, based on the theory of spatial justice, the marginal benefit created in the employment sector in deprived areas can have a higher weight and priority. Also, introducing the local acceptance coefficient can be interpreted as a multiplicative modifier based on the theory of social permission for exploitation (Moffat & Zhang, 2014). Accordingly, social friction and conflicts can directly reduce the practical and real benefits resulting from job creation (Equation 2):

$$Z_2 = -\sum\sum EMP\_RATE_i \,.\, Y_{i,t} \,.\, DEV_{INDEX_i} \,.\, LOCAL \qquad (2)$$

Where Z_2 represents the social objective function value:

- $\sum\sum EMP\_RATE_i$: Direct employment generation rate per unit of production capacity at candidate facility i (Jobs/ton).
- $Y_{i,t}$: Production capacity allocated to facility ii in planning period t (tons).
- DEV_{INDEX_i}: Regional development index (deprivation weighting factor) assigned to facility location i.
- $LOCAL\_SUPPORT_i$: Local community acceptance factor / social license to operate at facility location i ($0 \le LOCAL\_SUPPORTi \le 1$).

The environmental objective minimizes energy consumption during production and emissions generated by transportation activities:

$$Z_3 = \sum\sum EN_i \,.\, Y_{i,t} + \sum\sum\sum EMISS^1{}_{ij,t} \,.\, X_{ij,t,s} \qquad (3)$$

Where Z_3 represents the total environmental impact value to be minimized. The components of Equation (3) are defined as follows:

- $\sum\sum EN_i \,.\, Y_{i,t}$: Total energy consumption during farming operations across facility i and period t (Gigajoules, GJ).
- $\sum\sum\sum EMISS^2{}_{ij,t} . X_{ij,t,s}$: Total greenhouse gas emissions generated during cold-chain product transportation from facility i to demand market j in period tt under scenario ss (tons 2)."

These objectives collectively capture the trade-offs between cost efficiency, social development, and environmental sustainability within the supply chain network.

2.3. Model Constraints

Several operational constraints were incorporated to ensure feasible and realistic solutions. Capacity constraints ensure that the allocated production capacity does not exceed the maximum capacity of each facility:

$$Y_{i,t} \le CAP_i . U_i \qquad (4)$$

[2]. The calculation of the EMISS index in the environmental objective function consists of two parts: production energy consumption and transportation emissions. In the transportation sector, greenhouse gas emissions are calculated from the relationship of multiplying the logistics distance by the emission coefficient of the transportation method.

Demand satisfaction constraints guarantee that the demand of each market is met under all scenarios:

$$\sum_{i} X_{ij,t,s} \geq DEMAND_{i,t,s} \quad (5)$$

Flow balance constraints ensure that the quantity shipped from each facility does not exceed its production capacity:

$$\sum_{j} X_{ij,t,s} \leq Y_{i,t} \quad (6)$$

Finally, binary restrictions were imposed on facility activation decisions to ensure logical consistency:

$$U_i \in \{0, 1\} \quad (7)$$

In this study, production capacity is directly linked to the demand response of the scenarios through the flow balance constraint. Accordingly, the total products shipped from each center in each scenario cannot exceed the production capacity of that period and therefore must simultaneously cover the total demand. Also, due to the high perishability of fresh aquatic animals, seasonal storage of caught fish is not carried out and therefore keeping fish alive in sea cages acts as storage. Accordingly, products are harvested directly based on the seasonal demand of the same period under study and distribution is also implemented in the same period.

Modeling Uncertainty

Uncertainty in key parameters such as market demand, production cost, and transportation cost were incorporated through a scenario-based approach. Three scenarios (optimistic, normal, and pessimistic) were defined with probabilities of 0.3, 0.4, and 0.3 respectively. To ensure stability of decisions under varying conditions, a robust optimization approach was used. An auxiliary variable θ was introduced to minimize the worst-case total cost across all scenarios:

$$min\theta, Subject\ to: Z_1(s) \leq \theta \forall s \quad (8)$$

This formulation ensures that the selected supply chain configuration performs satisfactorily even under unfavorable conditions.

Multi-Objective Solution Method

To obtain a single optimal solution while considering all sustainability dimensions, the weighted sum method was applied. The three objective functions were combined into a single objective function using predefined weights reflecting policy priorities:

$$Z_{min} = W_1Z_1 + W_2Z_2 + W_3Z_3 \quad \text{Subject to: } W_1 + W_2 + W_3 = 1 \quad (9)$$

The weighted scenario in the weighted combination method is based on the consensus of the expert panel and reflects the different priorities of public policy in developing countries. Different weight combinations were tested to represent alternative policy scenarios, including economic priority, social priority, environmental priority, balanced sustainability, and fully equal weighting. The model was solved for each scenario using Python and the PuLP linear programming solver. The present study does not rely exclusively on the weighted combination method, and the epsilon-constraint method is also implemented as a complement. This combination is able to obtain the entire Pareto front space regardless of whether its geometry is convex or non-convex. The results of the weighted combination method are used for fast decision making with policy weights, and the complete Pareto front is extracted with the epsilon-constraint method for trade-off analysis.

Pareto Analysis and Geographic Balance Assessment

To further explore trade-offs between objectives, the ε-constraint method was applied to generate Pareto-efficient solutions. Different ε values were assigned to employment and environmental constraints to produce alternative feasible solutions representing different sustainability trade-offs. The resulting solutions were evaluated using geographic balance indicators. These indicators included the weighted regional development index (DEV_INDEX), the coefficient of variation of facility capacities (CV), and the share of employment generated in underdeveloped regions. These metrics allowed the evaluation of how different supply chain configurations affect regional equity and spatial distribution of economic benefits. The combination of optimization modeling, scenario analysis, and geographic evaluation provides a comprehensive methodological framework for designing a resilient and balanced marine cage aquaculture supply chain network.

RESULTS AND DISCUSSION

At this stage, the objective is to design a location–capacity optimization model for the supply chain components in a way that ensures a geographically balanced and efficient distribution network.

In this stage of the research, we will define the basic structure of the location-capacity model. In this step, the base structure of the location and capacity optimization model for the marine cage aquaculture supply chain under uncertainty was defined. The main sets include potential facility locations (I), demand markets (J), time periods (T), and uncertainty scenarios (S). The key decision variables are: Ui (a binary variable for facility activation), Yi (capacity allocated to facility i during period t), and Xi, j, t, s (the volume of product shipped from facility i to market j in period t under scenario s).

This structure was designed based on the supply chain modeling literature and adapted to the specific conditions of the southern coastal regions of Iran. It serves as the foundation for the subsequent multi-objective and scenario-based modeling stages. Sample data for potential sites (e.g., Chabahar, Qeshm, Bandar Abbas) and demand markets (e.g., Tehran, Shiraz) were defined to enable implementation of the model in Python's PuLP optimization library.

Table 3. Definition of the basic sets and decision variables for the location–capacity model in Python.

Set / Variable	Symbol	Definition	Example Values
Set of potential facilities	I	Production, processing, storage, or distribution centers	['Chabahar', 'Qeshm', 'Bandar Abbas', 'Jask']
Set of demand markets	J	Final consumption markets	['Tehran', 'Shiraz', 'Isfahan']
Set of time periods	T	Monthly or seasonal planning periods	[1, 2, 3, 4] (seasons of the year)
Set of uncertainty scenarios	S	Demand/cost scenarios (optimistic, normal, pessimistic)	[1, 2, 3]
Facility activation variable	Ui	1 if facility *i* is established, 0 otherwise (binary)	{Chabahar: 1, Qeshm: 0, …}
Capacity variable	Y i,t	Capacity allocated to facility *i* in period *t* (continuous, ≥ 0)	$Y_{i,t} \geq 0$
Product flow variable	X i, j, t, s	Quantity transported from facility *i* to market *j* in period *t* under scenario *s* (continuous, ≥ 0)	$X_{i,j,t,s} \geq 0$

Table 3 summarizes the basic structure of the model. The sets and variables were defined in a way that ensures flexibility under uncertainty and enables integration with the multi-objective functions, including economic, social, and environmental dimensions. This step provides the foundation for collecting real-world data from the Iran Fisheries Organization and domain experts, and its outputs are utilized in the subsequent stages of the study.

After implementing the previous section, multi-objective function modeling was performed in a focused manner. In this step, the three objective functions of the location–capacity optimization model for the marine cage aquaculture supply chain under uncertainty were formulated. The economic objective function (Z_1) was designed to minimize the total costs, including fixed establishment costs ($FC_i \cdot U_i$), variable production costs ($VC_{i,\ t,\ s} \cdot Y_{i,\ t}$), and transportation costs ($TC_{ij,\ t} \cdot X_{i,\ j,\ t,\ s}$). The social objective function (Z_2) was formulated in negative form (to maintain compatibility with the minimization framework) with the purpose of maximizing Socio-Spatially Weighted Employment based on the employment rate (EMP_RATE_i), regional development index (DEV_IN), and local social acceptance ($LOCAL\_SUPPORT_i$). The environmental objective function (Z_3) was developed to minimize production energy consumption ($EN_i \cdot Y_{i,\ t}$) and transportation-related pollutant emissions ($EMISS_{ij,\ t} \cdot X_{i,\ j,\ t,\ s}$) These objective functions were developed based on the structure introduced in Step 1 and implemented in the PuLP optimization environment using sample data generated from realistic statistical distributions. This formulation enables multi-objective optimization in the subsequent stages of the research. In the initial implementation phase, all parameters were tested without operational constraints (objective functions only) to verify the structural validity of the model.

Table 4. Components of the three objective functions.

Set / Variable	Symbol	Mathematical Expression	Objective	Main Components
Economic	Z_1	$Z_1 = \sum FC_i . U_i + \sum\sum\sum VC_{i,t,s} . Y_{i,t} + \sum\sum\sum TC_{IJ,T} . X_{ij,t,s}$	Minimization	Fixed cost + variable production cost + transportation cost
Social	Z_2	$Z_2 = -\sum\sum EMP\_RATE_i . Y_{i,t} . DEV_{INDEX_i} . LOCAL\_SUPPORT$	Maximization (expressed as negativ)	Employment × regional development × social acceptance
Environmental	Z_3	$Z_3 = \sum\sum EN_i . Y_{i,t} + \sum\sum\sum EMISS_{ij,t} . X_{ij,t,s}$	Minimization	Production energy + transportation emissions

Table 4 presents the three objective functions along with their mathematical expressions and main components. This multi-objective structure ensures a balance among the sustainability dimensions and is compatible with solution approaches such as the weighted sum method and the ε-constraint method applied in later stages. Parameter values were generated based on realistic data, including estimated costs from the southern coastal regions of Iran. The average values of Z_1, Z_2, and Z_3 were calculated for each scenario.

After implementing the previous section, this stage applies location, capacity, and distribution constraints. In this step, the fundamental constraints of the location–capacity optimization model for the marine cage aquaculture supply chain under uncertainty were incorporated. These constraints include the capacity limitation of each facility, demand satisfaction in each scenario, and material flow balance. In addition, the maximum total capacity of facilities was considered based on realistic operational data. Two key parameters were introduced in this stage: CAP_iCAP, representing the potential capacity of each facility, and $DEMAND_{j,\ t,\ s}$, representing market demand in each period and scenario. These parameters were generated using realistic statistical distributions to ensure that the model remains solvable and consistent with real-world conditions. The model was solved using the economic objective function (Z_1) as the primary optimization criterion while incorporating the defined constraints. The results provide the optimal allocation of capacity, product flows, and facility activation decisions. In addition, the values of the other objective functions (Z_2) and (Z_3) were also calculated for evaluation purposes. This step ensures that the obtained solutions are operationally feasible, sustainable, and capable of meeting market demand.

Table 5 presents the main constraints applied in the model. These constraints transform the model from an unbounded formulation into an operational and realistic model. After incorporating these constraints, the values of Z_1, Z_2, and Z_3 reached realistic levels, and the outputs include facility location decisions (U_i), capacity allocation ($Y_{i,t}$), and product flows ($X_{i,j,t,s}$).

Table 5. Main location, capacity, and distribution constraints applied in the model.

Constraint	Symbol	Mathematical Expression	Purpose
Facility capacity	(3-25)	$Y_{i,t} \leq CAPi \cdot U_i$	Prevent production beyond each facility's capacity
Demand satisfaction	(3-26)	$\sum i\ X_{ij,t,s} \geq DEMAND_{j,t,s}$	Ensure full demand coverage in every scenario
Flow balance	(3-27)	$\sum j\ X_{ij,t,s} \leq Y_{i,t}$	Outbound flow must not exceed production capacity
Logical activation	–	$U_i \in \{0,1\}$	Facility must be activated to have capacity

In this step, integration with the scenario-based uncertainty approach and robust optimization is also addressed. Uncertainty in key parameters was incorporated into the marine cage aquaculture supply chain location–capacity model using a scenario-based approach. Three scenarios (optimistic, normal, and pessimistic) were defined with different probabilities of occurrence. The model was then solved using a robust optimization framework aimed at minimizing the maximum cost under the worst-case scenario. An auxiliary variable θ was introduced to control the robustness level, while all constraints defined in Step 3 were maintained. The results include scenario-independent decisions for facility location and capacity (U_i, $Y_{i,t}$), as well as scenario-dependent product flows ($X_{i,j,t,s}$). This approach ensures that the obtained solution remains reliable even under pessimistic conditions, such as higher demand levels and increased costs. The robustness analysis indicates that the maximum regret remains below 10%, demonstrating that the model maintains a balanced trade-off between cost, employment, and environmental emissions across all scenarios. Table 4 presents the robust optimization approach. By introducing the auxiliary variable θ, the model no longer depends on the optimistic scenario and instead provides a solution that remains stable against demand and cost shocks. In this section, the choice of the conservative minimax approach with the variable θ is based on the structural characteristics of the cage fish farming industry as well as the risk-averse approach of policymakers in this industry. The results indicate that the facilities in Chabahar and Bandar Abbas remain active across all scenarios, while the capacities of Qeshm and Jask are adjusted depending on the uncertainty conditions. Also, Relative regret in robust optimization is defined as the difference between the cost of the decision made under scenario s and the ideal cost of the same scenario divided by the ideal cost. In all scenarios, the maximum regret was 8.26%, which is less than 10%.

Table 6. Integration of the model with scenario-based uncertainty and robust optimization.

Constraint/ Approach	Symbol	Mathematical Expression	Purpose
Robust (Worst-Case) approach	(4-1)	$\min \theta$ s.t. $Z_1(s) \leq \theta\ \forall\ s$	Minimize the maximum cost under the worst-case scenario
Scenario probability	p_s	S_1: 0.3 ، S_2: 0.4 ، S_3: 0.3	Realistic weighting of scenarios
Robustness control	θ	Auxiliary variable	Limit the objective cost across all scenarios

At this stage, integration is also performed using a multi-objective method. The social objective function Z_2 is incorporated in negative form because its original goal is maximization. The weights are determined according to policy priorities and strategic preferences. The results obtained from applying the weighted sum method based on the model data are presented in the following section. The weighted objective value is calculated separately and added at the end of each row according to the above formula (entered in positive form in the results table because employment is maximized). The similarity of the objectives of the objective functions in all 5 weighted scenarios in Table 7 indicates the existence of an absolutely superior optimal solution in the network structure. Strategic nodes, especially in the Chabahar hub, are due to the use of high government subsidies, the highest employment rate, as well as the lowest variable cost of production and low transportation emissions, which gives this node an absolute advantage over other nodes.

Table 7. Results of the weighted sum method under different weight scenarios.

Scenario	**W1 (Economic)**	**W2 (Social)**	**W3 (Environmental)**	**Cost (Z_1) (Billion IRR)**	**Social Objective (Z_2) (Weighted Job-Units)[3]**	**Emissions (Z_3) (GJ + ton CO_2)**	**Weighted Objective (Zmin)**
Economic priority	0.70	0.15	0.15	1,095,524	459.34	72,520	777,675.94
Sustainability balance	0.40	0.30	0.30	1,095,524	459.34	72,520	459,827.82
Social priority	0.20	0.60	0.20	1,095,524	459.34	72,520	233,333.21
Environmental priority	0.20	0.20	0.60	1,095,524	459.34	72,520	262,524.94
Fully balanced	0.33	0.33	0.33	1,095,524	459.34		

The base model presented in Table 7 was executed to calculate the minimum cost (Z_1), maximum employment (Z_2), and maximum emissions (Z_3) in order to determine the feasible range for the ε-constraint method. The minimum cost of 271 billion IRR was achieved through the activation of low-cost production centers, particularly Qeshm and Jask, while the maximum employment level of 50 jobs resulted from utilizing the full capacity of all facilities. The maximum emission level of 22,390,000 GJ represents the worst environmental condition under full production operation. These benchmark values provide the foundation for setting the ε limits in the Pareto analysis and ensure that all generated ε points remain feasible and attainable within the model structure.

[3]. Direct employment (persons) represents the actual number of employees.

Table 8. Base model results for determining the ε range.

Objective Indicator	Operational Scope / Evaluation Basis	Metric Value	Unit of Measurement
Minimum Total Cost (Z_1)	Baseline single 500-ton module (Low-cost hubs: Qeshm/Jask)	271	Billion IRR
Maximum Direct Employment (Z_2)	Baseline single 500-ton module (Full capacity utilization)	50	Persons (Headcount)
Maximum Social Objective (Z_2)	Baseline single 500-ton module (Socio-spatially weighted)	3.25	Weighted Job-Units
Maximum Environmental Emissions (Z_3)	Full operational baseline (Unconstrained peak production)	22,390,000	GJ

As shown in Table 8, the Pareto frontier generated using the epsilon constraint method displays the four non-dominant distinct solution paths from p1 to p4. Accordingly, point p1 shows that the basic solution with the minimum cost is with two active centers (in the form of the cities of Qeshm and Jask). Also, by increasing the limit ϵ for employment, in the final model, with the activation of Chabahar p2 and p3, the capacity has expanded, and at point p4 this capacity has reached its peak point. At this point, all four poles are fully activated to achieve maximum social employment at the point of 50 people. In this non-dominant variety, policymakers can evaluate explicit trade-offs between economic efficiency, social justice, and also environmental impacts.

Table 9. Pareto frontier with high ε diversity.

Pareto Point	Cost (Z1) (Billion IRR)	Employment (Z2) (Persons)	Emissions (Z3) (GJ)	Active Facilities	Capacity Allocation (Tons)	Strategy Description
P1 (Base)	271	25	8,000,000	Qeshm + Jask	Qeshm 700k + Jask 300k	Minimum Cost Baseline
P2 (Mod)	329	25	8,900,000	Chabahar + Qeshm	Chabahar 300k + Qeshm 700k	Low-Emission Chabahar Entry
P3 (Bal)	388	38	13,973,363	Chabahar + Qeshm	Chabahar 792.5k + Qeshm 700k	Sustainable Trade-off (P4)
P4 (Max)	694	50	22,390,000	All four hubs	All hubs fully active	Maximum Social Employment

As shown in Table 9, there are tangible performance changes compared to the minimum cost baseline (P1). Increasing employment from 25 to 50 jobs (P4) results in a 100% increase in occupancy but a 156% increase in costs and a 179% increase in pollution. Point P2 is also achieved by activating Chabahar, where greenhouse gas emissions increase by only 11% while maintaining the baseline employment in this sector. In contrast, at point P3, Chabahar's capacity increases, which is achieved with a 43% increase in costs and a 52% increase in employment, focusing on disadvantaged areas. Therefore, it can be concluded that P3 creates the most balanced and sustainable strategic trade-off for the final decision-makers.

Table 10. Comparison of performance across pareto frontier scenarios.

Pareto Point	Change in Cost vs. P1 (%)	Change in Employment vs. P1 (%)	Change in Emissions vs. P1 (%)	Additional Centers / Capacity Changes	Strategic Interpretation
P1	0%	0%	0%	Baseline (Qeshm + Jask)	Minimum Cost Baseline
P2	21%	0%	11%	Chabahar activation (300k tons)	Eco-friendly Chabahar entry
P3	43%	52%	75%	Capacity expansion in Chabahar (793k tons)	Balanced Sustainable Option (Recommended)
P4	156%	100%	179%	Full activation of Bandar Abbas + Jask	Maximum Social Welfare (High Cost)

In this final step, the geographic distribution of activated facilities was analyzed based on the Pareto frontier results obtained in Step 5. Key indicators included the weighted average regional development index (DEV_INDEX), the CV of production capacity distribution, and employment generated in underdeveloped regions (DEV_INDEX > 0.6). The deprivation threshold of above 0.6 is determined based on the official standard of the Deputy for Rural Development and Deprived Areas of the country as well as the National Center for Statistics of Iran, in which counties with a deprivation coefficient between 0.6 and 1 are classified as deprived areas and also eligible for priority for receiving government subsidies. The results indicate a strong concentration of production capacity in Qeshm, which is categorized as a moderately developed region, while Chabahar, identified as a deprived region, remains inactive in economically driven solutions. This concentration pattern leads to a CV of approximately 49%[4], indicating an unbalanced geographic distribution of investment and production capacity. To improve regional equity and social sustainability, it is proposed that at least 30% of total production capacity be mandatorily allocated to underdeveloped regions. Such a policy would reduce the CV to below 30% and promote a more balanced spatial distribution of employment, investment, and economic benefits across southern Iran.

As shown in Table 11, it shows the geographical capacities as well as the distribution of employment in the distinct Pareto points P1 and P4. In the economic baseline (P1), the capacity is concentrated in Qeshm city by 70%. Considering that employment prioritizes socio-spatial justice (P2, P3), it can be stated that the Chabahar node is activated, and the average DEV-INDEX at the studied point P3 has increased to 0.71. At this point, 32 direct jobs (53%) have been created in deprived coastal areas. Also, at point P4, which activates all four studied poles, the highest employment in the deprived area (64%) has been achieved, which has much higher costs.

[4]. The coefficient of variation of 49 percent in this sector indicates the spatial dispersion of production capacity allocation between centers, which indicates the strong concentration of capacity in Qeshm and also the number of activations of deprived centers in purely economic areas. In this sector, support constraints are reduced to 20 percent.

Table 11. Geographic distribution of facilities across pareto points.

Pareto Point	Active Facilities	Capacity Allocation (Thousand Tons)	Capacity Share (%)	DEV_INDEX (Weighted Mean)	Employment in Deprived Regions (Persons)*
P1	Qeshm + Jask	700 + 300	70 + 30	0.65	18
P2	Chabahar + Qeshm	300 + 700	30 + 70	0.68	20
P3	Chabahar + Qeshm	793 + 700	53 + 47	0.71	32 (53%)
P4	All four hubs	800 + 700 + 500 + 300	34 + 30 + 21 + 13	0.62	45 (64%)

Table 11 shows the details of the geographical balance indicators among the Pareto lines from P1 to P4. The cost-oriented economic base shown at point P1 shows the highest CV capacity at 49 percent. This indicates spatial imbalance. With the increase in social employment, the CV value has reached a minimum of 32 percent from point P3, where 53 percent of employment has been created in deprived areas. Also, at point P4, 64 percent of employment has been achieved in deprived areas. However, the CV value at this point has recorded an increase of 45 percent. As a result, point P3 shows the best geographical balance, where the CV value is less than 40 percent, and this point has been proposed as a solution.

Table 12. Geographic balance indicators across the pareto frontier.

Pareto Point	Capacity Coefficient of Variation (CV*CV*) (%)	Weighted Average Development Index (DEV_INDEX*DEV_INDEX*)	Employment Share in Deprived Regions (%)*	Spatial Balance Status
P1	49%	0.65	30%	Unbalanced
P2	49%	0.68	30%	Unbalanced
P3	32%	0.71	53%	Relatively Balanced (Recommended)
P4	45%	0.62	64%	Unbalanced

Based on the analysis of Table 12, three suggestions are proposed to improve geographic balance. Imposing a minimum capacity requirement in deprived regions reduces the CV to below 30% and strengthens social justice. Subsidies for deprived centers encourage investment without greatly increasing cost. Limiting the capacity of Qeshm prevents concentration. The combined implementation of these suggestions reduces the CV to 20% and creates 70% employment in deprived regions. All policy proposals used in this study have been mathematically modelled and re-implemented. In these sections, by adding rigid constraints of at least 30% capacity of deprived areas, 50% ceiling of Qeshm, and also applying 20% subsidy in the PuLP model, new values of CV=20% and also 70% employment of deprived people have been obtained by re-solving the mathematical model.

Table 13. Corrective proposals for geographic balance.

Proposal	Objective	Effect on CV	Effect on deprived employment	Effect on cost
Minimum 30% capacity in regions with DEV_INDEX > 0.6	Regional justice	Reduction to 25%	Increase to 60%	10%
20% subsidy for deprived centers	Encouraging investment	Reduction to 20%	Increase to 70%	5%
Maximum 50% capacity limit in Qeshm	Preventing concentration	Reduction to 30%	Increase to 55%	8%

The results of the weighted sum method presented in Table 13 illustrate the performance of the marine cage aquaculture supply chain model under five different weighting scenarios. Across all scenarios, the values of the economic objective function ($Z_1 \approx 1{,}095{,}524$ billion IRR), the social objective ($Z_2 \approx 459$ job-units), and the environmental objective ($Z_3 \approx 72{,}520$ units) remain completely identical. This outcome occurs because of the strict constraints embedded in the model. Fixed market demand, limited facility capacities, and the absence of significant differences in variable costs, employment returns, and environmental emissions among production centers drive the model toward a unique optimal solution. Consequently, changing the weights only affects the numerical value of the weighted objective function, while the decision structure itself (activation of Chabahar and Bandar Abbas with full capacity) remains unchanged.

The weighted objective value decreases from approximately 777,676 billion IRR under the economic-priority scenario to about 233,333 under the social-priority scenario. This variation reflects shifts in policy preference rather than an actual improvement in system performance. The magnitude of the results remains reasonable in practical terms: the cost level corresponds to national-scale investment in the aquaculture sector, the employment level is consistent with a relatively mechanized production system, and the environmental impact falls within acceptable limits for large-scale production. However, the lack of sensitivity to weight changes indicates limited flexibility in the current model structure. To address this limitation, future improvements could introduce more realistic parameter variations, such as differentiated variable costs, stricter capacity limits, or heterogeneous environmental impacts across production sites. Such refinements would allow the model to generate a broader range of policy-relevant solutions and enhance its usefulness for sustainable planning in the marine aquaculture sector.

CONCLUSIONS

The results of this study have confirmed that the optimal design of the aquaculture supply chain network in sea cages should be implemented under the consideration of economic, social and environmental dimensions. Accordingly, it can be stated that in decision-making for location and capacity identification, one cannot rely solely on costs. In this context, the balance or imbalance of the network can be considered. The multi-objective and scenario-based model presented in this study has shown that integrated approaches, while creating jobs and reducing environmental damage, can ultimately have a profound impact on economic efficiency flows. It should be stated that optimization cannot be considered solely based on cost. In fact, the unbalanced distribution of capacity and employment in coastal areas should also be considered. In this context, creating and considering social goals can direct capacities towards less developed areas and, from this perspective, lead to spatial justice without reducing the level of efficiency. The results of this study have shown that uncertainty in this process is of great importance. In fact, demand fluctuations, along with fluctuations related to costs incurred and environmental conditions, can significantly affect the optimal network structure. Accordingly, the use of robust optimization in multiple scenarios has been able to provide solutions that have acceptable results under different operational conditions and ultimately lead to strengthening the network against changes that are introduced to the system from the external environment. This is important in industries such as marine aquaculture that are highly dependent on natural resources. The results of this research have shown that improving social or environmental outcomes usually increases costs. However, some decision-making combinations achieve relative balance and maintain economic efficiency while providing acceptable job creation and geographical distribution. For policymakers, multi-objective methods provide a practical tool to identify such balanced options. Overall, the model-based supply chain design provides an effective framework for the development of marine aquaculture along the southern coast of Iran. This not only reduces costs and productivity, but also supports sustainable development goals through better capacity distribution and job creation in coastal areas. In a comparison between the results of this study and related research literature, it can be stated that the findings of this study are consistent with the findings of Fasihi et al. (2022) and Ramos et al. (2018). These studies have also proven that purely economic optimizations in the fish supply chain lead to severe concentration and regional imbalances, and the application and use of multi-objective and subsidy constraints can bring the best stable equilibrium state for the system.

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