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Multi-Objective Optimization of Supplier and Distribution Center Location Selection with Inventory Allocation in an Uncertain Environment Considering CO2 Emissions

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ABSTRACT

This research focuses on efficiently selecting supplier and distribution center locations in a stochastic supply chain environment. It formulates the problem as a multi-objective optimization model aiming to minimize establishment costs, inventory expenses, and transportation costs while considering capacity limitations. To solve this complex problem, the study uses a single-objective mixed integer programming model along with LP-metrics and the T-H method. The research conducts a thorough comparison of two different methods in terms of solution quality and computational efficiency, supported by statistical hypothesis testing. Additionally, multi-criteria decision-making techniques like VIKOR and PROMETHEE II are applied to rank the effectiveness of these methods. The proposed model is validated through thirty sample problems, demonstrating its reliability and suitability for addressing the challenges of supplier and distribution center location selection in an uncertain supply chain environment.

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1. Introduction

The challenge of location and allocation within a supply chain network is a critical aspect that encompasses the determination of both site selection and inventory quantity (Ghasemi et al. 2023). Designing an effective network comprising suppliers, manufacturing plants, and distribution centers plays a pivotal role in achieving customer satisfaction (Reza Pourhassan et al. 2023).

Addressing the intricacies of location and allocation in a supply chain network is a multifaceted challenge, as elucidated by Daneshvar et al. (2023). The nuanced process involves a careful balance, requiring astute decision-making not only in choosing optimal sites but also in fine-tuning inventory levels to meet demand fluctuations (Momenitabar et al. 2023, Ghsemi et al. 2022). The significance of this challenge is underscored by its direct impact on customer satisfaction, a key objective emphasized by Goodarzian et al. (2023). In essence, the design of a cohesive network, integrating suppliers, manufacturing plants, and distribution centers, becomes a linchpin for achieving operational efficiency and ensuring customer expectations are met with precision and reliability (Momenitabar et al. 2022, Babaeinesami et al. 2022).

In the past, significant research efforts have addressed this complex issue. For instance, Murtagh and Niwattisyawong (1982) introduced the location-allocation problem while accounting for capacity constraints. Owen and Daskin (1998) extended this work by considering time and uncertainty factors in their facility location models. Ho et al. (2008) explored the maximization of profit in location-allocation problems by employing the Analytic Hierarchy Process (AHP) to rank quantitative and qualitative criteria.

Furthermore, Manatkar et al. (2016) presented an optimization approach for an integrated inventory distribution model within a multi-echelon supply chain environment. Their model successfully minimized inventory holding, ordering, and transportation costs for both distributors and retailers, while also incorporating safety stock inventory through the application of practical constraints. These studies collectively contribute to the ongoing effort to enhance supply chain efficiency and effectiveness.

Arabzad et al. (2015) introduced a multi-objective robust model aimed at efficiently allocating customer demand while simultaneously considering supplier selection and order allocation. Hajipour et al. (2016) presented a multi-objective multi-layer facility location allocation model, focusing on determining the optimal number of facilities and service allocation at each layer. Zhang et al. (2016) introduced a multi-objective optimization approach to determine the location of healthcare facilities with the goal of enhancing accessibility for people while reducing the population outside of coverage areas. In another context, Yu and Solvang (2017) tackled the facilities location-allocation problem in municipal solid waste management. Their approach factored in waste treatment costs, environmental impact, and greenhouse gas emissions in the design of solid waste networks. Tezenji et al. (2016) developed a bi-objective model aiming to minimize both the mean and variance of costs. Their work considered supplier selection and order allocation between suppliers and plants when designing supply chains.

In this study, we extend Tezenji et al. (2016) model to a three-echelon supply chain by incorporating CO2 emissions into the network design. Our paper employs exact algorithms, specifically the TH method and LP-metric, to minimize the mean and variance of costs. Notably, our model introduces several novel features discussed below.

Addressing environmental pollution is a crucial aspect of effective supply chain management. Transportation activities, in particular, stand out as major sources of pollution, with CO2 emissions contributing to global warming and posing harmful effects on ecosystems and human health. Wang et al. (2011) considered two conflicting goals: optimizing the cost of the supply chain network while minimizing environmental pollution by reducing CO2 emissions in the forward network. In our model, we specifically define pollution as CO2 emissions between facilities, emphasizing the need to tackle this critical issue within supply chain design.

This paper addresses the optimization of a single-period, single-product, three-echelon logistics network encompassing suppliers, plants/stores, and distribution centers. We develop a comprehensive model that simultaneously considers the location and allocation of suppliers and distribution centers while accounting for capacity constraints. Within this framework, each plant/store and distribution center operates based on the Economic Order Quantity (EOQ) model, allowing for backorder.

In logistics network design, the uncertain nature of various parameters is a crucial concern, especially when considering environmental and economic factors. Our model tackles this challenge by incorporating stochastic costs, encompassing transportation, establishment, purchasing, inventory replenishment, holding, and shortage costs. This approach helps mitigate the impact of uncertainty on decision-making processes.

Notably, our model also introduces the concept of allowable CO2 emissions between facilities, which serves to mitigate environmental pollution within the network. To achieve these objectives, we present a stochastic multi-objective mixed-integer non-linear programming model. The aim is to identify potential sites for locating supply and distribution facilities, with the overarching goal of minimizing the combined costs of transportation and fixed expenses. The structure of the studied supply chain is presented in Figure 1.

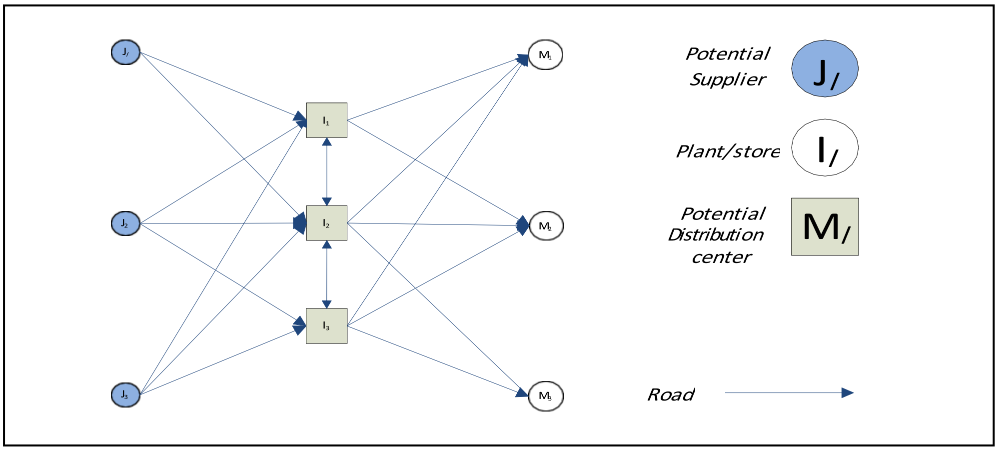

Fig. 1. Network consisting of suppliers, plant and distribution centers.

2. Proposed Multi-objective Non-Linear Programming (MONLP) Model

In order to present the proposed MONLP model, first, the assumptions and notations are provided as follows:

Assumptions

- All demands of plants/stores are satisfied by the suppliers;
- All candidate suppliers and sites meet the initial criteria;
- Each plant/store operates under the assumptions of the EOQ model with backordering allowed;
- Repletion of each plant/store is done by a single supplier and holds inventory to meet the deterministic stationary demand;
- Repletion of the distribution center is done by multiple plants/stores;
- The capacity of supplier is limited and dependent on site and supplier ability;
- Capacity of DC is limited and dependent on site and DC ability;
- Fixed and variable transportation costs are dependent on establishment sites, suppliers and DCs.

Sets

I	Set of plants/stores $i \in \{1,2,\ldots,I\}$
J	Set of candidate suppliers $j \in \{1,2,\ldots,J\}$
K	Set of candidate sites for suppliers $k \in \{1,2,\ldots,K\}$
M	Set of candidate distribution centers (DCs) $m \in \{1,2,\ldots,M\}$
N	Set of candidate sites for DCs $n \in \{1,2,\ldots,N\}$
G	Set of transportation modes $g \in \{1,2,\ldots,G\}$

Parameters

D_i	Annual demand of plants/stores i
D_m	Annual demand of DCs m
b_i	Amount of backordering allowed for plant i
b_m	Amount of backordering allowed for DC m
di_{ik}	Distance between plant/store i and supplier's candidate site k
di_{in}	Distance between plant/store i and DC's candidate site n
P_{jk}	Capacity of supplier j at site k
P_{mn}	Capacity of DC m at DC's candidate site n
h_i	Inventory holding cost rate for each unit of inventory at plant/store i
h_m	Inventory holding cost rate for DC m
O_i	Fixed ordering (Inventory replenishment) cost of plant/store i
O_m	Fixed ordering (inventory replenishment) cost of DC m
S_i	Storage cost rate for each unit commodity at plant/store i
S_m	Storage cost rate for each unit commodity at DC m
c_j	Per-unit cost offered by supplier j

c_i	Per-unit cost offered by plant i
f_{ik}	Fixed Cost of established supplier j at candidate site k
f_{mn}	Fixed cost of established DC m at DC's candidate site n
r_{ijk}	Per-mile (distance based transportation) cost to plant/supplier i from supplier established at candidate site k
r_{imn}	Per-mile (distance based transportation) cost to DC m from plant/store i
t_{ijk}	Fixed dispatch (transportation) cost to plant/store i from supplier j at site k
t_{imn}	Fixed dispatch (transportation) cost to DC m at site n from plant/store i
e_g	CO2 emission rate of transportation mode g
V	Maximum CO2 emission of transportation mode g between supplier j and plant/store i
W	Maximum CO2 emission of transportation mode g between plant/store i and DC m at DC's candidate cite n
m	The prefix indicates the mean of costs
s	The prefix indicates the standard deviation of costs

Variables

x_{jk}	1 if supplier j is established at supplier's candidate site k, otherwise 0,
xx_{mn}	1 if DC m is established at DC's candidate site n, otherwise 0,
y_{ijk}	1 if supplier j at candidate site k allocated to plant/store i, otherwise 0,
yy_{imn}	if DC m at DC's candidate site n allocated to plant/store i
Q_i	Order quantity of plant/store i
Q_m	Order quantity of DC m
T_i	D_i/Q_i order interval
T_m	D_m/Q_m order interval

Now, the suggested model is given as follows:

$$\min Z_{means} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(\mu_{C_i} D_i + (t_{ijk} + \mu_{di_{ik}})T_i)y_{ijk} + \sum_{i=1}^{I}(\mu_{O_i} T_i + \mu_{s_i}\frac{b_i}{2Q_i} + \mu_{h_i}\frac{(Q_i - b_i)^2}{2Q_i}) + \sum_{j=1}^{J}\sum_{k=1}^{K}\mu_{r_{jk}} x_{jk}$$
$$+\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}(\mu_{C_i} D_m + (t_{imn} + \mu_{di_{in}})T_m)yy_{imn} + \sum_{m=1}^{M}(\mu_{O_m} T_m + \mu_{s_m}\frac{b_m}{2Q_m} + \mu_{h_m}\frac{(Q_m - b_m)^2}{2Q_m}) + \sum_{m=1}^{M}\sum_{n=1}^{N}\mu_{r_{mn}} xx_{mn}$$

$$\min Z_{Variance} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(\sigma_{C_i} D_i y_{ijk})^2 + (\sigma_{r_{ijk}} di_{ik} T_i y_{ijk})^2 + \sum_{i=1}^{I}(\sigma_{O_i} T_i)^2 + (\sigma_{s_i}\frac{b_i}{2Q_i})^2 + (\sigma_{h_i}\frac{(Q_i - b_i)^2}{2Q_i})^2 + \sum_{j=1}^{J}\sum_{k=1}^{K}(\sigma_{r_{jk}} x_{jk})^2$$
$$+\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}(\sigma_{C_i} D_m yy_{imn})^2 + (\sigma_{r_{imn}} di_{in} T_m yy_{imn})^2 + \sum_{m=1}^{M}(\sigma_{O_m} T_m)^2 + (\sigma_{s_m}\frac{b_m}{2Q_m})^2 + (\sigma_{h_m}\frac{(Q_m - b_m)^2}{2Q_m})^2 + \sum_{m=1}^{M}\sum_{n=1}^{N}(\sigma_{r_{mn}} xx_{mn})^2$$

subject to

$$\sum_{j=1}^{J} x_{jk} \leq 1 \qquad \forall k \in K \tag{1}$$

$$\sum_{m=1}^{M} xx_{mn} \leq 1 \qquad \forall n \in N \tag{2}$$

$$\sum_{k=1}^{K} x_{jk} \leq 1 \qquad \forall j \in J \tag{3}$$

$$\sum_{n=1}^{N} xx_{mn} \leq 1 \qquad \forall m \in M \tag{4}$$

$$\sum_{k=1}^{K} \sum_{j=1}^{J} y_{ijk} = 1 \qquad \forall i \in I \tag{5}$$

$$\sum_{n=1}^{N} \sum_{m=1}^{M} yy_{imn} = 1 \qquad \forall i \in I \tag{6}$$

$$y_{ijk} < x_{jk} \qquad \forall i \in I, j \in J, k \in K \tag{7}$$

$$\sum_{i=1}^{I} D_i y_{ijk} \leq P_{jk} x_{jk} \quad \forall j \in J, k \in K \tag{8}$$

$$yy_{imn} < xx_{mn} \qquad \forall i \in I, m \in M, n \in N \tag{9}$$

$$\sum_{m=1}^{M} D_m yy_{imn} \leq P_{mn} xx_{mn} \quad \forall m \in M, n \in N \tag{10}$$

$$\sum_{g=1}^{G} e_g y_{ijk} < V \qquad \forall i \in I, j \in J, k \in K \tag{11}$$

$$\sum_{g=1}^{G} e_g yy_{imn} < W \qquad \forall i \in I, m \in M, n \in N \tag{12}$$

$$x_{jk}, xx_{mn}, y_{ijk}, yy_{imn} \in \{0,1\} \tag{13}$$

3. Proposed Solution Method

The solution method has two parts: The multi-objective model and the comparison techniques. Herby, the solution method is presented.

3.1. Multi-Objective Method

The literature offers various approaches to address multi-objective problems, and this study employs two distinct methods, the LP-metric, and the T-H method, to solve the proposed Multi-Objective Non-Linear Problem (MONLP). The LP-metric, as outlined in Wang et al. (2020), is a global criterion method that seeks to minimize the distance to the ideal objective vector. It is important to note that different metrics, such as the Lp-metric where $1 \leq p \leq \infty$, can be applied within this method.

The second method falls under the category of fuzzy interactive methods and is considered effective due to its ability to incorporate decision-maker preferences interactively. Torabi and Hassini (2008) introduced an improved aggregation function designed to transform a multi-objective model into a single-objective one. This transformation guarantees the discovery of only Pareto-optimal (i.e., efficient) solutions.

3.2. Comparison Method

To facilitate a comparison of multi-objective methods, this study employs two distinct approaches: VIKOR and PROMETHEE. Both of these methods fall under the umbrella of Multi-Criteria Decision Making (MCDM) or Multi-Criteria Decision Analysis (MCDA), with the key difference being that VIKOR is categorized as a Compensatory method, whereas PROMETHEE belongs to the Outranking method category (Choukolaei et al. 2023).

Herein, we provide an overview of the two proposed methods:

VIKOR Method: VIKOR is a Multi-Criteria Decision Making (MCDM) or Multi-Criteria Decision Analysis (MCDA) method (Zeng et al., 2019). It was originally developed by Serafim Opricovic to address decision problems involving conflicting and non-commensurable criteria (i.e., criteria with different units of measurement). This method assumes that compromise is an acceptable approach for conflict resolution. It aims to find a solution that is closest to the ideal, taking into account all established criteria. VIKOR ranks alternatives and identifies the "compromise" solution, which is the one closest to the ideal among the alternatives considered.

PROMETHEE Method: PROMETHEE is classified as an Outranking method designed for ranking a finite number of alternatives based on a finite number of criteria, which often exhibit conflicting characteristics (Tong et al., 2020, Ghasemi and Talebi Brijani, 2014). The PROMETHEE family includes several variations (PROMETHEE I, II, III, IV, V, and VI), with PROMETHEE II being particularly relevant for decision-making in process development and innovation (Tong et al., 2020).

PROMETHEE II was developed to provide a comprehensive ranking of a finite set of alternatives, ranging from the best to the worst (Ghasemi et al. 2021). This ranking is calculated through pairwise comparisons of alternatives for each criterion, using preference functions. These preference functions are then aggregated using criteria weighting to determine a net outranking flow, thus generating a complete ranking of alternatives.

Within a PROMETHEE model, each criterion used to rank alternatives is assigned a preference function by the decision maker. This preference function translates the difference (either positive or negative) in the criterion values between two alternatives in a pairwise comparison into a preference degree, typically ranging from zero to one. Typically, six preference functions are utilized: Usual criterion, Quasi-criterion, Criterion with linear preference, Level criterion, criterion with linear preference and indifference area, and Gaussian criteria. It is important to note that criteria weighting in PROMETHEE involves the use of pairwise comparison methods, where the decision maker evaluates each possible pair of criteria and assigns a preference on a 9-point scale, ranging from equal preference to moderate, strong, very strong, and extreme preference. Once all pairwise comparisons are completed, scores for each criterion are aggregated and normalized.

4. Results and Discussion

In this section, a set of test problems has been formulated to assess the validity of the proposed model. To this end, we have created 30 sample problems of various sizes and conducted a comparative analysis of the results obtained using the T-H method and the LP-Metric method. This comparison is based on three key criteria, namely: "Value of the first objective," "Value of the second objective," and "CPU time."

The parameter values utilized for solving the proposed model are outlined in Table 1. It is important to note that we have employed a Uniform distribution for all the parameters to ensure fairness and consistency in our analysis. Additionally, Table 2 provides an overview of the different sizes of model indices for the 30 sample problems presented for evaluation.

Table 1. Parameters and values.

Parameter	Values	Parameter	Values	Parameter	Values
D_i	Uniform(800-1600)	P_{mn}	Uniform(10000-40000)	μ_{cj}	Uniform(0.05-02
D_m	Uniform(400-1400)	μ_{hi}	Uniform(5-10)	μ_{cm}	Uniform(0.5-1)
b_i	Uniform(50-100)	μ_{hm}	Uniform(5-12)	μ_{fik}	Uniform(50000-100000)
b_m	Uniform(50-100)	μ_{Ki}	Uniform(50-200)	μ_{fmn}	Uniform(25000-75000)
d_{iik}	Uniform(50-150)	μ_{Km}	Uniform(75-300)	μ_{rijk}	Uniform(0.5-3)
d_{iin}	Uniform(50-150)	μ_{Si}	Uniform(10-20)	μ_{rimn}	Uniform(0.5-3)
P_{jk}	Uniform(30000-50000)	μ_{Sm}	Uniform(15-25)	t_{ijk}	Uniform(500-1500)
t_{imn}	Uniform(500-1500)	σ_{Sm}	Uniform(1-10)	t_{imn}	Uniform(500-1500)
e_g	Uniform(10-100)	σ_{cj}	Uniform(0.0001-0.01)	e_g	Uniform(10-100)
σ_{hi}	Uniform(1-9)	σ_{cm}	Uniform(0.0001-0.01)	σ_{hi}	Uniform(1-9)
σ_{hm}	Uniform(1-9)	σ_{fik}	Uniform(100000-500000)	σ_{hm}	Uniform(1-9)
σ_{Ki}	Uniform(10-100)	σ_{fmn}	Uniform(100000-500000)	σ_{Ki}	Uniform(10-100)
σ_{Km}	Uniform(50-150)	σ_{rijk}	Uniform(0.01-0.25)	σ_{Km}	Uniform(50-150)
σ_{Si}	Uniform(1-10)	σ_{rimn}	Uniform(0.01-0.25)	σ_{Si}	Uniform(1-10)

Table 2. Size of sample problems.

Sample problem	*i*	*j*	*k*	Sample problem	*i*	*j*	*k*	Sample problem	*i*	*j*	*k*	Sample problem	*i*	*j*	*k*	Sample problem	*i*	*j*	*k*
1	1	2	3	7	2	2	4	13	2	3	6	19	3	2	5	25	3	4	5
2	1	2	4	8	2	2	5	14	2	4	4	20	3	3	3	26	4	2	3
3	1	2	5	9	2	2	6	15	2	4	5	21	3	3	4	27	4	3	3
4	1	2	6	10	2	3	3	16	2	4	6	22	3	3	5	28	4	4	4
5	2	2	2	11	2	3	4	17	3	2	3	23	3	4	3	29	4	4	5
6	2	2	3	12	2	3	5	18	3	2	4	24	3	4	4	30	4	5	5

Table 3 shows the results of sample problems defined in the previous section when solved by the LP-metric method and T-H method. The values of Z1, Z2 and CPU time for each method are shown in Table 3.

Table 3. Results of sample problems based on LP-metric and T-H methods.

Sample problem	LP-Metric			T-H			Sample problem	LP-Metric			T-H		
	Z1	Z2	*t*	Z1	Z2	*t*		Z1	Z2	*t*	Z1	Z2	*t*
1	164846	422904	544	241498	376214	639	16	173423	500312	1582	257632	406323	1338
2	152490	448652	690	239823	380647	677	17	175865	495646	1621	259489	400654	1331
3	160642	439062	496	247321	379211	709	18	170925	501248	1579	256302	401776	1328
4	164206	442913	630	246402	379632	737	19	169953	520318	1734	254760	413365	1430
5	149752	476429	719	233234	396956	833	20	174432	481428	1822	258034	399461	1550
6	142646	503104	859	230541	403512	851	21	171787	507825	1910	253356	403587	1590
7	145123	517842	927	232170	405726	903	22	167074	524692	2165	256247	408813	1730
8	155085	501584	970	238653	400923	952	23	174246	489650	2157	259035	402313	1870
9	164386	498788	1050	244219	399637	998	24	172866	520242	2342	257674	411158	1959
10	163585	469442	990	243117	383574	1151	25	172102	536759	2479	258515	423154	2066
11	165691	475302	114	245325	386231	1077	26	178271	518624	2866	269353	409865	2131
12	16634	483642	1153	248696	392719	1089	27	177938	532240	2822	264867	422649	2224
13	167230	488347	1275	253455	398945	1181	28	175944	541780	3053	263541	428973	2414
14	163286	518643	1358	247117	408987	1215	29	173084	552434	3444	260112	436481	2504
15	169192	509331	1423	255348	409469	1454	30	171994	559922	4251	258347	441687	2875

To compare the two multi-objective optimization methods, we conducted an analysis of the means for 30 different sample problems across various criteria. To assess the quality of these means, we employed a quality of means test, as outlined by Du et al. (2017). This test involves formulating two hypotheses: the null hypothesis, which posits the equality of means, and the alternative hypothesis, which suggests a significant difference between means. The results of the hypothesis testing are presented in Table 4. Based on the table and at a significance level of 95%, the null hypothesis is rejected for all criteria, including CPU time and the values of the two objectives.

Table 4. Results of hypothesis testing.

Multi-objective method	Value of Z1	Value of Z2	CPU-Time
LP-metric	159821.4	469345.3	2495.3
T-H	236071.1	387604.5	2023.6
Hypothesis testing result	Rejecting the null hypothesis	Rejecting the null hypothesis	Rejecting the null hypothesis

To compare the two aforementioned multi-objective methods, we employed the VIKOR and PROMETHEE II approaches. The VIKOR method, as depicted in Figure 2, was used to calculate the rankings of these two multi-objective optimization methods. The results of this ranking are presented in Table 5. According to the data in Table 5, it is evident that the T-H method outperforms the LP-metric method in the proposed model. It is worth noting that the criteria weighting process was carried out within a pairwise comparison matrix, the results of which are displayed in Table 6.

Table 5. Results of VIKOR technique for comparing two multi-criteria optimization method.

Multi-objective optimization method	Q_i	Rank
LP- Metric	0.34125645	2
T-H	0.65874355	1

Table 6. Pairwise comparison matrices' results for criteria weighting.

	Z1	Z2	CPU-time	weight	Normal weight
Z1	1	1	5	1.7099	0.4545
Z2	1	1	5	1.7099	0.4545
CPU-time	1/5	1/5	1	0.3420	0.0910

Furthermore, Moreover, the PROMETHEE II method, illustrated in Figure 3, was employed to calculate the rankings of the two multi-objective optimization methods. The outcomes of this ranking are summarized in Table 7. Based on the table, it is evident that the T-H method outperforms the LP-metric method within the proposed model.

Table 7. Results of PROMETHEE II technique for comparing two multi-criteria optimization methods.

Multi-objective optimization method	Φ^+	Φ^-	Φ	Rank
LP- Metric	0.1649	0.0983	0.0666	2
T-H	0.2126	0.1029	0.1097	1

Consistently, the T-H method demonstrates superior performance in both of these approaches. To assess the impact of changes in problem size on the objective functions and CPU time, we conducted a comparative analysis of the values of Z1, Z2, and CPU time for 30 different models. These results are presented graphically in Figure 4. It is noteworthy that as the number of sample problems increases, so does the size of the problem.

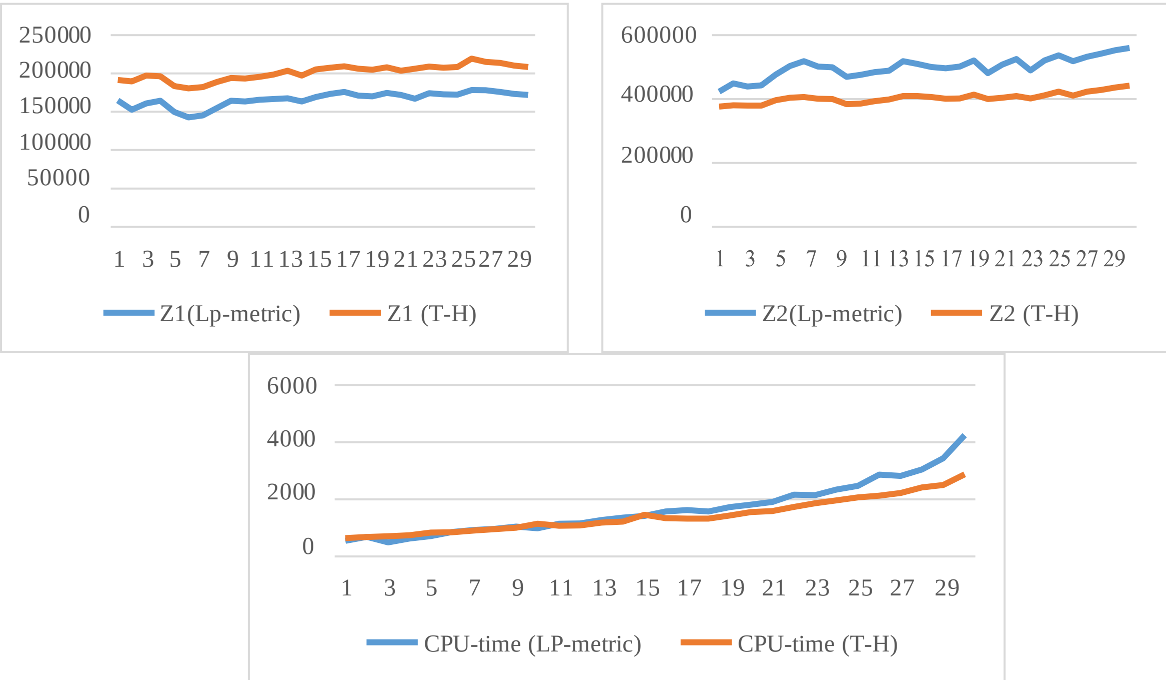

Fig. 4. Change in the value of Z1 , Z2 , and CPU-time by increasing the size of the model in two multi-objective optimization methods.

5. Conclusion

Location Efficiently managing location, allocation, and supplier selection within a supply chain network represents a pivotal challenge in the realm of supply chain management. This multifaceted problem involves not only determining the optimal sites for various facilities but also appropriately allocating inventory quantities. Additionally, supplier selection, a traditional yet continually relevant concern in supply chain management, plays a significant role in addressing these complex issues.

This paper introduces a novel multi-objective model that tackles the integration of location-allocation problems with supplier selection and order allocation for a three-echelon supply chain, encompassing suppliers and plants/stores. Moreover, an inventory policy is proposed as an integral component of the model. This model's overarching objective is to minimize the mean and variance associated with establishment costs, inventory expenses, and transportation outlays.

To address this intricate problem, we employ the T-H model and LP-metrics model, treating the multi-objective problem as a single-objective mixed-integer programming model. Subsequently, we conduct a comparative analysis of two distinct approaches: VIKOR and PROMETHEE II methods. This comparison hinges on evaluating solution quality and computational efficiency.

Incorporating insights gained from thirty sample problems, our findings reveal that the T-H method consistently outperforms the LP-metric approach in terms of solution quality. This study underscores the importance of selecting the appropriate optimization technique when addressing the intricate dynamics of supply chain management, shedding light on the superior performance of the T-H model in this context.

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