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Multicriteria Logistic Hub Location by Network Segmentation under Criteria Weights Uncertainty

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ABSTRACT

Third party service providers locate logistic hub for operating their tasks. Finding a proper location helps them to have better performance in the competitive environment. Multiple characteristics of proper location selection faces the decision maker to have a multi criteria decision making problem. Since the location decision is a long term planning, the robustness of the decision is getting more highlighted so we applied a statistical based decision making approach to reduce uncertainty effect. Hub facilities are reducing the serving cost due to economies of scale. In this paper, in order to enhance such effect we applied the clustering analysis to find similar regions by consideration of different characteristics. The approach is implemented in an Iranian case study and the validity of the approach is investigated.

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1. INTRODUCTION

Decision making in supply chain can be categorized into three main levels: strategic, tactical and operational level[1, 2]. In the strategic level, long term decisions such as number of facilities, geographical location and allocation structure are made. Decisions of optimal flow in the supply chain and other related subjects can be classified as tactical level decisions. Short term decisions such as production planning are categorized as operational decisions.

To reduce the total cost, companies outsource some of their activities such as transportation and warehousing to a third party logistic provider (3PL). In addition to the lower cost, 3PLs may provide advantages such as market knowledge, operational efficiencyand customer services [3]. Logistic services providers accomplish their assigned tasks like managing shipment consolidation, warehousing, transportation and packing in a logistic hub [4].The role of a logistic hub in a supply chain is depicted in Figure1.

Providing facilities such as warehouses, trucks and logistic sites needs a large investment and time for each supply chain member. Therefore, logistic hubs can be used as a complex to release the logistic activities from each supply chain member, so it is obvious that locating the logistic hubs is an important strategic decision which can attract domestic manufacturers and suppliers to use the public integrated logistic hub complex instead of self-investment.

Consolidation of outsourced transportation activities in a logistic hub leads to decreasing the transportation cost due to economies of scale [5]. In order to enhance consolidation and cost reduction in logistic hub activities such as loading and packaging and also better management of logistic tasks, it is beneficial that similar manufactures and suppliers should be identified and assigned to their specific logistic hub. In the literature efficient strategy has been used in marketing which is named as market segmentation. In this strategy, customers are divided into partitions based on their similarity. Market segmentation is aimed to decrease supplier’s expenses such as advertising expense, production and distribution [6]. In this strategy, to segment and explore similarities of customers, several

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methods have been used such as K-means clustering, hierarchical clustering, self-organization feature maps [7] or hybrid techniques [8, 9]. In this study, similar approaches are used to segment suppliers and manufactures in different groups. After partitioning of similar manufactures and suppliers, a logistic hub is established in the segmented network to provide logistic services.For efficient location of logistic hubs, several factors should be considered. Blair and Premus listed some effective factors such as markets, labor, financial incentives and adequate transportation system [10]. By considering the effective criteria in the logistic hub location problem it seems that the network designer is faced to a multi criteria decision analysis. In order to solve a multi criteria decision making problem, several methods have been proposed. Examplesare Technique for Order Preference by Similarity to Ideal (TOPSIS) which ranks alternatives based on their distance to the positive and negative ideal points [11] or data envelopment analysis (DEA) which is based on the linear programming for evaluating the efficiency of decision making units (DMU) [12]. Also other different methods such as PROMETHEE [13],AHP [14] and ELECTRE [15, 16] have been used for decision making problems with multi criteria. In most of these methods, criteria have predefined weights and according to these weights alternatives are ranked. The uncertainty is an inherent characteristic of strategic decisions like logistic hub location. Therefore, changing of the criteria importance may lead to change the best location decision. In this situation, the inattention of uncertainty in decision making process may lead to improper decision and failing to achieve perspective goals. Using fuzzy logic is a common method in order to overcome this problem [17, 18]. Moreover a statistical based approach which is named Meta-model has been implemented in literature for considering uncertain factors [19, 20]. Meta-model is defined as regression model and is calculated based on factorial design experiment. Uncertain factors under predefined levels are used to create some treatments and then result of each treatment is measured. Then, Meta-model (regression model) under certain *P*-value is extracted and applied to analyze the problem with uncertain factors. In empirical cases, usually a fractional factorial design is implemented instead of the full one. Recently, İchas proposed an integrated MCDM form of Meta-model [21] which is named TOPSIS-DOE approach. More details of his approach are provided in the next section.In hub location literature, researchers investigated the location of hub facility. Lee et al. investigated the location of hub facility in the telecommunication network. They proposed a zero-one mathematical model for selection of proper hub location in the network. However, they did not consider any uncertainty in their decision-making procedure [22]. Moreover, some researches considered the uncertainty

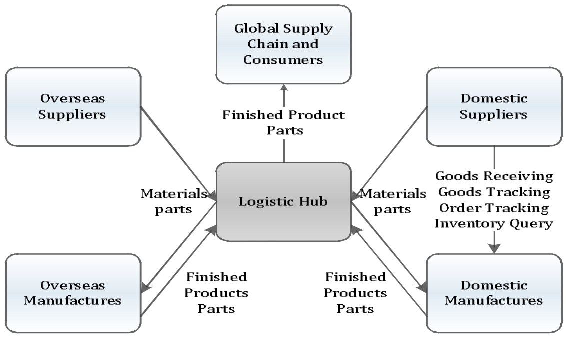

Figure 1. Logistic hub in a supply chain [4]

using fuzzy logic, for example, Chou[23] proposed a Fuzzy MCDM approach to select marine transportation hub and linguistic importance weight of various criteria was considered for criteria and sub criteria. Besides, Yu et al. proposed a fuzzy AHP approach for evaluating each of the candidate transit hub location plans [24].In this paper, as first stage, low potential candidate locations (cities) are eliminated then TOPSIS-DOE is applied to extract Meta-models. In the next stage of this paper called clustering stage, overall average silhouette width (OASW) approach is applied to find the proper number of clusters and K-means method is applied to cluster regions. Then, in each cluster Meta-model is applied to rank the alternatives. The remainder of this paper has been organized as follows: in the next section the proposed methodology is explained. In section 3, the proposed method is implemented in the location of logistic hubs in Iran and the conclusion is described in the last section.

2. METHODOLOGY

2. 1. TOPSIS-DOE Method

In some cases, there exist inappropriate alternatives that should be removed from alternatives list, so by an approach alternatives with unacceptable values in all criteria should be omitted from the decision making space. In order to rank and select logistic hub location by considering multiple criteria, an integrated TOPSIS-DOE method has been applied. In the following section, TOPSIS and DOE are explained and then integrated method for constructing the Meta-model is described.

2. 1. 1. TOPSIS

TOPSIS is a well-known technique in MCDM problems to find the best alternative with ranking all alternatives. This technique considers alternatives based on their closeness to positive ideal solution and their farness from a negative ideal point [11]. TOPSIS is a priori technique in which decision maker preferences are determined before decision-making process. It has a wide application in lots of areas such as location problems, for example Azizi and Memariani applied a TOPSIS to rank potential sites for location analysis of wood industry plants [25]. Recently, Behzadian et al. reported a survey in TOPSIS applications and methodologies [26].

2. 1. 2. Design of Experiment (DOE) DOE is a systematic process examination that tries to determine the controllable variables effect on the response variable through some independent experiments. The relationship between response variable and controllable variables is estimated by a regression model. Factorial experiment is one of the major categories of DOE which is implemented when *K* controllable variables effects and their interaction effects on the response variable are investigated. The 2^K design is one ofthe factorial designs which considers high and low levels for each factor [27].

2. 1. 3. TOPSIS-DOE Approach It is clear that the criteria weights are an important parameter which affect the final decision, so the decision is changed by different weight values. This method tries to estimate effects of *K* criteria weights as experiment independent factors on TOPSIS score as a response. To have an effective performance as a Meta-model; different random sets of criteria weights are considered. A replicated full factorial design with replication on different random generated weights assures that the response estimation is robustly independent to criterion weights. The scheme of TOPSIS-DOE has been proposed in the following steps:

Step 1: Determination of factors levels

In this step, minimum and maximum value of each criterion according to the existing alternatives are considered as high and low factors levels, respectively.

Step2: Implement TOPSIS through DOE

A replicated full factorial experiment $(n \times 2^k)$ is designed and in this design, each criterion is considered as a factor, where *n* is the number of generated criteria weight sets. In each experiment, the treatment is considered as a simulated alternative which is named DOE alternative and is added to the decision matrix then the final extracted TOPSIS score will be considered as the experiment response (Figure 2).

Step3: fitting the regression Meta-model

DOE result is investigated to determine important factors and also interaction between factors. In the experiment result, factors with P-value less than the level of significance (α value) should be considered in the extracted Meta-model.

Step 4: ranking of alternatives

The robust TOPSIS score for each alternative is estimated by the extracted Meta-model. Similar to classic TOPSIS, the larger value indicates better performance.

2. 2. Clustering Analysis and K-Means Clustering analysis (CA) is an explorative multivariate technique that aimed to discover groups of similar observations. Each observation has some characteristics and CA makes some distinct groups and allocates them to a specified group based on getting maximum homogeneity within groups and also maximizes heterogeneity of observations in different clusters. CA applications are varied from archaeology for classification of art in different time periods to selection of test markets [28].

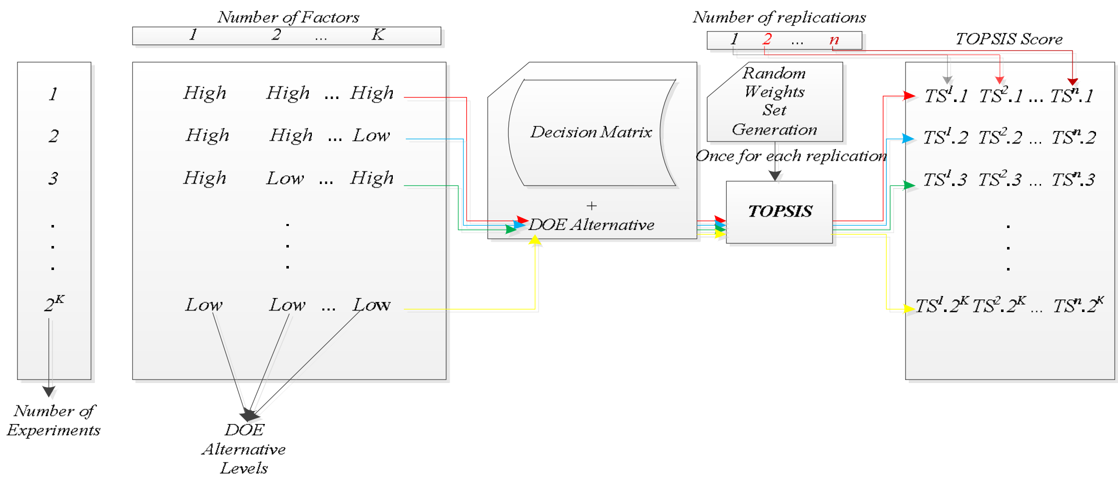

Figure 2. Evaluation of DOE alternative in integrated method

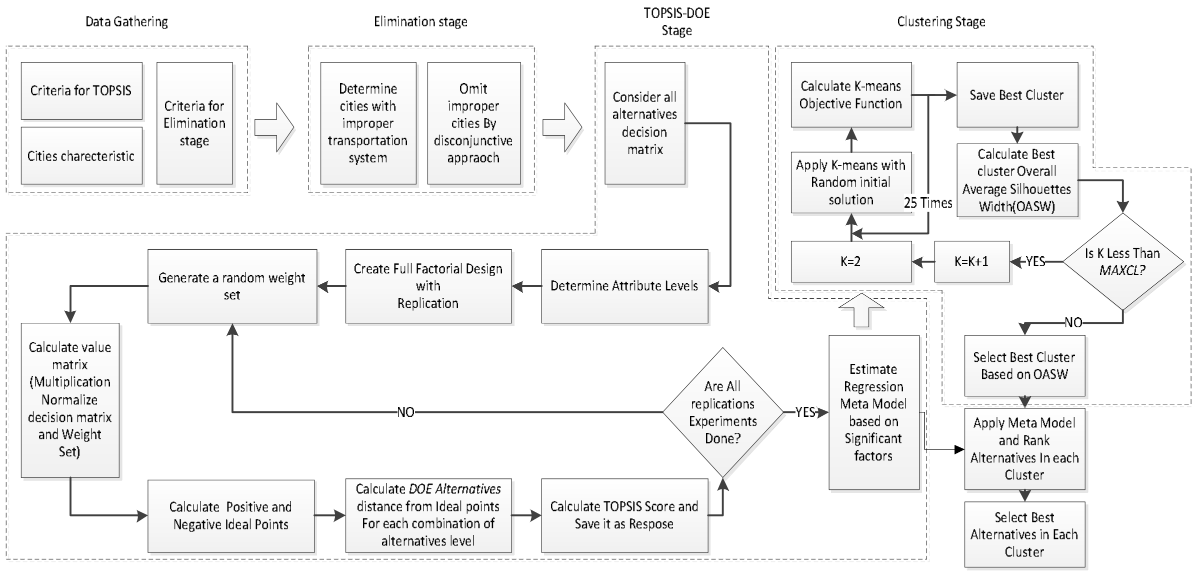

Figure 3. Overlook of the proposed methodology

CA is divided into two main categories; hierarchical and non-hierarchical method. Hierarchical method is astepwise approach which contains two methods of agglomerative and divisive hierarchical method.

In the non-hierarchical clustering method, number of clusters is predefined. K-means is the most common algorithm in this category. Cox introduced general algorithm [29] and MacQueen named it as K-means for the first time [30]. It tries to find c_l clusters which have the lowest sum of squared distances between observations within each cluster and mean of cluster observations. The following equation represents relative mathematical programing for mentioned approach [31]:

$$\min \quad Z=\sum_{k=1}^{cl}\sum_{x_i\in c_k}\| x_i-m_k \|^2 ; \tag{1}$$

where c_l is the predefined number of clusters; x_i is an observation which is member of cluster c_k. In comparison between hierarchical and non-hierarchical methods it can be stated that hierarchical methods are completely exploratory because they are not in need of number of clusters but empirical studies in performance of clustering methods show more efficiency of non-hierarchical methods [8]. Besides, K-means is a highly accurate technique if proper starting point and cluster number is provided and it can handle large amounts of data [32]. Due to these reasons, we implemented K-means in this study.

2. 2. 1. Proper Cluster Number One of the weaknesses of K-means is its inability to determine the number of clusters [32]. To amend this weakness, OSAW [33] is used to determine the number of clusters. OSAW value indicates that how proper is the whole observations membership to their clusters. In order to calculate OSAW, it is needed to calculate silhouette value for each observation. Silhouette value for ith observation (s(i)) is calculated as follows:

$$s(i)=\frac{b(i)-a(i)}{\max\{a(i),b(i)\}} \tag{2}$$

where a(i) and b(i) are average dissimilarity of ith observation with its cluster and average dissimilarity of ith observation with closest cluster to it, respectively.a(i) is calculated by Equation (3):

$$a(i)=\frac{\sum_{j\in c}D(i,j)}{n_c-1}; \qquad n_c\geq 2 \tag{3}$$

where D(i,j) indicates dissimilarity between ith and jth observations and n_c is number of observations in cth cluster. Minimum of average dissimilarity between ith observation in c_{th} cluster with other clusters is calculated according to Equation (4):

$$b(i)=\min\left\{\frac{\sum_{j\in c'}D(i,j)}{n_{c'}}\,|\,c'=1,...,K;c'\neq c\right\} \tag{4}$$

where b(i) is equal to minimum of average dissimilarity between ith observation in cth cluster other clusters. It is worth to mention that s(i) varies from -1 to +1. Near to -1 means that ith observation has clustered with dissimilar observations and +1 means oppositetrend. Then, overall average silhouette width is average of whole silhouette values.

2. 3. Proposed Methodology In this part, the proposed approach is presented based on the techniques introduced. As a first stage, important criteria of decision making should be collected. Then, each city characteristics such as manufacturing and supply characteristics are gathered for clustering stage. In the elimination stage, candidate points of logistic hub with improper transportation facilities are omitted from decision space.

In TOPSIS-DOE stage, highest and lowest values of each alternative areconsidered as DOE experiment levels. According to the designed experiments there are 2k treatments and each treatment is added to the decision matrix as DOE alternative. After calculation of TOPSIS scores for all alternatives, the score of DOE alternative is supposed as its response value. The same steps are done by random generated weights and they are added as replications of experiments. Finally, the experiments are analyzed to achieve a TOPSIS Meta-model. In the clustering stage which considers the allocation structure, the logistic network is clustered to find logistic homogenous regions. In order to determine the proper number of clusters, K-means method with different *K* value is applied. For each *K* value, a K-means algorithm is repeated and after these replications, the solution with the best objective function value is selected. Then the best *K* valueis selected according to OSAW. Finally, the calculated Meta-model is used in each cluster to rank its alternatives and the best node in each cluster is selected as location of the logistic hub. It is clear that the allocation decisions are made according to the clustering result. The proposed methodology has been depicted in Figure 3.

3. COMPUTATIONAL EXPERIMENT

To illustrate the proposed method, it was applied in a case study of Iran to select a proper logistics hub. This data set consists of 260 cities (The data can be accessed through the following address:
http://www.shahed.ac.ir/bashiri/SitePages/Files.aspx).
For selection of logistic hub location between selected cities, the transportation system is a critical characteristic so availability of airport or high standard roads and railway is an initial requirement. By considering such criterion 77 cities are remained for TOPSIS-DOE stage. In the location decision stage, following criteria have been used:

a) City population

More population in the city provides more labor force and cities with more populations have stronger financial institutes that attract more traders due to this reason.

b) Being on the major transportation corridors

Being on the major corridors leads to easy connection to international and national suppliers and markets. In the selected case, three major corridors are considered: Bandar Abbas – Bandar Torkaman with a million ton transportation capacity, Bandar Abbas – Jolfa with two million tons transportation capacity and Sarakhs – Jolfa with two million tons transportation capacity in each year. The city which is connected to these corridors has more chance to be selected as a logistic hub.

c) Tourism attractions

Tourism industry in recent decades has become the most important resource for the city economy. The logistic hub in a touristic place has a synergy and it is assumed that the candidate point with higher tourism attractions has more chance to be selected as a logistic hub as well. In the selected case,number of hotels has been selected as a measure of tourism attractions.

d) Transportation cost

Locating logistic hub is a discrete single facility location problem (distance between cities are considered as Euclidian distance).This problem isstated as Equation(5):

$$f(x_j, y_j) = \sum_{i=1}^{m} w_i[(x_j - a_i)^2 + (y_j - b_i)^2]^{\frac{1}{2}} \quad (5)$$

where m is the number of existing facilities (cities); a_i, $b_i$are the coordinate of ith city and w_i is its weight. While x_j, y_j are the coordinate of jth candidate point. Equation(5) shows transportation cost function for the jth city as a candidate point of logistic hub location.
For generating the replications of designed experiments, six random weight sets have been generated according to Table 1. In this case, an experiment was designed which has 6×2^4 experiments. For each experiment (which contains 6 replicates by mentioned weights) the TOPSIS score is calculated as experiment response value. Then the designed experiments are analyzed considering the confidence level of 0.95.In our computational experiment, Minitab 14.0 was used for analysis. Result of DOE has been reported in Table 2.

TABLE 1. Random weights set of criteria

Criterion	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6
City population (A)	0.29	0.413	0.313	0.077	0.259	0.2
Major transportation corridors (B)	0.323	0.059	0.313	0.192	0.148	0.2
Tourism attractions (C)	0.065	0.176	0.062	0.385	0.296	0.3
Transportation cost (D)	0.323	0.353	0.312	0.346	0.296	0.3

TABLE 2. Result of DOE using the Minitab software

Term	Coefficient	*P*-value
Constant	0.469	0
A	0.209	0
B	0.132	0
C	0.062	0
D	-0.031	0.027
A*B	0.016	0.251
A*C	0.004	0.743
A*D	-0.002	0.874
B*C	0.004	0.777
B*D	-0.002	0.889
C*D	-0.001	0.946
A*B*C	0.022	0.11
A*B*D	-0.018	0.185
A*C*D	-0.013	0.339
B*C*D	-0.013	0.344
A*B*C*D	-0.001	0.915

R-Sq = 81.84%
R-Sq(adj) = 78.44%

TABLE 3. Selected logistic hubs in the case study

Region number	Region center	Meta-model score
1	Shiraz	0.330
2	Tabriz	0.306
3	Tehran	0.661
4	Mashhad	0.484
5	Esfahan	0.356

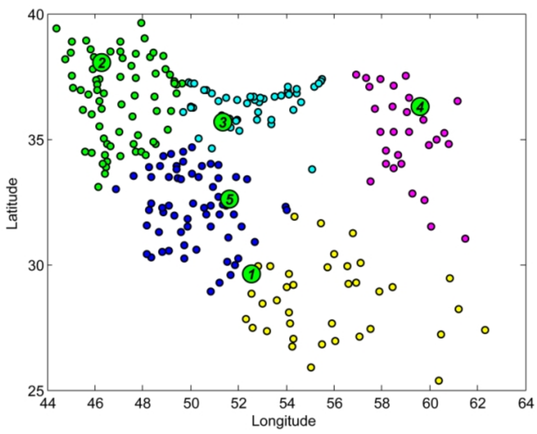

Figure 4. Regions and final location of logistic hubs in the selected case study

R-Sq of 81.84% and R-Sq(adj) of 78.44% show the adequacy of the model. Significant factors according to Table 2 are: A, B, C and D; and all interactions between factors are not significant. Coefficient column shows the coefficient of factors in the regression model and if factor is significant the coefficient corresponding to this factor is used in the Meta-model.Finally, the extracted Meta-model can be shown as follows:

$$Score = 0.469 + 0.209\times A + 0.132\times B + 0.062\times C - 0.031\times D \tag{6}$$

After estimation of the Meta-model, now the homogenous regions should be determined using the clustering approach. In this stage, the production network is segmented. It is assumed that neighbor cities have more similar product and logistic properties, so longitude and latitude of cities have been considered as important characteristics for clustering. In this case, it is assumed that the lower and upper values of cluster number are 2 and 10, respectively. In order to avoid trapping into local minimum for each value of *K*, 25 replications with random initial solution are generated. The best number of clusters was 5 according to overall average silhouette width (It was 0.4022). After clustering of cities by 5-means, Meta-model is used to rank each member of the clusters. Selected cities as the logistic hubs have been reported in Table 3. Selected logistic hubs and their allocated cities have been depicted in Figure4. In mentioned figure the cities with the same color indicate their allocation to their regional logistic hub.

3. 1. Model Validity Analysis

In the clustering stage OSAW value is also a measure to show the clustering validity and its value of 0.4022in our case study confirms the clustering stage validity. Moreover, in order to check the validity of decision making stage, another well-known decision making technique (DEA) is applied. They have been compared for the case study as well. Table 4 shows the comparison of results of the proposed approach and DEA for the 4th cluster in the case study. It shows that the alternative approach confirms the result of the proposed approach. For full consideration and validity checking of the proposed approach, the results were compared to the results of the DEA approach using the Spearman's rank correlation test [34] by considering Equations (7) and (8):

$$C_s = 1 - \left[\frac{6\times\sum_{i=1}^{N}(d_i)^2}{N(N^2-1)} \right] \tag{7}$$

$$Z_s = C_s\sqrt{(N-1)} \tag{8}$$

where N is the number of ranked data, d_i is the difference between two methods in ranking of ith observation, C_s is the Spearman rank correlation coefficient and Z_s is the test statistic.

TABLE 4. Comparison of TOPSIS-DOE and DEA for 4stcluster in the case study

City	Population	Corridors	Hotel number	Transportation cost	Meta-model score	DEA score	Meta-model rank	DEA rank
Sarakhs	33571	2	2	9852141	0.235	0.417	3	3
Tabas	30681	0	1	14927823	0.203	0.004	6	6
Mashad	2410800	2	117	4110481	0.445	1	1	1
Bojnourd	172772	0	5	11562408	0.216	0.025	4	4
Birjand	157848	0	3	14244011	0.212	0.019	5	5
Neyshabour	205972	2	2	5015984	0.244	0.819	2	2

TABLE 5. Spearman's rank correlation for all clusters

Cluster	1	2	3	4	5
C_s	0.8	0.73	0.38	1	0.98
Z_s	2.53	2.75	1.99	2.28	3.93

TABLE 6. Comparison of ranking resolution

Cluster	1	2	3	4	5
DEA	0.82	0.94	0.81	1.00	0.94
Meta-model	1	1	1	1	1

TABLE 7. Known criteria weights

Set 1	Set 2	Set 3
0.38	0.15	0.26
0.19	0.3	0.04
0.35	0.24	0.33
0.08	0.3	0.37

TABLE 8. Comparison of TOPSIS and TOPSIS-DOE

Cluster		Set1	Set2	Set3
1	C_s	0.9727273	0.9545455	0.9545455
	Z_s	3.0760337	3.0185378	3.0185378
2	C_s	0.9821429	0.9071429	0.8607143
	Z_s	3.1058084	2.8686376	2.7218176
3	C_s	0.8823932	0.9049573	0.8557265
	Z_s	2.7903722	2.8617261	2.7060448
4	C_s	0.9428571	0.9428571	0.9428571
	Z_s	2.9815761	2.9815761	2.9815761
5	C_s	0.9436275	0.8308824	0.7990196
	Z_s	2.984012	2.6274807	2.5267219
$Z_{critical}=Z_{0.025}=1.96$				

The level of significance α value and critical Z are 0.025 and 1.96, respectively. In all clusters, the statistics values (Z_s) are more than critical value therefore there is no significant difference between twomethods. The results have been reported in Table 5.As a report on Meta-model efficiency compared to DEA, we define ranking resolution (RR) as follows:

$$RR = \frac{number\ of\ different\ ranks\ used\ in\ output}{number\ of\ total\ alternatives}$$

According to results reported in Table 6, Meta-model outperforms DEA in RR aspect. We can apply this decision making approach to handle uncertainty and attain a more robust decision in selection of alternatives. In order to check this ability, we generated random criteria weight sets which are assumed as real value of criteria weight as demonstrated in Table 7. According to these known weights, we applied TOPSIS approach to rank the alternatives. We also used our Meta-model to rank the alternatives.

Once more, Spearman rank correlation coefficient has been implemented and the result shows consistency of the Meta-model ranking and TOPSIS as reported in Table 8. According to this result, it can be concluded that the Meta-model can be robust under the weights uncertainty.

4. CONCLUSION

In this paper, an analytical approach for logistic hubs location that is operated by 3Pls is investigated. In order to have succeeded locating, a multi criteria approach has been used for considering the effective parameters. Since the characteristic is a strategic decision, the decision parameters may involve the uncertainty by changing the situation. Therefore a Meta-model based concept has been used to improve the robustness of decision. Beside this, to enhance the consolidation, effect which leads to cost reduction has been considered. So the clustering approach has been used to find similar manufacturing cities and they areassigned to a logistic hub for servicing. Finally, this approach is implemented in Iran cities and the validations of Meta-model results have been compared with DEA through the Spearman rank test. The results show the approach validity. Consideration of C-means and also the relation between logistic hubs can help to realization of the proposed problem and they can be suggested as future studies.

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Multicriteria Logistic Hub Location by Network Segmentation under Criteria Weights Uncertainty

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چکیده

چکیده شرکت‌های خدمات لجستیکی طرف سوم برای اجرای وظایف لجستکی اقدام به برپایی‌هاب‌های لجستیکی می- نمایند. انتخاب بهترین مکان برای احداث این هاب‌ها موجب عملکرد بهتر این شرکت‌ها در فضای رقابتی می‌شود. در نظر گرفتن ویژگی‌های چندگانه برای انتخاب مکان مناسب باعث می‌شود تا تصمیم‌گیرنده با یک مساله چند معیاره روبه‌رو باشد. از آنجایی که تصمیمات مکانیابی جز برنامه‌های بلند مدت هستند، استواری در اینگونه تصمیمات پررنگتر است. بنابراین ما با بکارگیری رویکردتصمیم‌گیری آمار بنیان درصدد کاهش اثر عدم قطعیت در تصمیم گیری برآمدیم. با توجه به وجود صرفه‌جوئی‌های مقیاس در تسهیلات هاب، هزینه‌های خدماتی آنها کاهش می‌یابد. در این مقاله برای افزایش این اثر، از تحلیل خوشه‌بندی برای پیدا کردن مناطق مشابه استفاده شده است تا ویژگی‌های مختلف مناطق در آن ملاحظه شود. این رویکرد برای مطالعه مورد کشورایران استفاده شده است و اعتبار نتایج آن مورد تحقیق قرار گرفته است.

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