Journal of Artificial Intelligence and Data Mining (JAIDM), Vol. 9, No. 4, 2021, 543-554.

Shahrood University of Technology

Journal of Artificial Intelligence and Data Mining (JAIDM)
Journal homepage: http://jad.shahroodut.ac.ir

Research paper

A New Data-driven and Knowledge-driven Multi-criteria Decision-making Method

Y. Dorfeshan[1], R. Tavakkoli-Moghaddam[1*], F. Jolai[1] and S.M. Mousavi[2]

1. School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran.
2. Department of Industrial Engineering, Faculty of Engineering, Shahed University, Tehran, Iran.

Article Info

Article History:
Received 09 May 2021
Revised 16 August 2021
Accepted 12 October 2021

DOI:10.22044/JADM.2021.10803.2218

Keywords:
Data-driven and Knowledge-Driven MCDM Methods, DEMATEL, ELECTRE, VIKOR Methods.

**Corresponding author: tavakoli@ut.ac.ir (R. Tavakkoli-Moghaddam).*

Abstract

Multi-criteria decision-making (MCDM) methods have been received considerable attention for solving problems with a set of alternatives and conflict criteria in the last decade. Previously the MCDM methods have primarily relied on the judgment and knowledge of the experts for making decisions. This paper introduces a new data- and knowledge-driven MCDM method in order to reduce the experts' assessment dependence. The weight of the criteria is specified using the extended data-driven DEMATEL method. Then, the ranking of alternatives is determined through the knowledge-driven ELECTRE and VIKOR methods. All the proposed methods for weighting and rankings are developed under grey numbers for coping with the uncertainty. Finally, the practicality and applicability of the proposed method are proved by solving an illustrative example.

1. Formal Problem Statement

Multi criteria decision-making (MCDM) problem involves choosing the best alternative based on not only one criterion of optimality but also several criteria of optimality that may conflict with each other. Also, for making the right decision, the weight of the criteria should be considered differently from each other. In this situation, the ratings of each alternative based on the conflict criteria and the importance of criteria are determined through the experts' judgment. However, when the historical data is available, it is better to use the data. In this paper, unlike the traditional methods, the weight of criteria is specified through the data-mining tools.

In many real situations, a MCDM problem is solved based on the experts' experience and opinions. In this condition, the data-driven approach is more reliable since the results obtained depend on the historical data's performance score, and the results do not change from one expert to another.

There is a tendency to use the data analytics instead of trusting experience and insight to decide effectively. The data-driven methods are better when the data is available. When the data is unavailable, the knowledge-driven techniques play a vital role.

With the gradual growth and development of the data analysis methods in the companies and organizations, the basis of decision modeling has gradually shifted from dependence on the expert experience to extract the potential behavioral rules from the data. The previous MADM studies have shown that the researchers have distanced themselves from the modeling perspectives using the specialist judgment and tend to discover the behavioral patterns in real databases. The main reason for this is that the companies have accumulated vast amounts of data in their information system, and the calculation speed has become faster. In practice, each company defines the standards/characteristics for different suppliers, and each has its unique work environment. For example, Liu et al. [4] have evaluated a Taiwanese electronics company. This company has a specialized supplier evaluation department and has collected 191 observations about the company's green suppliers and used the data science methods to evaluate green metrics.

With this in mind, in this paper, a new MCDM method to specify the weight of criteria is proposed based on the available data. Moreover, due to the unavailability of data in determining the performance score for alternatives based on the criteria, the experts' opinions are gathered and used through grey sets for coping with the ambiguities and uncertainty.

In order to show the inputs and outputs of the proposed method, a graphical presentation of the proposed method is represented in Figure 1.

2. Introduction

As the environment and technology for the analysis of the data slowly elaborate within enterprises, the foundation of making decisions has slowly been directed from dependence on the experience of an expert to the mining of data in order to find the possible behavioral principles. An inconsistent vision is that the modern techniques of data analysis have replaced the jobs done by the humans. However, the reality is that the technological improvement aims to assist the jobs done by the humans, not to eradicate or change them. The modern technologies are aimed to enhance the human-technology interaction, not to substitute the human portion [1]. The analysis of data facilitates the job, and decreases the human mistakes. Today, there is a tendency to use data analytics instead of trusting experience and insight to make decisions effectively. The scholars are providing a practical and strategic guidance for gaining from data. However, the utilization outlook of the data employing academic attention and theorization is still extending. Data analytics has absorbed a great attention from the researchers and practitioners as the next major topic in management. Some researchers have even introduced it as the subsequent management revolution [2] and [3].

Using a data-driven approach leads to robust results. When each alternative's performance data concerning each metric has been available for many years, mining the data is more logical, and helps the managers make better decisions. Many researchers have always considered choosing the best alternative among a set of alternatives based on the conflict criteria. Many MCDM methods have been applied to it. However, a few researchers have integrated the data mining techniques into the decision-making approaches. In this paper, to use the advantages of the data-mining process and the MCDM methods, a new extended decision-making trial and evaluation laboratory (DEMATEL) method is introduced for the weight determination criteria. This concept also opens a new approach for the researchers to use the classic multi-attribute decision-making (MADM) methods in data-mining procedures.

The first part of the MCDM method is related to the determination of the weight of efficient factors. The second part is relevant to the ranking of the alternatives based on the conflict criteria. This paper's first part is extended by combining the data mining and DEMATEL approaches to achieve robust and reliable weights. In the second part, the alternatives' ranking is based on the aggregation of the knowledge-driven methods and integrated elimination and choice translating reality (ELECTRE) and VlseKriterijuska Optimizacija Komoromisno Resenje (VIKOR) approach.

Concerning the first part, being influenced by the subjectivity of the experts' judgments and their knowledge limitations makes the results of the MCDM methods unreliable [4]. In order to solve this problem and achieve the robust results, the data-driven MCDM methods are employed [5].

Concerning the second part, since the ELECTRE method is an outranking method and cannot generate the final ranking for the alternatives and introduces a set of the best options, it has been improved by the VIKOR method to produce the final ranking for each alternative.

3. Literature Review

The basic data-driven techniques are categorized into several groups, for instances, logistic regression (LR) [6], evidence's weight [9], documentary belief functions (DBF) [8], neural networks (NN) [6], baking vector machines (BVM) [9] and [10], and random forest (RM) method [11], and Bayesian categorizer (BC) [9] and [12].

Furthermore, the basic data-driven techniques are categorized in manifolds areas, for instance, index overlay (IO) [13], Boolean concept (BC) [14], fuzzy theory (FT) [4] and [15], Dempster-Shafer belief theory (DSBT) [16], wildcat mapping (WM) [4], data envelopment analysis (DEA) [17], and outranking methods (OM) [18]. Another type of decision-making is the knowledge-driven methods. In fact, in this method, the expertise of an expert is used.

Some researchers have sought to merge the MADM methods with data mining algorithms to make a new kind of decision-making method that varies from the earlier, more straightforward MADM approaches.

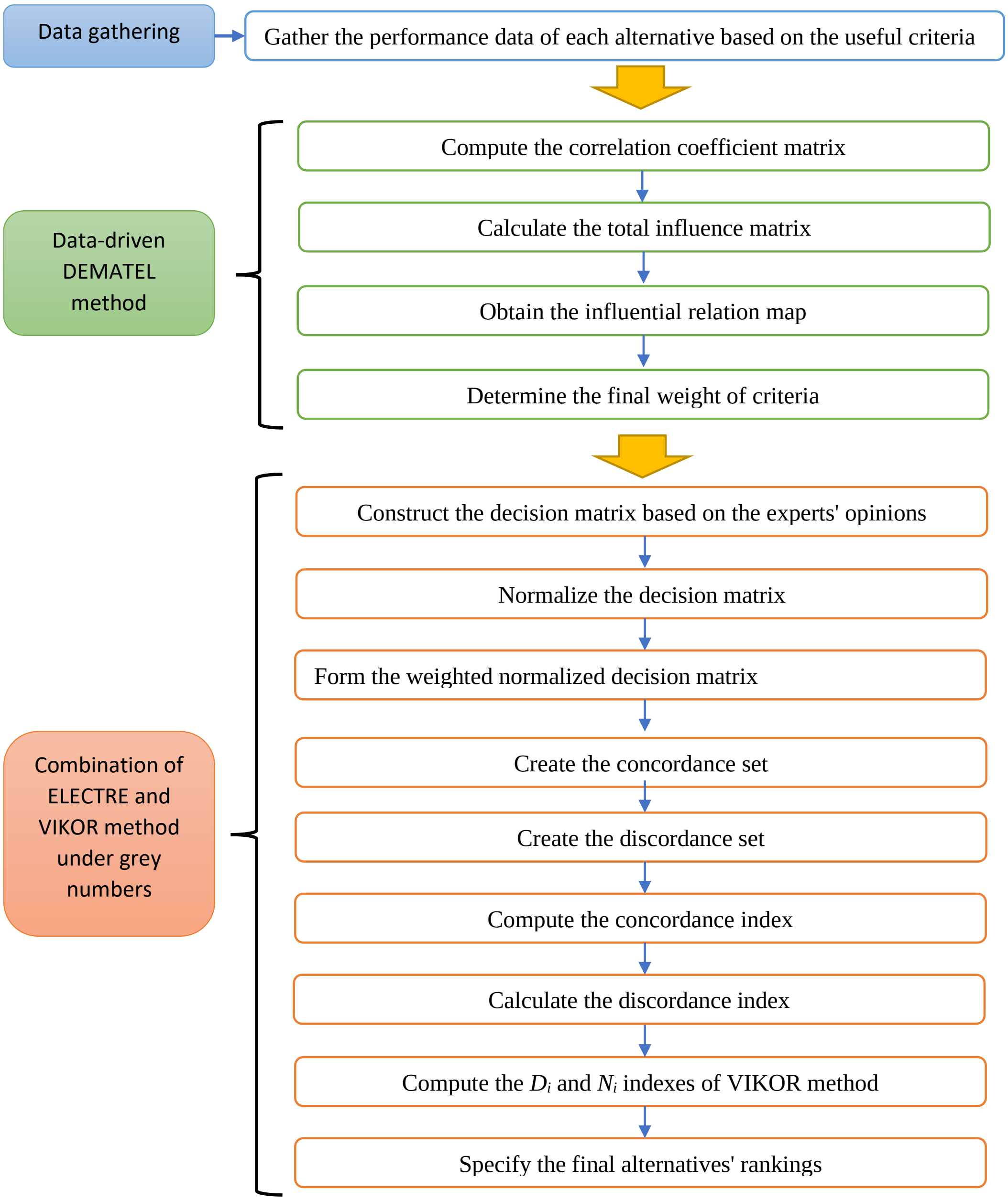

Figure 1. Graphical presentation of

For instance, Bai and Sarkis [19] have applied a DEA model based on the neighborhood rough set theory (RST) in order to specify the critical factors involved for a sustainable supplier performance. Akman [20] has aggregated the fuzzy VIKOR and c-means methods and evaluated a green supplier performance and extended betterment programs. Bai et al. [21] have used fuzzy c-means and RST methods in order to explore complex finance decisions relevant to the green supplier expansion. Shabanpour et al. [22] have introduced a new model to anticipate green suppliers' efficiency based on an artificial neural network (ANN) and a dynamic DEA. These researchers tried to formed the data-driven decision-making models based on the real performance data.

Regarding the knowledge-driven MCDM methods, Chen et al. [23] have proposed a knowledge-driven analytic network process (ANP) method for vendor evaluation in a sustainable construction. Abedi et al. [24] have introduced a knowledge-driven method for copper exploration based on the preference ranking organization method to enrich the evaluations (PROMETHEE)-II. Abedi et al. [15] have applied a fuzzy outranking method for mineral prospectivity mapping. Arabameri et al. [25] have compared three data-driven methods and knowledge-based analytic hierarchy process (AHP) methods. In this paper, the ranking of the alternatives is specified using an ELECTRE-VIKOR method based on the experts' knowledge.

On the one hand, one of the significant issues with the existing MCDM approaches is their dependency on the initial input on the domain experience and knowledge of experts, which can result in various conclusions owing to the diversity of expert judgment. On the other hand, the results based on the data are more reliable than the derived results from the experts' assessments. Also, the certainty of the data-driven approach is more than a judgment-based system. For this purpose, a new version of the DEMATEL method is proposed in order to determine the weight of criteria based on the data-mining process.

Regarding the second part, regarding the ELECRE method, Sevkli [26] has extended an ELECTRE method to choose the best supplier among a set of suppliers. Fahmi et al. [27] have applied an ELECTRE method for the supplier selection problems. Celik et al. [28] have used the ELECTRE method to choose the best green logistic service provider. Compared with the other approaches, the outranking approaches allow incomparability among the alternatives that can happen due to the loss of data or the decision maker's inability to compare the options [29]. Indifference and priority thresholds can equip significant data when modeling incomplete information [30].

The ELECTRE method uses outranking relations based on the concordance and discordance indices. In the process of choosing an alternative over the other alternatives, the concordance and discordance sets can be illustrated as an evaluation of dissatisfaction [31]. This method utilizes the non-compensatory logic for choosing the best alternative. The ELECTRE method provides the comparative analysis among the alternatives but cannot assign a rank to each alternative and ranks a group of alternatives [32]. The compromise solution methods are applied to achieve a unique ranking for each alternative.

One of the famous compromise solution approaches is the VIKOR method. It is utilized for solving discrete decision-making problems with conflicting and non-commensurable criteria [33]. It concentrates on choosing the best alternative based on the compromise solution with inconsistent criteria that can assist the decision-makers in achieving a unique ranking. The compromise means an accord determined employing reciprocal concessions [34]. In order to acquire a reliable ranking method and use the advantages of the ELECTRE and VIKOR methods simultaneously, a developed MCDM method based on the combination ELECTRE and VIKOR is extended.

Regarding the VIKOR method, Wu et al. [35] have selected the best supplier in the nuclear power industry with a developed VIKOR method. Hu et al. [36] have proposed a new system for a new doctors' ranking using the VIKOR method. VIKOR is categorized as a compromise solution MCDM method. It uses the ideal and anti-ideal points for ranking of the alternatives. The choice problematic in ELECTRE and ranking problematic in VIKOR is the solution target. Zandi and Roghanian [30] have developed the ELECTRE method with the VIKOR method to achieve unique rankings. In this paper, to simultaneously use the advantages of the ELECTRE and VIKOR methods, a new knowledge-driven MCDM method is presented.

The ELECTRE method is classified as an outranking method and cannot assign a rank to each alternative, and ranks a group of alternatives. For this purpose and using the advantages of outranking (ELECTRE) and compromise solution (VIKOR) methods, the ELECTRE method is extended based on the VIKOR method to achieve a unique ranking of alternatives. The ranking part of the proposed MCDM method is performed based on a combination of the ELECTRE and VIKOR methods. Regarding the weighting method, the DEMATEL method is used.

The DEMATEL method can facilitate the cluster of interlocked issues, particularly problematic, and help recognize infeasible solutions based on the hierarchy [37]. Unlike the common approaches by assuming the independence of the criteria, the method can consider the interdependence among criteria [38, 39]. The most important capability of this method is to consider the relationship among the criteria. As a matter of fact, in order to achieve reliable weighing results, the DEMATEL method is developed to use the historical data based on the data-mining tool. All in all, using the new ranking method and the data-driven DEMATEL method together leads to a robust and reliable multi-criteria decision-making method. Moreover, grey numbers are applied to tackle the uncertainty in making decisions and catch the experts' judgment.

Due to a lack of data, the experts' judgments are gathered for making a decision procedure. It is very tough for the experts to explain their decisions using a crisp number. In this situation, grey numbers can be applied. With the grey numbers, the experts can describe their idea and judgment reasonably and logically [40]. Zhou et al. [41] have presented a new stochastic grey MCDM method based on the regret theory and the TOPSIS (technique for order of preference by similarity to ideal solution) method. Ulutaş et al. [42] have solved the personnel selection problem by using a new MCDM method under the grey environment. Ulutaş et al. [43] have developed a new approach under the grey sets to choose the best warehouse location.

All in all, to use the advantages of the data-mining method and opens up a new direction for combining the data-mining and MCDM models, a new data-driven approach based on the regression model and DEMATEL is introduced to determine the weight of the criteria. Furthermore, a new version of a combination of the ELECTRE and VIKOR methods is extended under the grey numbers to the rank of alternatives. The contributions of this paper are clarified as follows:

- The DEMATEL method is combined with the data-mining tools to achieve a reliable weight of criteria. In fact, the correlation coefficient matrix is utilized as input of the DEMATEL method to attain a data-driven DEMATEL method. Furthermore, the DEMATEL method is extended to produce the weight of criteria.
- The ELECTRE method is extended based on the VIKOR method in order to use the advantages of the outranking method and the compromise solution method for ranking alternatives simultaneously. Then, a data-driven DEMATEL method is added to the ranking method to enrich the proposed MCDM method.
- The grey numbers as a valuable tool for addressing the uncertainty are applied to the proposed methodology for better coping with the practical conditions of the MCDM problems.

4. Proposed Data- and Knowledge-driven Method

This section first expresses a new data-driven MCDM method based on the regression model and the DEMATEL method. Then, a new knowledge-driven method using the combination of ELECTRE and VIKOR methods under the grey number is developed for rankings of the alternatives. In fact, to determine the weight of practical criteria, a new data-driven method is presented. Then, a new knowledge-driven method is extended for ranking of the alternatives.

Notations:

CC_{ij}	Correlation coefficient of criterion *i* with criterion *j*
TI	Total-influence matrix
I	Identity matrix
θ	Sum of rows
v	Sum of columns
i	Number of criteria
j	Number of criteria
σ_i	Final weight of criteria
$\bar{X}_{ki}$	Upper bound of rating of alternative *k* based on criterion *i*
$\underline{X}_{ki}$	Lower bound of rating of alternative *k* based on criterion *i*
k	Number of alternatives
$\bar{\phi}_{ki}$	Upper bound of rating of alternative *k* based on criterion *i* in normalize decision matrix
$\underline{\phi}_{ki}$	Lower bound of rating of alternative *k* based on criterion *i* in normalize decision matrix
$[\psi_{ki}]$	Weighted normalized decision matrix
C_{qy}	Concordance set
O_{qy}	Discordance set
P_{qy}	Including all indices that $alternative_q$ is superior to $alternative_y$
q , y	Number of alternatives in concordance and discordance sets
ζ_{qy}	Concordance index for each pair of *q* and *y* alternatives
T_{qy}	Discordance index for each pair of *q* and *y* alternatives
D_i	Global strength and global utility of each alternative
N_i	Minimum individual regret of each alternative
p	Weight of maximum group utility
1-*p*	Importance of individual regret
Ω_i	Final score of alternatives

Step 1. In this step, the historical data is gathered. The performance data of alternatives based on the criteria is collected.

Step 2. The correlation coefficient matrix among the criteria is extracted from the historical data. The correlation coefficient matrix among the collected information is discovered.

$$\left[CC_{ii}\right]_{m\times m} = \begin{array}{c} \\ \alpha_1 \\ \vdots \\ \alpha_m \end{array} \begin{array}{c} \begin{array}{ccc} \alpha_1 & \cdots & \alpha_m \end{array} \\ \begin{bmatrix} cc_{11} & \cdots & cc_{1m} \\ \vdots & \ddots & \vdots \\ cc_{m1} & \cdots & cc_{mm} \end{bmatrix} \end{array} \qquad (1)$$

where $1 \le i, j \le M$ represents the number of criteria, and $\alpha_1 \ldots \alpha_m$ illustrates the decisive criteria. The absolute values of the correlation coefficient matrix are used as the input of the DEMATEL method. This matrix is used as a normalized direct-influence matrix.

Step 3. The total-influence matrix (*TI*) is then computed by summing the direct effects and all of the indirect impacts by:

$$\begin{aligned} TI &= \left[ti_{ij}\right]_{m\times m} = \left[CC_{ij}\right]_{m\times m} + \left[CC_{ij}\right]^2_{m\times m} + \\ &\left[CC_{ij}\right]^3_{m\times m} + \ldots + \left[CC_{ij}\right]^f_{m\times m} \\ &= \left[CC_{ij}\right]_{m\times m}\left(I - \left[CC_{ij}\right]_{m\times m}\right)^{-1} \text{ when } f \to \infty \end{aligned} \qquad (2)$$

where *I* demonstrates the identity matrix.

Step 4. The influential relation map is produced as follows:

The vectors θ and v illustrate the sum of the rows and columns from the *TI* matrix, respectively. They are computed by:

$$\theta = [\theta_i]_{m\times 1} = \left[\sum_{j=1}^{m} ti_{ij}\right] \qquad (3)$$

$$\upsilon = [\upsilon_j]_{1\times m} = \left[\sum_{i=1}^{m} ti_{ij}\right] \qquad (4)$$

where, $i = j$ and $i = j = \{1, 2, \ldots, m\}$. θ as the sum of the rows demonstrates the direct and indirect effects of criterion *i* to the other criteria. Furthermore, ν as the sum of the columns illustrates the direct and indirect effect of criterion *j* from the other criteria.

Step 5. The horizontal axis vector ($\theta + v$) and the vertical axis vector ($\theta - v$) are calculated. Then, due to the use of a symmetric matrix as input, the amounts of ($\theta - v$) are equal to zero. The ($\theta + v$) axis vector demonstrates the strength of the influences specified and received of the factor, called a prominence. Moreover, ($\theta + v$) stands for the grade of the central role that the factor plays in the system. When *i=j*, (θ + ν) demonstrates the total effects received and given by criterion *i*, and (θ - ν) illustrates the net effect that criterion *i* contributes to the system.

The following procedure is added to the DEMATEL method to determine the weight of the criteria.

$$\max_i \left|\theta + \upsilon\right|_i = \beta \qquad (5)$$

$$(\theta + \upsilon)_i + \beta = \gamma_i \quad \forall i \qquad (6)$$

$$\sigma_i = \frac{\gamma_i}{\sum_{i=1}^{m} \gamma_i} \qquad (7)$$

The larger values of ($\theta + v$) get a higher weight. Steps 1 to 5 use the weight determination process based on a new data-driven approach using the DEMATEL method. Steps 6 to 13 are applied to rank alternatives using a new knowledge-driven approach based on the combination of ELECTRE and VIKOR methods under the grey environment.

Step 6. In this step, after determining the weight of the criteria with the correlation coefficient matrix and DEMATEL method, the decision matrix is constructed by gathering the ratings of the alternatives based on the criteria from the expert as follows:

$$\left[X_{ki}\right]_{n\times m} = \begin{bmatrix} (\underline{X}_{11}, \overline{X}_{11}) & \cdots & (\underline{X}_{1i}, \overline{X}_{1i}) \\ \vdots & \ddots & \vdots \\ (\underline{X}_{k1}, \overline{X}_{k1}) & \cdots & (\underline{X}_{ki}, \overline{X}_{ki}) \end{bmatrix} \qquad (8)$$

where $1 \le k \le n$ displays the number of alternatives.

Table 1 illustrates the linguistic variables and their equivalent grey numbers to judge the ratings of alternatives based on the decisive criteria. The experts evaluate the ratings of qualitative criteria using linguistic variables, and the qualitative criteria are gathered from the historical data.

Table 1. Linguistic variables and their grey equivalent

Linguistic variables	Equivalent grey numbers
Very Poor (VP)	(0, 1)
Poor (P)	(1, 3)
Medium Poor (MP)	(3, 5)
Fair (F)	(5, 7)
Medium Good (MG)	(7, 8)
Good (G)	(8, 9)
Very Good (VG)	(9, 10)

Step 7. The normalized decision matrix is computed by:

$$\left[\phi_{ki}\right]_{n\times m} = \begin{bmatrix} (\underline{\phi}_{11}, \overline{\phi}_{11}) & \cdots & (\underline{\phi}_{1i}, \overline{\phi}_{1i}) \\ \vdots & \ddots & \vdots \\ (\underline{\phi}_{k1}, \overline{\phi}_{k1}) & \cdots & (\underline{\phi}_{ki}, \overline{\phi}_{ki}) \end{bmatrix} \qquad (9)$$

$$(\underline{\phi}_{ki}, \overline{\phi}_{ki}) = \left(\frac{\underline{X}_{ki}}{\overline{X}^{+}_{ki}}, \frac{\overline{X}_{ki}}{\overline{X}^{+}_{ki}}\right) \text{ for benefit criteria}$$

$(\underline{\phi}_{k\,i}, \bar{\phi}_{k\,i}) = (\frac{\underline{X}^{-}_{k\,i}}{\bar{X}_{k\,i}}, \frac{\underline{X}^{-}_{k\,i}}{\underline{X}_{k\,i}})$ for cost criteria

where, $\bar{X}^{+}_{k\,i} = \max_{i} \bar{X}_{k\,i}$, $\underline{X}^{-}_{k\,i} = \max_{i} \underline{X}_{k\,i}$.

Step 8. The computed weights in step 5 are multiplied by the normalized decision matrix to achieve the weighted normalized decision matrix, as below:

$$\left[\psi_{k\,i}\right]_{n\times m} = \sigma_i \times \left[\phi_{k\,i}\right]_{n\times m} =$$

$$\begin{bmatrix} (\underline{\phi}_{11}\times\sigma_1, \bar{\phi}_{11}\times\sigma_1) & \cdots & (\underline{\phi}_{1i}\times\sigma_i, \bar{\phi}_{1i}\times\sigma_i) \\ \vdots & \ddots & \vdots \\ (\underline{\phi}_{k1}\times\sigma_1, \bar{\phi}_{k1}\times\sigma_1) & \cdots & (\underline{\phi}_{k\,i}\times\sigma_i, \bar{\phi}_{k\,i}\times\sigma_i) \end{bmatrix} \quad (10)$$

Step 9. The concordance (C_{qy}) set and discordance (O_{qy}) set for each pair of q and y alternatives are specified. Note that, $q = 1, 2, \ldots, Q; q \neq y$.

Concordance set (P_{qy}), including all indices that $alternative_q$ is superior to $alternative_y$.

$$C_{q\,y} = \left\{ i \,|\, \left[\psi_{q\,i}\right] \geq \left[\psi_{y\,i}\right] \right\} \quad (11)$$

where $C_{q\,y}$ is the summation of attributes that $alternative_q$ is superior or equal to $alternative_y$. Also, the discordance set is determined by:

$$O_{q\,y} = \left\{ i \,|\, \left[\psi_{q\,i}\right] < \left[\psi_{y\,i}\right] \right\} = I - C_{q\,y} \quad (12)$$

Discordance set contains all criteria that $alternative_q$ is worse than $alternative_y$.

Step 10: In this step, the concordance matrix is defined. Then, the concordance index is computed based on the members of C_{qy}. Thus, the concordance index is obtained as follows:

$$\zeta_{q\,y} = \sum_{i \in \tilde{C}_{q\,y}}^{n} \sigma_i^{*} \quad (13)$$

$\zeta_{q\,y}$ in the ELECTRE and D_i in the VIKOR method illustrate the global strength and global utility with similar functions.

Step 11: The decision by N_i in the VIKOR method and discordance condition in ELECTRE under deterministic assumptions have similar MCDM characteristics (minimum individual regret). The discordance condition does not supply a perfect ranking, although it allows for a pair-wise comparison.

The discordance matrix is computed. Then the discordance index is calculated based on the members of W_{qy}. Thus, the discordance index is obtained by:

$$T_{q\,y} = \frac{\max_{i \in w_{q\,y}} \left|\psi_{q\,i} - \psi_{y\,i}\right|}{\max_{i \in I} \left|\psi_{q\,i} - \psi_{y\,i}\right|} \quad (14)$$

Step 12: D_i and N_i of the VIKOR method are defined based on the concordance and discordance indices using the following:

$$N_i = T_i \times \max \sigma_i^{*}, \quad D_i = 1 - \zeta_i$$

$$\text{where } \zeta_i = \frac{\sum_{i \neq q}^{n} o_{iq}}{m-1} \quad (15)$$

Step 13: The best alternative is determined by:

$$\Omega_i = p(D_i - D^{*}) / (D^{-} - D^{*}) + (1-p)(N_i - N^{*}) / (N^{-} - N^{*}) \quad (16)$$

where $D^{*} = \min D_i, D^{-} = \max D_i,$ $N^{*} = \min N_i, N^{-} = \max N_i$.

where p demonstrates the weight of the maximum group utility, and (1-p) displays the importance of the individual regret. Furthermore, the final values of the alternatives are ranked in the ascending orders. Steps 6 to 13 presented a new combination of the ELECTRE and VIKOR methods.

5. Illustrative Example

In this section, an adopted illustrative case [44] from the literature about 3PL services (3PLS) selection problems are solved for the internet of things-based SCM. There is a company that wants to outsource some of its services. Three 3PLS providers prepare their services in several sections of countries are chosen to assess their performance. A performance score system assigned 0-10 to 3PLS providers based on the nine efficient criteria. Notably, 0 represents the worst, and 10 displays the best values. This system assigned scores to the 3PLS providers based on the specified criteria that each of the criteria has specific sub-criteria with a particular score. The sub-criteria are clearly defined, and if observed by the 3PLS providers, the score will be given to the 3PLS providers. This system is evaluated every month. The performance values of the performance score system are available for 36 months ago (3 years).

Nine decisive criteria are considered for the 3PL services selection as follows: 1) privacy protection, 2) data quality and uncertainty, 3) congestion and overload of the user, 4) identification, 5) standardization, 6) scalability of services, 7) software and algorithm cost, 8) logistic support, and 9) architecture of networks.

Step 1. The historical data of the third parties based on the considered criteria are categorized. The data evaluation system appointed scores among 0-10, in which 10 and 0 are the best and worst values, respectively. Note that score values of the criteria of the past 36 months were straightly used.

Step 2. The correlation coefficient matrix among the criteria is determined using EViews software. The absolute values of the correlation coefficient matrix are used as the input of the DEMATEL method. This matrix is applied as a normalized direct-influence matrix.

Step 3. The total-influence matrix (TI) is calculated by using Eq. (2).

Step 4. The influential relation map is computed using Eqs. (3) and (4).

Step 5. The horizontal axis vector $(\theta+\upsilon)$ and vertical axis vector $(\theta-\upsilon)$ are obtained. Then, the final weight of the criteria is determined by Eqs. (5) - (7), which is displayed in Table 2.

Step 6. The decision matrix is formed by gathering the judgments of experts for ratings of third parties based on the crucial criteria via Eq. (8).

The most crucial criterion, according to Table 2, is the privacy protection. It can be clearly seen that the customers have focused on the quality of service rather than the cost of service in the last decade. Privacy protection is a more critical criterion when things manage the whole supply chain; Otherwise, it appears as a dark side of the internet of things. The second important criterion is the scalability of services. After the quality of services, the cost of services is considered the most crucial criterion. In order to reduce the cost of the services when the internet of things has to manage the thousands of devices, scalability of services plays a vital role in cost reduction.

Table 2. Final weight of criteria

Criteria	Final weight of criteria
Privacy protection	0.169201
Data quality and uncertainty	0.114692
Congestion and overload of user	0.082561
Identification	0.092032
Standardization	0.110872
Scalability of services	0.135995
Software and algorithm cost	0.115482
Logistic support	0.075853
Architecture of networks	0.103313

Step 7. The normalized decision matrix is obtained by Eq. (9).

Step 8. The weighted normalized decision matrix is specified using the obtained data-driven weight and knowledge-driven decision matrix based on Eq. (10).

Step 9. The concordance and discordance sets are determined by Eqs. (11) and (12).

Step 10. The concordance matrix is computed by Eq. (13).

Step 11. The discordance matrix is calculated by Eq. (14).

Step 12. D_i and N_i are computed by Eq. (15).

Step 13. The final values of the third parties and the final ranks are calculated through Eq. (16). The final results are displayed in Table 3.

Third-party 3 was selected as the best alternative. In fact, when the quality of services and cost of services are the most critical issues in the supply chain, making a decision is very hard. For instance, the two most essential criteria in this paper have conflict purposes at a lower level. In this situation, the introduced model was selected the third party 3 as the best alternative.

Table 3. Final values and ranking of alternatives

Alternatives	Final values	Final rankings
Third party 1	0.5	3
Third party 2	0.122748	2
Third-party 3	0	1

Comparative analysis: In this paper, the results of the proposed method and a well-known MCDM method (i.e., TOPSIS) are compared. The results of the comparative analysis are depicted in Table 4. The proposed method's validity was confirmed by using the presented results in this table. According to the results of the ELECTRE method in Table 4, this method cannot rank all the alternatives. The ELECTRE method assigns one rank to both third party 1 and 2. It is developed by the VIKOR method in order to avoid the shortcomings of the ELECTRE method.

The different degree (DD) among the amounts of alternatives is calculated using the following [45]: F and G can be two alternatives' values, categorized in descending order. DD is computed by:

$$\frac{final\,value\,G - final\,value\,F}{final\,value\,F} \times 100, \quad (17)$$

$$final\,value\,G \geq final\,value\,F$$

Note that the higher value shows the best method [45]. When a technique earns a higher DD among a set of methods with identical results, it makes more distinction among the final amounts [45]. DD of the proposed method and the TOPSIS method was computed and tabulated in Table 5. As shown in this Table, DD of the proposed method is much larger than the TOPSIS method. Nevertheless, the proposed method is superior to the TOPSIS method.

Table 4. Comparative analysis

Alternatives	Final values	Final rankings	Final values of TOPSIS method [46]	Final rankings	Final values of the ELECTRE method	Final ranking
Third party 1	0.5	3	0.334228	3	-3	2
Third party 2	0.122748	2	0.563111	2	-3	2
Third party 3	0	1	0.68155	1	-1	1

Table 5. Different degrees

Alternatives	Final values	Different degree	Alternatives	Final values of the TOPSIS method [46]	Different degree
Third party 1	0.5	3.07	Third party 3	0.68155	0.21
Third party 2	0.122748	∞	Third party 2	0.563111	0.68
Third party 3	0		Third party 1	0.334228	

6. Conclusions

In this paper, a new multi-criteria decision-making (MCDM) method based on a combination of the knowledge-driven ELECTRE-VIKOR method and the data-driven DEMATEL method and regression model was presented. The regression model was given to achieve the correlation coefficient matrix as the input of DEMATEL. Furthermore, the DEMATEL method was extended to gain the weight of the criteria. Then a combination of the ELECTRE and VIKOR methods under the grey numbers was developed. On the one hand, a new data-driven approach was applied to reduce the dependence on the experts' judgments.

On the other hand, a new ELECTRE and VIKOR method under the grey number was extended to help the experts explain their judgments properly. The comparative analysis was done by comparing the proposed method with TOPSIS as a well-known MCDM method. The results confirmed the validity of the proposed method. For future studies, the dynamic MCDM method can be added to the proposed method. Moreover, the other MCDM problems can be applied to the proposed method to determine the best alternatives among a set of alternatives.

References

[1] Y. Duan, J. S. Edwards, and Y. K. Dwivedi, "Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda," *International Journal of Information Management*, Vol. 48, pp. 63-71, 2019.

[2] A. McAfee, E. Brynjolfsson, T. H. Davenport, D. J. Patil, and D. Barton, "Big data: the management revolution," *Harvard Business Review*, Vol. 90(10), pp. 60-68, 2012.

[3] S. Ji-fan Ren, S. Fosso Wamba, S. Akter, R. Dubey, and S. J. Childe, "Modelling quality dynamics, business value and firm performance in a big data analytics environment," *International Journal of Production Research*, Vol. 55(17), pp. 5011-5026, 2017.

[4] J. J. Liou, Y. C. Chuang, E. K. Zavadskas, and G. H. Tzeng, "Data-driven hybrid multiple attribute decision-making model for green supplier evaluation and performance improvement," *Journal of Cleaner Production*, Vol. 241, pp. 118321, 2019.

[5] A. Baykasoğlu, and İ. Gölcük, "An interactive data-driven (dynamic) multiple attribute decision making model via interval type-2 fuzzy functions," *Mathematics*, Vol. 7(7), pp. 584, 2019.

[6] P. Mejía-Herrera, J. J. Royer, G. Caumon, and A. Cheilletz, "Curvature attribute from surface-restoration as predictor variable in Kupferschiefer copper potentials," *Natural Resources Research*, Vol. 24(3), pp. 275-290, 2015.

[7] E. J. M. Carranza, and M. Hale, "Where are porphyry copper deposits spatially localized? A case study in Benguet province, Philippines," *Natural Resources Research*, Vol. 11(1), pp. 45-59, 2002.

[8] E. J. M. Carranza, H. Wibowo, S. D. Barritt, and P. Sumintadireja, "Spatial data analysis and integration for regional-scale geothermal potential mapping, West Java, Indonesia," *Geothermics*, Vol. 37(3), pp. 267-299, 2008.

[9] M. Abedi, G. H. Norouzi, and A. Bahroudi, "Support vector machine for multi-classification of mineral prospectivity areas," *Computers and Geosciences*, Vol. 46, pp. 272-283, 2012.

[10] R. Zuo, and E. J. M. Carranza, "Support vector machine: a tool for mapping mineral prospectivity," *Computers and Geosciences*, Vol. 37(12), pp. 1967-1975, 2011.

[11] E. J. M. Carranza, and A. G. Laborte, "Random forest predictive modeling of mineral prospectivity with small number of prospects and data with missing values in Abra (Philippines)," *Computers and Geosciences*, Vol. 74, pp. 60-70, 2015.

[12] A. Porwal, E. J. M. Carranza, and M. Hale, "Bayesian network classifiers for mineral potential mapping," *Computers and Geosciences*, Vol. 32(1), pp. 1-16, 2006.

[13] E. J. M. Carranza, J. C. Mangaoang, and M. Hale, "Application of mineral exploration models and GIS to generate mineral potential maps as input for optimum land-use planning in the Philippines," *Natural Resources Research*, Vol. 8(2), pp. 165-173, 1999.

[14] F. K. Zaidi, Y. Nazzal, I. Ahmed, M. Naeem, and M. K. Jafri, "Identification of potential artificial groundwater recharge zones in Northwestern Saudi Arabia using GIS and Boolean logic," *Journal of African Earth Sciences*, Vol. 111, pp. 156-169, 2015.

[15] M. Abedi, G. H. Norouzi, and N. Fathianpour, "Fuzzy outranking approach: A knowledge-driven method for mineral prospectivity mapping," *International Journal of Applied Earth Observation and Geoinformation*, Vol. 21, pp. 556-567, 2013.

[16] E. J. M. Carranza, F. J. A. Van Ruitenbeek, C. Hecker, M. van der Meijde, and F. D. van der Meer, "Knowledge-guided data-driven evidential belief modeling of mineral prospectivity in Cabo de Gata, SE Spain," *International Journal of Applied Earth Observation and Geoinformation*, Vol. 10(3), pp. 374-387, 2008.

[17] S. A. Hosseini, and M. Abedi, "Data envelopment analysis: a knowledge-driven method for mineral prospectivity mapping," *Computers and Geosciences*, Vol. 82, pp. 111-119, 2015.

[18] M. Abedi, G. H. Norouzi, and N. Fathianpour, "Fuzzy outranking approach: a knowledge-driven method for mineral prospectivity mapping," *International Journal of Applied Earth Observation and Geoinformation*, Vol. 21, pp. 556-567, 2013.

[19] C. Bai, J. Sarkis, "Determining and applying sustainable supplier key performance indicators," *Supply Chain Management*, Vol. 19 (3), pp. 275-291, 2014.

[20] G. Akman, "Evaluating suppliers to include green supplier development programs via fuzzy c-means and VIKOR methods," *Computers and Industrial Engineering*, Vol. 86, pp. 69-82, 2015.

[21] C. Bai, D. Dhavale, and J. Sarkis, "Complex investment decisions using rough set and fuzzy c-means: an example of investment in green supply chains," *European Journal of Operational Research*, Vol. 248(2), pp. 507-521, 2016.

[22] H. Shabanpour, S. Yousefi, and R. F. Saen, "Forecasting efficiency of green suppliers by dynamic data envelopment analysis and artificial neural networks," *Journal of Cleaner Production*, Vol. 142, pp. 1098-1107, 2017.

[23] Z. Chen, H. Li, A. Ross, M. M. Khalfan, and S. C Kong, "Knowledge-driven ANP approach to vendors evaluation for sustainable construction," *Journal of construction Engineering and Management*, Vol. 134(12), pp. 928-941, 2008.

[24] M. Abedi, S. A. Torabi, G. H. Norouzi, M. Hamzeh, and G. R Elyasi, "PROMETHEE II: A knowledge-driven method for copper exploration," *Computers and Geosciences*, Vol. 46, pp. 255-263, 2012.

[25] A. Arabameri, K. Rezaei, H. R. Pourghasemi, S. Lee, and M. Yamani, "GIS-based gully erosion susceptibility mapping: A comparison among three data-driven models and AHP knowledge-based technique," *Environmental Earth Sciences*, Vol. 77(17), pp. 628, 2018.

[26] Sevkli, M, "An application of the fuzzy ELECTRE method for supplier selection". *International Journal of Production Research*, Vol. 48(12), pp. 3393-3405, 2010.

[27] A. Fahmi, C. Kahraman, and Ü. Bilen, "ELECTRE I method using hesitant linguistic term sets: An application to supplier selection," *International Journal of Computational Intelligence Systems*, Vol. 9(1), pp. 153-167, 2016.

[28] E. Celik, A. T. Gumus, and M. Erdogan, "A new extension of the ELECTRE method based upon interval type-2 fuzzy sets for green logistic service providers evaluation," *Journal of Testing and Evaluation*, Vol. 44(5), pp. 1813-1827, 2016.

[29] J. Siskos, "A way to deal with fuzzy preferences in multi-criteria decision problems," *European Journal of Operational Research*, Vol. 10(3), pp. 314-324, 1982.

[30] A. Zandi, and E. Roghanian "Extension of Fuzzy ELECTRE based on VIKOR method". *Computers and Industrial Engineering*, Vol. 66(2), pp. 258-263, 2013.

[31] S. Amirghodsi, A. B. Naeini, and A. Makui, "An integrated Delphi-DEMATEL-ELECTRE method on gray numbers to rank technology providers," *IEEE Transactions on Engineering Management*, Doi: 10.1109/TEM.2020.2980127, Article in Press, 2020.

[32] R. Lin, S. Lu, A. Yang, W. Shen, and J. Ren, "Multi-criteria sustainability assessment and decision-making framework for hydrogen pathways prioritization: An extended ELECTRE method under hybrid information," *International Journal of Hydrogen Energy*, Vol. 46(24), pp. 13430-13445, 2021.

[33] H. Gao, L. Ran, G. Wei, C. Wei, and J. Wu, "VIKOR method for MAGDM based on q-rung interval-valued orthopair fuzzy information and its application to supplier selection of medical consumption products," *International Journal of Environmental Research and Public Health*, Vol. 17(2), pp. 525, 2020.

[34] P. Liu, X. Zhang, and Z. Wang, "An extended VIKOR method for multiple attribute decision making with linguistic d numbers based on fuzzy entropy," *International Journal of Information Technology and Decision Making*, Vol. 19(01), pp. 143-167, 2020.

[35] Y. Wu, K. Chen, B. Zeng, H. Xu, and Y. Yang, "Supplier selection in nuclear power industry with extended VIKOR method under linguistic information," *Applied Soft Computing*, Vol. 48, pp. 444-457, 2016.

[36] J. Hu, X. Zhang, Y. Yang, Y. Liu, and X. Chen, "New doctors ranking system based on VIKOR method," *International Transactions in Operational Research*, Vol. 27(2), pp. 1236-1261, 2020.

[37] Y. W. Du, and X. X. Li, "Hierarchical DEMATEL method for complex systems," *Expert Systems with Applications*, Vol. 167, pp. 113871, 2021.

[38] C. Feng, and R. Ma, "Identification of the factors that influence service innovation in manufacturing enterprises by using the fuzzy DEMATEL method," *Journal of Cleaner Production*, Vol. 253, 120002, 2020.

[39] J. Zhang, D. Yang, Q. Li, B. Lev, and Y. Ma, "Research on sustainable supplier selection based on the rough DEMATEL and FVIKOR Methods," *Sustainability*, Vol. 13(1), 88, 2021.

[40] F. Balderas, E. Fernandez, C. Gomez, and L. Cruz-Reyes, "TOPSIS-grey method applied to project portfolio problem," *In Nature-inspired design of hybrid intelligent systems*, Vol. 667, Springer, pp. 767-774. 2017.

[41] H. Zhou, J. Q. Wang, and H. Y. Zhang, "Grey stochastic multi-criteria decision-making based on regret theory and TOPSIS," *International Journal of Machine Learning and Cybernetics*, Vol. 8(2), pp. 651-664, 2017.

[42] A. Ulutaş, G. Popovic, D. Stanujkic, D. Karabasevic, E. K. Zavadskas, and Z. Turskis, "A new hybrid MCDM model for personnel selection based on a novel grey PIPRECIA and grey OCRA methods," *Mathematics*, Vol. 8(10), 1698, 2020.

[43] A. Ulutaş, F. Balo, L. Sua, E. Demir, A. Topal, and V. Jakovljević, "A new integrated grey mcdm model: case of warehouse location selection," *Facta Universitatis, Series: Mechanical Engineering*. 2021.

[44] S. Yadav, D. Garg, and S. Luthra, "Selection of third-party logistics services for internet of things-based agriculture supply chain management," *International Journal of Logistics Systems and Management*, Vol. 35(2), pp. 204-230, 2020.

[45] W. Wu, G. Kou, and Y. Peng, "A consensus facilitation model based on experts' weights for investment strategy selection," *Journal of the Operational Research Society*, Vol. 69(9), pp. 1435-1444, 2018.

[46] P. Biswas, S. Pramanik, and B. C. Giri, "TOPSIS method for multi-attribute group decision-making under single-valued neutrosophic environment," *Neural Computing and Applications*, Vol. 27(3), pp. 727-737, 2016.

[47] M. Sevkli, "An application of the fuzzy ELECTRE method for supplier selection," *International Journal of Production Research*, Vol.48(12), 3393-3405, 2010.

[48] S. Sirait, D. Y. Saragih, H. Sugara, M. Yunus, M. H. Ali, V. M. M. Siregar, and D. Defliyanto, "Selection of the Best Administrative Staff Using Elimination Et Choix Traduisant La Realite (ELECTRE) Method," In *Journal of Physics: Conference Series*, Vol. 1933(1), pp. 012068, 2021.

[49] G. H. Tzeng, C. H. Chiang, and C. W. Li, Evaluating intertwined effects in e-learning programs: A novel hybrid MCDM model based on factor analysis and DEMATEL. *Expert systems with Applications*, Vol. 32(4), pp. 1028-1044, 2007.

[50] M. Sharma, S. Joshi, and A. Kumar, "Assessing enablers of e-waste management in circular economy using DEMATEL method: An Indian perspective," *Environmental Science and Pollution Research*, Vol. 27(12), pp. 13325-13338, 2020.

[51] H. Haghshenas Gorgani, and A. R. Jahantigh Pak, "Identification of Factors Affecting Quality of Teaching Engineering Drawing using a Hybrid MCDM Model," *Journal of AI and Data Mining*, Vol. 8(2), pp. 247-267, 2020.

Appendix

ELECTRE Method

Suppose, that there is a multi-criteria decision problem consisting of g alternatives $(Q_1, Q_2, ..., Q_g)$ and f criteria $(r_1, r_2, ..., r_f)$. The decision matrix is defined as follows [47, 48]:

$$Y_{gf} = \begin{bmatrix} Y_{11} & \cdots & Y_{1f} \\ \vdots & \ddots & \vdots \\ Y_{g1} & \cdots & Y_{gf} \end{bmatrix}$$

where, Y_{gf} illustrates the rating of alternative g with respect to criterion f. The following is a summary of the ELECTRE method:

The normalized decision matrix is calculated by:

$$S_{gf} = \begin{bmatrix} S_{11} & \cdots & S_{1f} \\ \vdots & \ddots & \vdots \\ S_{g1} & \cdots & S_{gf} \end{bmatrix}$$

where,

$$S_{gf} = \frac{Y_{gf}}{\sqrt{\sum_{g=1}^{G} Y_{gf}^2}} \quad \text{for the benefit criteria}$$

$$S_{gf} = \frac{\frac{1}{Y_{gf}}}{\sqrt{\sum_{g=1}^{G} \frac{1}{Y_{gf}^2}}} \quad \text{for the cost criteria}$$

Also, $(e_1, e_2, ..., e_f)$ demonstrates the weight of criteria.

The weighted normalized decision matrix is computed by:

$$P_{gf} = S_{gf} \times e_f$$

Afterwards, the concordance and discordance sets are defined. For each pair of alternative Q_z and Q_x ($z, x = 1, 2, ..., g$ and $z \neq x$) the set of criteria is categorized into two different subsets. If alternative Q_z is preferred to alternative Q_x for all criteria, the concordance set is composed by:

$$O(z, x) = \{ f \mid P_{zg} \succ P_{xg} \}$$

where P_{zg} illustrates the rating of alternative Q_z with respect to alternative *g*. The discordance set contains all criteria for which Q_z is worse than Q_x. It is defined by:

$$K(z, x) = \{ f \mid P_{zg} \prec P_{xg} \}$$

Then, the concordance and discordance indexes are computed by:

$$O_{zx} = \sum_{g^*} e_{g^*}$$

where g^* are factors included in the concordance set $O(z, x)$.

$$K_{zx} = \frac{\sum_{g^+} \left| S_{zg^+} - S_{xg^+} \right|}{\sum_{g} \left| S_{zg} - S_{xg} \right|}$$

where g^+ are factors included in the discordance set $K(z, x)$. The method expresses that Q_z outranks Q_x when $O_{zx} \geq \bar{O}$ and $K_{zx} \geq \bar{K}$. Notably, the $\bar{O}$ and $\bar{K}$ are the averages of O_{zx} and K_{zx}.

DEMATEL Method

At first, each expert evaluates the direct influence between each two criteria by 0, 1, 2, and 3 that represents "no influence", "low influence", "medium influence", and "high influence", respectively. L_{ij} illustrates the grade of criterion *i* affecting criterion *j* [49, 50]. For *i*=*j*, the diagonal elements are set to zero. The initial direct-relation matrix is computed as follows [49, 51]:

$$L_{ij} = \begin{bmatrix} 0 & \cdots & L_{1j} \\ \vdots & \ddots & \vdots \\ L_{i1} & \cdots & 0 \end{bmatrix}$$

The normalized initial direct-relation matrix is calculated by:

$$\beta_{ij} = L_{ij} \times Q$$

where, $Q = \dfrac{1}{\max\limits_{1 \leq i \leq n} \sum_{j=1}^{n} L_{ij}}$.

Then, the total relation matrix (α) is obtained as $\alpha = \beta(I - \beta)^{-1}$. Describe z and x be $n \times 1$ and $1 \times n$ vectors illustrating the sum of rows and columns of the total relation matrix α, respectively. z and x summarize both the direct and indirect effects given by criterion *i* to the other criteria and both the direct and indirect effects by factor j from the other factors.

Also, the sum $(z_i + x_j)$ demonstrates the total effects received and given by criterion *i*. Furthermore, $(z_i - x_j)$ demonstrates the net effect that criterion *i* contributes to the system. The digraph is obtained by setting up a threshold value. Usually, the threshold value is set up by calculating the average of the total relation matrix. The digraph can be provided using the dataset of $(z_i + x_j, z_i - x_j)$.

یک روش تصمیم‌گیری چند معیاره جدید مبتنی بر داده و دانش

یحیی درفشان[۱]، رضا توکلی مقدم[۱،*]، فریبرز جولای[۱] و سید میثم موسوی[۲]

[۱] دانشکده مهندسی صنایع، پردیس دانشکده فنی، دانشگاه تهران، تهران، ایران.

[۲] گروه مهندسی صنایع، دانشکده فنی و مهندسی، دانشگاه شاهد، تهران، ایران.

ارسال ۲۰۲۱/۰۵/۰۹؛ بازنگری ۲۰۲۱/۰۸/۱۶؛ پذیرش ۲۰۲۱/۱۰/۱۲

چکیده:

در یک دهه گذشته روش‌های تصمیم‌گیری چند معیاره (MCDM) برای حل مسائل با مجموعه ای از گزینه‌ها و معیارهای متضاد، مورد توجه زیادی قرار گرفته است. در گذشته، روش‌های MCDM برای تصمیم‌گیری عمدتاً بر قضاوت و دانش متخصصان متکی بوده است. این مقاله یک روش MCDM جدید مبتنی بر داده و دانش را به منظور کاهش وابستگی به ارزیابی کارشناسان معرفی می‌کند. وزن معیارها با استفاده از روش توسعه یافته DEMATEL مبتنی بر داده تعیین می‌شود. سپس، رتبه بندی گزینه‌ها با استفاده از روش‌های مبتنی بردانش ELECTRE و VIKOR تعیین می‌شود. همه روشهای پیشنهادی برای وزن دهی و رتبه بندی برای مواجهه با عدم قطعیت، در محیط خاکستری توسعه داده می‌شوند. در نهایت، عملی و کاربردی بودن روش پیشنهادی با حل یک مثال واضح و کاربردی مشخص می‌شود.

کلمات کلیدی: روش‌های تصمیم‌گیری مبتنی بر داده و دانش، روش‌های DEMATEL، ELECTRE، VIKOR.