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New hybrid multi-criteria decision-making DEMATEL-MAIRCA model: sustainable selection of a location for the development of multimodal logistics centre

Dragan S. Pamucar[a], Snezana Pejcic Tarle[b] and Tanja Parezanovic[b]

[a]Department of Logistics, University of Defence in Belgrade, Belgrade, Serbia; [b]Faculty of Transport and Traffic Engineering, University of Belgrade, Belgrade, Serbia

ABSTRACT
The paper describes the application of a new multi-criteria decision-making (MCDM) model, MultiAtributive Ideal-Real Comparative Analysis (MAIRCA), used to select a location for the development of a multimodal logistics centre by the Danube River. The MAIRCA method is based on the comparison of theoretical and empirical alternative ratings. Relying on theoretical and empirical ratings the gap (distance) between the empirical and ideal alternative is defined. To determine the weight coefficients of the criteria, the DEMATEL method was applied. In this paper, through a sensitivity analysis, the results of MAIRCA and other MCDM methods – MOORA, TOPSIS, ELECTRE, COPRAS and PROMETHEE – were compared. The analysis showed that a smaller or bigger instability in alternative rankings appears in MOORA, TOPSIS, ELECTRE and COPRAS. On the other hand, the analysis showed that MAIRCA and PROMETHEE offer consistent solutions and have a stable and well-structured analytical framework for ranking the alternatives. By presenting a new method MCDM expands the theoretical framework of expertise in the field of MCDM. This enables the analysis of practical problems with new methodology and creates a basis for further theoretical and practical upgrade.

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1. Introduction

The logistics centre (LC) is a unique technological, spatial, organisational and economic entity bringing together different providers and users of logistics services. The optimal LC location reduces transportation costs, improves business performance, competitiveness and profitability. The objective is to identify the location that operates at minimal cost and maximum efficiency, while meeting operational and strategic requirements.

LC location selection is the process in which one of the possible alternatives is chosen. A large number of heterogeneous location factors make the location problem an interdisciplinary one, requiring a complex selection procedure. There are many

CONTACT Dragan Pamucar dpamucar@gmail.com

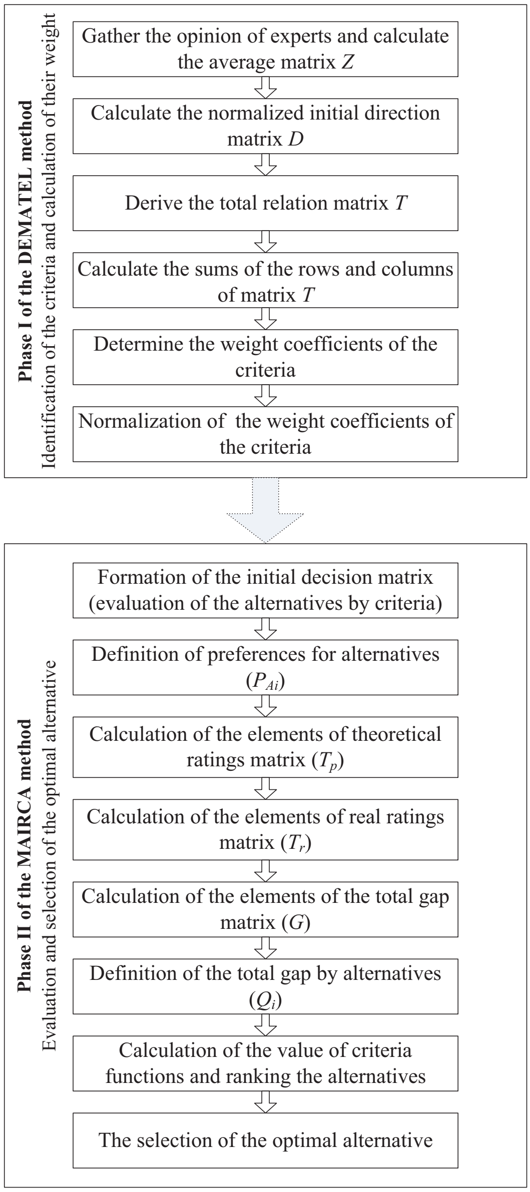

Figure 1. Phases of the hybrid DEMATEL–MAIRCA model. Source: Provided by authors.

methodologies and procedures available in this area (Badi and Ballem, 2018; Milosavljevic, Bursać, & Tričković, 2018). The selection of the location for LC development can be considered to be a special case within a general facility location problem. The facility location problem usually involves a set of locations (alternatives) which are evaluated against a set of weighed criteria independent from each other.

There are many ways to solve facility location problems including the dual-based algorithm proposed by Erlenkotter (1978). Several improved versions of this idea have been proposed to solve the problem (Janáček & Buzna, 2008; Ji, Tang, Li, Yang,

& Liao, 2016; Mladenović, Brimberg, Hansen, & Moreno-Pérez, 2007). Other popular methods include local search (Brimberg, Drezner, Mladenović, & Salhi, 2014), tabu search (Wang, Li, Yuan, Ye, & Wang, 2016b), neighbourhood search (Qazi, Lam, Xiao, Ouyang, & Yin, 2016), etc.

Many classical and heuristic methods have been proposed to solve a location problem, like linear, non-linear programming, simplex algorithm, lagrangian relaxation, branch and cut methods, branch and bound (Liu, Wang, & Jin, 2016c), artificial neural network (Wan, Huang, & Li, 2007), generic algorithms, expert systems, multi-agent systems, hybrid algorithms (Han, Li, Wang, & Shi, 2016; Xu, Law, Chen, & Tang, 2016a; Zare et al., 2013) and so on.

There are different studies associated with location selection decisions that have been commonly carried out using MCDM techniques, such as distribution centre selection with weighted fuzzy factor rating system (Ou & Chou, 2009; Xu, Dong, Zhang, & Xu, 2016b; Zhang, Xie, & Wang, 2016), location problem with fuzzy-AHP (Petrović and Kankaraš, 2018), location problem with MOORA and COPRAS methods (Kracka, Brauers, & Zavadskas, 2010; Rezaeiniya, Zolfani, & Zavadskas, 2012), intermodal freight hub location decision with multi-objective evaluation model (Sirikijpanichkul & Ferreira, 2006; Yang, Sun, Deng, Zhang, & Liao, 2016), selection of LC location with fuzzy TOPSIS based on entropy weight (Chen & Liu, 2006), deep-water port location with AHP and fuzzy ratio assessment methods (Zavadskas, Turskis, & Bagočius, 2015), construction site selection with fuzzy AHP and weighted aggregated sum-product assessment method (Turskis, Zavadskas, Antucheviciene, & Kosareva, 2015), facility location selection with AHP and ELECTRE (Yang & Lee, 1997), port selection with AHP and PROMETHEE (Zecevic, 2006), reverse logistics location selection with MOORA (Kannan, Nooral Haq, & Sasikumar, 2008) and selecting a site for a logistical centre on factor and methods (Chen & Liu, 2006).

The research listed above singles out MOORA, COPRAS, TOPSIS, ELECTRE and PROMETHEE as most frequently used in the LC location selection process. In this paper the MAIRCA method was used to select the LC location. The next step was to compare the MAIRCA results with the results obtained when MOORA, COPRAS, TOPSIS, ELECTRE and PROMETHEE methods were applied. Based on a subsequent sensitivity analysis, these methods were assessed objectively and the method maintaining the consistency of results selected. Two consistency criteria were defined to gauge the sensitivity of the results: (1) the consistency of results depending on a varying value scale and (2) the consistency of results depending on the formulation of criteria, if the same criteria can be presented in two normatively equivalent ways. The LC site selection showed that some of the MCDM methods used did not meet one of the criteria or, very often, both of them.

The paper presents a MCDM hybrid model (Figure 1), incorporating a fuzzy DEMATEL method (Dalalah, Hayajneh, & Batieha, 2011) and a new MCDM method, MAIRCA, developed by Professor Dragan Pamučar in the Logistics Research Centre at the Belgrade-based Defence University. The modified fuzzy DEMATEL method was used to estimate the criteria and define the criterion weights.

Having defined the weights of the criteria based on the MAIRCA method, the optimal LC location was selected.

2. Setting up the hybrid DEMATEL–MAIRCA model

The causal relationship among the criteria is determined by using a modified fuzzy DEMATEL method. The modified fuzzy DEMATEL method which is used in this paper is adapted from the studies of Dalalah et al. (2011).

The problem is formally presented by choosing one of the m options (alternatives), $A_i, i = 1, 2, \ldots, m$, which we evaluate and compare with each other based on the n criteria $(X_j,\ j = 1, 2, \ldots, n)$, the values of which are known to us. The alternatives are described by the vectors x_{ij}, where x_{ij} is the value of the i-alternative by the j-criterion. As the impact of the criteria on the final ranking of alternatives varies, each criterion is assigned a weight ratio $w_j,\ j = 1, 2, \ldots, n$ (where $\sum_{j=1}^{n} w_j = 1$), reflecting its relative significance in evaluating the alternatives. In this step of the proposed model, the relationship among the criteria is determined by using the modified fuzzy DEMATEL method. The implementation process for the modified fuzzy DEMATEL method is described in the next section.

Step 1 serves to collect expert scores and calculate the average matrix $\tilde{Z}$. A group of m experts and n factors are used in this step. Each expert is to determine the influence level of factor i on factor j. Comparative analysis of the ith and jth factors' pair by kth expert is labelled with ${z_{ij}}^{e}$, where $i = 1, \ldots, n$; $j = 1, \ldots, n$; $e = 1, \ldots, m$.

For each expert, a $n \times n$ non-negative matrix is constructed (n represents the number of criteria) as $\tilde{Z}^{e} = [\tilde{z}_{ij}^{e}]$, where e is the expert number of participating in evaluation process with $1 \le e \le m$. Thus, $\tilde{Z}^{1}, \tilde{Z}^{2}, \ldots, \tilde{Z}^{m}$ are the matrices from m experts. In this method, the effects of the criteria on each other are expressed in terms of linguistic expressions. The experts list the pairwise comparisons based on a fuzzified scale, where the linguistic expressions are described by triangular fuzzy numbers $\tilde{z}_{ij}^{e} = (z_{ij,e}^{(l)}, z_{ij,e}^{(s)}, z_{ij,e}^{(r)}), e = 1, 2, \ldots, m$, where e is the expert number, and m represents a total number of experts. The aggregation of expert opinions results in the final matrix $\tilde{Z} = [\tilde{z}_{ij}]$.

Equations (1), (2) and (3) are the formulas for obtaining the matrix $\tilde{Z}$ elements:

$$z_{ij,e}^{(l)} = \min_{M} \left\{ z_{ij,e}^{(l)} \right\},\ \ M = \{1, 2, \ldots, e, \ldots, m\} \tag{1}$$

$$z_{ij,e}^{(s)} = \frac{1}{m} \sum_{k=1}^{m} z_{ij,k}^{(s)} \tag{2}$$

$$z_{ij,e}^{(r)} = \max_{M} \left\{ z_{ij,e}^{(r)} \right\},\ \ M = \{1, 2, \ldots, e, \ldots, m\} \tag{3}$$

where $z_{ij,e}^{(l)}$, $z_{ij,e}^{(s)}$ and $z_{ij,e}^{(r)}$ represent a preference by e-expert, M is a set of experts taking part in the research, e is the expert score, and m a total number of experts.

Having calculated the elements of the matrix $\tilde{Z}$, the next step defines the elements of the normalised initial direct-relation matrix $\tilde{D} = [\tilde{d}_{ij}]$. The elements of the matrix $\tilde{D}$ (Eq. 4) are calculated based on formulas (5) and (6).

$$\widetilde{D} = \begin{bmatrix} \widetilde{d}_{11} & \widetilde{d}_{12} & \dots & \widetilde{d}_{1n} \\ \widetilde{d}_{21} & \widetilde{d}_{22} & \dots & \widetilde{d}_{2n} \\ \dots & \dots & \dots & \dots \\ \widetilde{d}_{n1} & \widetilde{d}_{n2} & \dots & \widetilde{d}_{nn} \end{bmatrix} \tag{4}$$

The matrix $\widetilde{D}$ elements are obtained by summing up the elements of the average matrix $\widetilde{Z}$ by rows. Having applied Eq. (6), the maximum element $\widetilde{R}$ is identified among the summed elements. By simple normalisation, Eq. (5), each element of the matrix $\widetilde{Z}$ is divided by the result of formula (6).

$$\widetilde{d}_{ij} = \frac{\widetilde{z}_{ij}}{\widetilde{R}} = \left(\frac{z_{ij}^{(l)}}{r^{(l)}}, \frac{z_{ij}^{(s)}}{r^{(s)}}, \frac{z_{ij}^{(r)}}{r^{(r)}} \right) \tag{5}$$

$$\widetilde{R} = \max\left(\sum_{j=1}^{n} \widetilde{z}_{ij}\right) = \left(r^{(l)}, r^{(s)}, r^{(r)}\right) \tag{6}$$

where n represents the total number of criteria.

In the next step the elements of the total relation matrix $\widetilde{T}$are calculated. Therefore, the total-relation fuzzy matrix $\widetilde{T}$ can be acquired by calculating the following term (Dalalah et al., 2011):

$$\widetilde{T} = \lim_{w \to \propto} \left(\widetilde{D} + \widetilde{D}^2 + \dots + \widetilde{D}^w\right) = \widetilde{D}(I - \widetilde{D})^{-1} \tag{7}$$

Based on the above, the total-relation matrix for the criteria ($\widetilde{T}$) can be presented as:

$$\widetilde{T} = \begin{bmatrix} \widetilde{t}_{11} & \widetilde{t}_{12} & \dots & \widetilde{t}_{1n} \\ \widetilde{t}_{21} & \widetilde{t}_{22} & \dots & \widetilde{t}_{2n} \\ \dots & \dots & \dots & \dots \\ \widetilde{t}_{n1} & \widetilde{t}_{n2} & \dots & \widetilde{t}_{nn} \end{bmatrix} \tag{8}$$

where $\widetilde{t}_{11} = (t_{ij}^{(l)}, t_{ij}^{(s)}, t_{ij}^{(r)})$ is the overall influence rating by a decision-maker for each criterion i against criterion j.

In the last step of the DEMATEL method, summing by rows and columns of the matrix elements $\widetilde{T}$ is completed. The sum of rows and the sum of columns of the sub-matrices T_1, T_2 and T_3 denoted by the fuzzy numbers $\widetilde{D}_i$ and $\widetilde{R}_i$, respectively, can be obtained through Eqs. (9) and (10), respectively:

$$\widetilde{D}_i = \sum_{i=1}^{n} \widetilde{t}_{ij}, \quad i = 1, 2, \dots, n \tag{9}$$

$$\widetilde{R}_j = \sum_{j=1}^{n} \widetilde{t}_{ij}, \quad j = 1, 2, \dots, n \tag{10}$$

where n is the number of criteria.

Based on the values obtained from formulas (9) and (10), the criterion weights are calculated. The criterion weights are calculated using formulas (11) and (12):

$$\widetilde{W}_i = \left[\left(\widetilde{D}_i + \widetilde{R}_j\right)^2 + \left(\widetilde{D}_i - \widetilde{R}_j\right)^2\right]^{1/2} \tag{11}$$

By formula (11) the fuzzy value of weight coefficients $\widetilde{W}_i = (W_i^{(l)}, W_i^{(s)}, W_i^{(r)})$is obtained and it has to be normalized by formula (12). To simplify the normalisation of weight coefficients, defuzzification of the value of weight coefficients from the formula (11) is preformed prior to normalisation. Defuzzification of weight coefficients is carried out by implementing the formula:

$$W = \left[\left(W^{(r)} - W^{(l)}\right) + \left(W^{(s)} - W^{(l)}\right)\right] \cdot 1/3 + W^{(l)}.$$

Weight coefficient values after defuzzification are normalised by formula (12):

$$w_i = \frac{W_i}{\sum_{i=1}^{n} W_i} \tag{12}$$

where w_i represents the final criteria weights to be used in the decision making process (Dalalah et al., 2011).

Defining the criterion weights creates conditions for presenting a mathematical formulation of the MAIRCA model. The basic MAIRCA set up is to define the gap between ideal and empirical ratings. Summing the gap by each criterion generates the total gap for each alternative observed. Ranking the alternatives comes at the end of the process, where the best-ranked alternative is the one with the lowest gap value. The alternative with the lowest total gap value is the alternative, by most of the criteria, with the values closest to the ideal ratings (the ideal criteria values).

The MAIRCA method is carried out in six steps.

Step 1. Formulation of the initial decision-making matrix (X). The initial decision-making matrix (13) determines the criteria values ($x_{ij},\;\; i = 1, 2, \ldots n;\;\; j = 1, 2, \ldots m$) for each alternative observed.

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \ldots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & & x_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ x_{m1} & x_{22} & \ldots & x_{mn} \end{bmatrix} \end{array} \tag{13}$$

The criteria from the matrix (13) can be quantitative (measurable) and qualitative (descriptive). The quantitative criteria values in the matrix (13) are obtained by quantification of real indicators which present the criteria. The qualitative criteria values are determined by decision-maker's preferences or, in the case of a large number of experts, by aggregating the experts' opinions.

Step 2. Defining preferences for the choice of alternatives P_{A_i}. While selecting the alternatives, the decision-maker (DM) is neutral, meaning there's no preference for any of the offered alternatives. The assumption is that the DM does not take into account the probability of choosing any particular alternative, and has no preference in the alternative selection process.

$$P_{A_i} = \frac{1}{m}; \ \sum_{i=1}^{m} P_{A_i} = 1, \ i = 1, 2, \ldots, m \tag{14}$$

where m is the total number of the alternatives being selected.

In a decision-making analysis with *a priori* probabilities we proceed from the point that the DM is neutral to selection probability of each alternative. In that case, all preferences for the selection of individual alternatives are equal, i.e.,

$$P_{A_1} = P_{A_2} = \ldots = P_{A_m} \tag{15}$$

where m is the total number of the alternatives being selected.

Step 3. Calculation of the elements of the theoretical ratings matrix (T_p).

The format of the matrix (T_p) is $n \ x \ m$ (where n is the total number of criteria, m is the total number of alternatives). The elements of the theoretical ratings matrix (t_{pij}) are calculated as a product of preferences for the selection of alternatives P_{A_i} and criterion weights ($w_i, \ i = 1, 2, \ldots, n$)

$$T_p = \begin{array}{c} \\ P_{A_1} \\ P_{A_2} \\ \ldots \\ P_{A_m} \end{array} \begin{array}{c} \begin{array}{cccc} w_1 & w_2 & \ldots & w_n \end{array} \\ \begin{bmatrix} t_{p11} & t_{p12} & \ldots & t_{p1n} \\ t_{p21} & t_{p22} & & t_{p2n} \\ \ldots & \ldots & \ldots & \ldots \\ t_{pm1} & t_{pm2} & \ldots & t_{pmn} \end{bmatrix} \end{array} = \begin{array}{c} \\ P_{A_1} \\ P_{A_2} \\ \ldots \\ P_{A_m} \end{array} \begin{array}{c} \begin{array}{cccc} w_1 & w_2 & \ldots & w_n \end{array} \\ \begin{bmatrix} P_{A_1} \cdot w_1 & P_{A_1} \cdot w_2 & \ldots & P_{A_1} \cdot w_n \\ P_{A_2} \cdot w_1 & P_{A_2} \cdot w_2 & & P_{A_2} \cdot w_n \\ \ldots & \ldots & \ldots & \ldots \\ P_{A_m} \cdot w_1 & P_{A_m} \cdot w_2 & \ldots & P_{A_m} \cdot w_n \end{bmatrix} \end{array} \tag{16}$$

As the DM is neutral towards the initial alternative selection, the preferences (P_{A_i}) are the same for all alternatives. As the preferences (P_{A_i}) are the same for all alternatives, we can also present matrix (16) in the format $n \ x \ 1$ (where n is the total number of criteria).

$$T_p = P_{A_i} \begin{array}{c} \begin{array}{cccc} w_1 & w_2 & \ldots & w_n \end{array} \\ \begin{bmatrix} t_{p1} & t_{p2} & \ldots & t_{pn} \end{bmatrix} \end{array} = P_{A_i} \begin{array}{c} \begin{array}{cccc} w_1 & w_2 & \ldots & w_n \end{array} \\ \begin{bmatrix} P_{A_i} \cdot w_1 & P_{A_i} \cdot w_2 & \ldots & P_{A_i} \cdot w_n \end{bmatrix} \end{array} \tag{17}$$

where n is the total number of criteria, and t_{pi} theoretical rating.

Step 4. Definition of the elements of real ratings matrix (T_r).

$$T_r = \begin{array}{c} \\ A_1 \\ A_2 \\ \ldots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{bmatrix} t_{r11} & t_{r12} & \ldots & t_{r1n} \\ t_{r21} & t_{r22} & & t_{r2n} \\ \ldots & \ldots & \ldots & \ldots \\ t_{rm1} & t_{rm2} & \ldots & t_{rmn} \end{bmatrix} \end{array} \tag{18}$$

where n represents the total number of criteria, and m the total number of alternatives.

In calculation of the elements of the real ratings matrix (T_r) the elements of the theoretical ratings matrix (T_p) are multiplied by the elements of the initial decision-making matrix (X) using the following formulas:

- For the benefit type criteria (preferred higher criteria value):

$$t_{rij} = t_{pij} \cdot \left(\frac{x_{ij} - x_i^-}{x_i^+ - x_i^-} \right) \tag{19}$$

- For the cost type criteria (preferred lower criteria value):

$$t_{rij} = t_{pij} \cdot \left(\frac{x_{ij} - x_i^+}{x_i^- - x_i^+} \right) \tag{20}$$

where x_{ij}, x_i^+ and x_i^- represent the elements of the initial decision-making matrix (X), and x_i^+ and x_i^- are defined as: $x_i^+ = \max(x_1, x_2, \ldots, x_m)$, representing the maximum values of the observed criterion by alternatives; $x_i^- = \min(x_1, x_2, \ldots, x_m)$, representing the minimum values of the observed criterion by alternatives.

Step 5. The calculation of the total gap matrix (G). The elements of the G matrix are obtained as a difference (gap) between the theoretical (t_{pij}) and real ratings (t_{rij}), i.e., a difference between the theoretical ratings matrix (T_p) and the real ratings matrix (T_r)

$$G = T_p - T_r = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ g_{m1} & g_{m2} & \cdots & g_{mn} \end{bmatrix} = \begin{bmatrix} t_{p11} - t_{r11} & t_{p12} - t_{r12} & \cdots & t_{p1n} - t_{r1n} \\ t_{p21} - t_{r21} & t_{p22} - t_{r22} & \cdots & t_{p2n} - t_{r2n} \\ \cdots & \cdots & \cdots & \cdots \\ t_{pm1} - t_{rm1} & t_{pm2} - t_{rm2} & \cdots & t_{pmn} - t_{rmn} \end{bmatrix} \tag{21}$$

where n represents the total number of criteria, m is the total number of the alternatives being selected.

The gap g_{ij} takes the values from the interval $g_{ij} \in [0, \infty)$, by Eq. (22):

$$g_{ij} = t_{pij} - t_{rij} \tag{22}$$

The preferable option is that g_{ij} gravitates towards zero ($g_{ij} \to 0$), because we are choosing the alterative with the smallest difference between theoretical ratings (t_{pij}) and real ratings (t_{rij}). If for criterion C_i the alternative A_i has a theoretical rating value equal to the real rating value ($t_{pij} = t_{rij}$), the gap for alternative A_i, by criterion C_i, is $g_{ij} = 0$. In other words, by criterion C_i, alternative A_i is the best (ideal) alternative (A_i^+).

If by criterion C_i alternative A_i has the value of theoretical ratings t_{pij}, and the value of real ratings $t_{rij} = 0$, the gap for alternative A_i, by criterion C_i, is $g_{ij} = t_{pij}$. In other words, alternative A_i is the worst (anti-ideal) alternative (A_i^-) by criterion C_i.

Table 1. Fuzzy scal.

NO.	LINGUISTIC TERMS	TRIANGULAR FUZZY NUMBERS
1.	Very high influence (VH)	(4.50, 5.00, 5.00)
2.	High influence (H)	(2.50, 3.50, 4.50)
3.	Low influence (L)	(1.50, 2.50, 3.50)
4.	Very low influence (VL)	(0.00, 1.50, 2.50)
5.	No influence (No)	(0.00, 0.00, 1.50)

Source: Vasiljevic et al, (2018).

Step 6. The calculation of the final values of criteria functions (Q_i) by alternatives. The values of criteria functions are obtained by summing the gap (g_{ij}) by alternatives, that is, by summing the elements of matrix (G) by columns, Eq. (23):

$$Q_i = \sum_{j=1}^{n} g_{ij}, \ \ i = 1, 2, \dots, m \tag{23}$$

where n is the total number of criteria, and m is the total number of the alternatives being selected.

3. Selection of a location for the development of multimodal logistics centre based on the DEMATEL–MAIRCA method

This paper has focused on the selection of a multimodal LC location, linking three modes of transportation (river, railway and road transportation). As an example, eight potential locations for the development of the multimodal LC have been considered in Serbia, along the Danube River (Transportation Corridor VII). Having analysed the above-mentioned literature, the characteristics of the multimodal LC and the logistic trends, the authors identified 11 criteria against which to select the LC location: Connectivity to Multimodal Transport (CMT), Estimate of Infrastructure Development (EID), Environmental Impact (EI), Conformity With Spatial Planning Policy and Economic Growth Strategy (CSPPEGS), Gravitating Intermodal Transport Units (GITU), Reload LC Capacity (RC), Area Available for LC Development and Capacity Expansion (AADCE), Distance Between the User and the LC (DBULC), Transportation Safety (TS), Length of the Railway Reload Front (RRF), and Estimated Quality of Transportation Access to Internal Transport (EQTAIT).

A total of eight locations along the Danube River were discussed for the LC development. Eight experts took part in the research, defining the weights of the criteria based on the DEMATEL method.

In Step 1 of the DEMATEL method, a fuzzy scale (Camparo, 2013; Li, 2013), Table 1, is used to evaluate the criteria.

The collected questionnaires produced a total of eight average matrices $\widetilde{Z} = [\widetilde{z}_{ij}]_{C_i \times C_i}$. The expert opinions were aggregated using Eqs. (1), (2) and (3). After the aggregation of expert opinions, the unique average matrix $\widetilde{Z}$ (Table 2) was obtained.

The elements of the initial direct-relation matrix $\widetilde{D}$ are defined using Eq. (5). The elements of matrix $\widetilde{D}$ are normalised by dividing each element of the matrix $\widetilde{Z}$ by the value $\widetilde{R}$ obtained using formula (6).

Table 2. Average matrix.

	CSPPEGS	EID	EI	GITU	RRF	DBULC	TS	EQTAIT	CMT	RC	AADCE
CSPPEGS	(0.0,0.0,0.0)	(2.5,3.3,4.5)	(1.5,4.5,5.0)	(1.5,2.2,3.5)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(1.5,2.5,4.5)	(0.0,0.0,0.0)	(2.5,3.6,4.5)	(2.5,3.5,4.5)
EID	(3.5,4.6,5.0)	(0.0,0.0,0.0)	(0.0,2.3,3.5)	(0.0,2.1,2.5)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,1.1,1.5)	(1.5,2.7,4.5)	(1.5,3.7,4.5)
EI	(3.5,4.2,5.0)	(3.5,4.8,5.0)	(0.0,0.0,0.0)	(3.5,4.3,5.0)	(1.5,2.9,4.5)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,1.6,2.5)	(0.0,1.4,3.5)	(2.5,2.6,3.5)
GITU	(1.5,2.7,3.5)	(3.5,3.6,4.5)	(2.5,3.6,4.5)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(2.5,2.7,3.5)	(2.5,2.9,5.0)	(1.5,3.4,4.5)
RRF	(3.5,4.1,5.0)	(3.5,4.4,5.0)	(3.5,4.1,4.5)	(3.5,4.1,4.5)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(1.5,1.6,3.5)	(2.5,3.8,5.0)	(2.5,3.7,5.0)
DBULC	(3.5,4.4,5.0)	(3.5,4.4,5.0)	(3.5,4.6,5.0)	(3.5,4.3,5.0)	(1.5,2.6,3.5)	(0.0,0.0,0.0)	(2.5,3.5,3.5)	(2.5,3.5,5.0)	(1.5,2.3,3.5)	(3.5,4.1,4.5)	(1.5,2.6,4.5)
TS	(3.5,4.6,5.0)	(3.5,4.6,5.0)	(3.5,4.6,5.0)	(3.5,4.1,4.5)	(3.5,4.4,5.0)	(1.5,2.3,3.5)	(0.0,0.0,0.0)	(0.0,2.5,3.5)	(0.0,1.7,2.5)	(3.5,4.3,4.5)	(0.0,2.4,3.5)
EQTAIT	(2.5,3.5,4.5)	(1.5,3.7,5.0)	(2.5,3.3,4.5)	(3.5,4.2,4.5)	(1.5,3.7,5.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(3.5,4.3,5.0)	(3.5,4.3,4.5)
CMT	(3.5,4.5,5.0)	(3.6,4.2,4.8)	(3.5,4.4,5.0)	(3.5,4.3,5.0)	(3.5,4.6,5.0)	(3.5,4.1,4.5)	(3.5,4.2,5.0)	(3.5,4.5,5.0)	(0.0,0.0,0.0)	(3.5,4.4,5.0)	(1.5,2.4,3.5)
RC	(0.0,1.7,2.5)	(1.5,2.6,3.5)	(1.5,2.3,4.5)	(0.0,2.2,2.5)	(0.0,2.2,2.5)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,1.2,3.5)	(0.0,1.9,4.5)	(0.0,0.0,0.0)	(1.5,3.7,5.5)
AADCE	(1.5,1.6,2.5)	(2.5,2.4,3.5)	(1.5,2.1,2.5)	(1.5,2.7,3.5)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,0.0,0.0)	(0.0,2.6,3.5)	(0.0,0.0,0.0)

Source: Provided by authors - from calculations.

Table 3. Defuzzified total-relation matrix (T).

	CSPPEGS	EID	EI	GITU	RRF	DBULC	TS	EQTAIT	CMT	RC	AADCE
CSPPEGS	0.069	0.158	0.170	0.124	0.029	0.003	0.003	0.073	0.028	0.144	0.157
EID	0.161	0.066	0.120	0.115	0.024	0.007	0.007	0.022	0.061	0.112	0.147
EI	0.181	0.187	0.083	0.177	0.083	0.008	0.008	0.024	0.070	0.109	0.139
GITU	0.125	0.157	0.152	0.066	0.029	0.010	0.010	0.023	0.083	0.116	0.152
RRF	0.197	0.205	0.199	0.194	0.035	0.009	0.009	0.028	0.077	0.167	0.183
DBULC	0.252	0.262	0.255	0.248	0.127	0.019	0.104	0.135	0.115	0.238	0.206
TS	0.244	0.254	0.247	0.240	0.164	0.071	0.017	0.102	0.095	0.230	0.199
EQTAIT	0.176	0.185	0.180	0.175	0.119	0.004	0.005	0.023	0.038	0.185	0.202
CMT	0.281	0.292	0.284	0.277	0.187	0.125	0.129	0.164	0.070	0.265	0.232
RC	0.108	0.131	0.127	0.125	0.085	0.008	0.008	0.057	0.064	0.062	0.155
AADCE	0.077	0.099	0.096	0.094	0.014	0.002	0.002	0.010	0.018	0.090	0.042

Source: Provided by authors - from calculations.

Table 4. Criterion weights (w_i).

	D_i	R_i	$D_i + R_i$	$D_i - R_i$	W_i	w_i
CSPPEGS	0.80	1.79	2.60	−0.99	2.78	0.097
EID	0.70	2.00	2.69	−1.30	2.99	0.105
EI	0.93	1.82	2.75	−0.89	2.89	0.101
GITU	0.77	1.74	2.51	−0.97	2.69	0.094
RRF	1.12	0.90	2.02	0.22	2.03	0.071
DBULC	1.76	0.27	2.02	1.49	2.51	0.088
TS	1.66	0.30	1.97	1.36	2.39	0.084
EQTAIT	1.09	0.66	1.75	0.43	1.80	0.063
CMT	2.08	0.72	2.80	1.36	3.11	0.109
RC	0.77	1.72	2.49	−0.94	2.67	0.094
AADCE	0.50	1.81	2.32	−1.31	2.66	0.093

Source: Provided by authors - from calculations.

Table 5. Fuzzy scale for the evaluation of alternatives.

NO.	LINGUISTIC TERMS	LINGUISTIC VALUES
1.	Very good (VG)	(4.5,5,5)
2.	Good (G)	(3.5,4,4.5)
3.	Fair (F)	(2.5,3,3.5)
4.	Poor (P)	(1.5,2,2.5)
5.	Very poor (VP)	(1,1,1)

Source: Pamucar and Cirovic (2015).

Equation (7) produces the elements of the total-relation matrix ($\widetilde{T}$). The elements of matrix $\widetilde{T}$ (Table 3) are summed by rows ($\widetilde{G}_i$) and columns ($\widetilde{R}_i$) using formulas (9) and (10), respectively. Based on the sum of values by rows and columns, formulas (11) and (12) give us the criterion weights. Equation (24) defuzzifies the fuzzy numbers obtained from Eqs. (9), (10), (11) and (12).

$$A = \left[\left(a^{(r)} - a^{(l)}\right) + \left(a^{(s)} - a^{(l)}\right)\right] \cdot 1/3 + a^{(l)} \tag{24}$$

where $a^{(l)}$ and $a^{(r)}$represent the left and right limit of the fuzzy number, respectively, and $a^{(m)}$ is the value at which the triangular function reaches the maximum.

Table 4 presents the summed values of the matrix T by rows (D_i) and columns (R_i) and the criterion weights (w_i).

After the calculation of criterion weights (w_i), the alternatives are evaluated (Table 6) and selected based on the MAIRCA method. To evaluate the alternatives by the qualitative criteria, a fuzzy scale was used (Camparo, 2013), Table 5.

Table 6. Evaluation of locations for the development of multimodal LC by the Danube River.

	CRITERIA										
ALTERNATIVE	CMT *(max)*	EID *(max)*	EI *(min)*	CSPPEGS *(max)*	GITU *(max)*	RC *(max)*	AADCE *(max)*	DBULC *(min)*	TS *(max)*	RRF *(max)*	EQTAIT *(max)*
LC 1	G	71%	G	F	45000	150	1056	P	4	478	G
LC 2	G	85%	G	G	58000	145	2680	P	VG	564	G
LC 3	G	76%	G	G	56000	135	1230	P	G	620	F
LC 4	F	74%	P	G	42000	160	1480	G	F	448	VG
LC 5	VG	82%	F	VG	62000	183	1350	P	G	615	G
LC 6	G	81%	F	VG	60000	178	2065	P	F	580	G
LC 7	G	80%	F	VG	59000	160	1650	F	VG	610	G
LC 8	F	82%	G	G	54000	120	2135	F	G	462	VG

Source: Provided by authors - from calculations.

Table 7. Theoretical ratings matrix T_p.

	CRITERIA										
ALTERNATIVE	CMT	EID	EI	CSPPEGS	GITU	RC	AADCE	DBULC	TS	RRF	EQTAIT
LC 1	0.0136	0.0131	0.0126	0.0121	0.0117	0.0117	0.0116	0.0110	0.0105	0.0089	0.0079
LC 2	0.0136	0.0131	0.0126	0.0121	0.0117	0.0117	0.0116	0.0110	0.0105	0.0089	0.0079
LC 3	0.0136	0.0131	0.0126	0.0121	0.0117	0.0117	0.0116	0.0110	0.0105	0.0089	0.0079
LC 4	0.0136	0.0131	0.0126	0.0121	0.0117	0.0117	0.0116	0.0110	0.0105	0.0089	0.0079
LC 5	0.0136	0.0131	0.0126	0.0121	0.0117	0.0117	0.0116	0.0110	0.0105	0.0089	0.0079
LC 6	0.0136	0.0131	0.0126	0.0121	0.0117	0.0117	0.0116	0.0110	0.0105	0.0089	0.0079
LC 7	0.0136	0.0131	0.0126	0.0121	0.0117	0.0117	0.0116	0.0110	0.0105	0.0089	0.0079
LC 8	0.0136	0.0131	0.0126	0.0121	0.0117	0.0117	0.0116	0.0110	0.0105	0.0089	0.0079

Source: Provided by authors - from calculations.

In Table 6 the criteria are categorised; *max* stands for the benefit-type criteria (higher values are preferable), and *min* stands for the cost-type criteria (lower values are preferable).

After the formulation of the initial decision-making matrix (X), Table 6, the preferences for the alternatives P_{A_i} were defined:

$$P_{A_i} = \frac{1}{m} = \frac{1}{8} = 0.125$$

The calculation of the elements of the theoretical ratings matrix (T_p), Table 7, is the result of Equation (15). The following formula defines the element of the theoretical ratings matrix on the position t_{p32}:

$$t_{p32} = P_{A_3} \cdot w_2 = 0.125 \cdot 0.105 = 0.0131$$

After forming the theoretical ratings matrix (T_p), the real ratings matrix (T_r) is calculated. The elements of the real ratings matrix (Table 8) are calculated by multiplying the elements of the theoretical ratings matrix (T_p) and normalised elements of the initial decision-making matrix (X). The elements of the initial decision-making matrix are normalised using formulas (19) and (20). The element of the real ratings matrix on the position t_{r32} is defined based on formula (19):

$$t_{r32} = t_{pij} \cdot \left(\frac{x_{ij} - x_i^-}{x_i^+ - x_i^-} \right) = 0.0131 \cdot \left(\frac{76-71}{85-71} \right) = 0.0047$$

Table 8. Real ratings matrix T_r.

	CRITERIA										
ALTERNATIVE	CMT	EID	EI	CSPPEGS	GITU	RC	AADCE	DBULC	TS	RRF	EQTAIT
LC 1	0.0068	0.0000	0.0000	0.0000	0.0018	0.0056	0.0000	0.0110	0.0052	0.0015	0.0039
LC 2	0.0068	0.0131	0.0000	0.0061	0.0094	0.0047	0.0116	0.0110	0.0105	0.0060	0.0039
LC 3	0.0068	0.0047	0.0000	0.0061	0.0082	0.0028	0.0012	0.0110	0.0052	0.0089	0.0000
LC 4	0.0000	0.0028	0.0126	0.0061	0.0000	0.0075	0.0030	0.0000	0.0000	0.0000	0.0079
LC 5	0.0136	0.0103	0.0063	0.0121	0.0117	0.0117	0.0021	0.0110	0.0052	0.0086	0.0039
LC 6	0.0068	0.0094	0.0063	0.0121	0.0106	0.0108	0.0072	0.0110	0.0000	0.0068	0.0039
LC 7	0.0068	0.0084	0.0063	0.0121	0.0100	0.0075	0.0042	0.0055	0.0105	0.0084	0.0039
LC 8	0.0000	0.0103	0.0000	0.0061	0.0070	0.0000	0.0077	0.0055	0.0052	0.0007	0.0079

Source: Provided by authors - from calculations.

Table 9. Total gap matrix.

	CRITERIA										
ALTERNATIVE	CMT	EID	EI	CSPPEGS	GITU	RC	AADCE	DBULC	TS	RRF	EQTAIT
LC 1	0.0068	0.0131	0.0126	0.0121	0.0100	0.0061	0.0116	0.0000	0.0052	0.0073	0.0039
LC 2	0.0068	0.0000	0.0126	0.0061	0.0023	0.0071	0.0000	0.0000	0.0000	0.0029	0.0039
LC 3	0.0068	0.0084	0.0126	0.0061	0.0035	0.0089	0.0104	0.0000	0.0052	0.0000	0.0079
LC 4	0.0136	0.0103	0.0000	0.0061	0.0117	0.0043	0.0086	0.0110	0.0105	0.0089	0.0000
LC 5	0.0000	0.0028	0.0063	0.0000	0.0000	0.0000	0.0095	0.0000	0.0052	0.0003	0.0039
LC 6	0.0068	0.0037	0.0063	0.0000	0.0012	0.0009	0.0044	0.0000	0.0105	0.0021	0.0039
LC 7	0.0068	0.0047	0.0063	0.0000	0.0018	0.0043	0.0074	0.0055	0.0000	0.0005	0.0039
LC 8	0.0136	0.0028	0.0126	0.0061	0.0047	0.0117	0.0039	0.0055	0.0052	0.0081	0.0000

Source: Provided by authors - from calculations.

The elements of the total gap matrix (G) are calculated as a difference (gap) between theoretical ratings (t_{pij}) and real ratings (t_{rij}). Equation (21) gives the final total gap matrix, Table 9. The element of the total gap matrix on the position g_{32} is determined by Equation (22).

$$g_{22} = t_{p32} - t_{r32} = 0.0131 - 0.0047 = 0.0084$$

The gap for the alternative A_3 by criterion EID is $g_{32} = 0.0084$. By criterion EID, the ideal alternative is made conditional on $t_{pi2} = t_{ri2}$, i.e. $g_{i2} = 0.00$. For the anti-ideal alternative by criterion EID, the condition is $t_{ri2} = 0$, i.e. $g_{i2} = t_{pi2}$. The conclusion is that alternative A_3, by criterion PIF, is not the best (ideal) alternative (A_i^+). In addition, alternative A_3 is closer to the ideal alternative than to the anti-ideal alternative, because the distance from the ideal alternative is $g_{32} = 0.0084$.

The values of criteria functions (Q_i) by alternatives (Table 10) is the sum of the gaps (g_{ij}) by alternatives, i.e., the sum of the matrix elements (G) by columns, Equation (23).

Preferably, the alternative should have the lowest possible value of the total gap (alternative no. 5).

4. Sensitivity analysis

The sensitivity analysis of the MAIRCA method is carried out in three steps. Step 1 analyses the stability of a solution, while the weights of the criteria and degrees of preference for specific alternatives are varied. Step 2 analyses the stability of a solution depending on the change of a scale representing the values of individual criteria.

Table 10. The alternatives ranked by the MAIRCA method.

ALTERNATIVE	Q	RANK
LC 1	0.0889	8
LC 2	0.0417	4
LC 3	0.0698	5
LC 4	0.0849	7
LC 5	0.0281	1
LC 6	0.0398	2
LC 7	0.0411	3
LC 8	0.0743	6

Source: Provided by authors - from calculations.

The last, Step 3, analyses the stability of the results depending on the criteria formulation.

Phase 1. Stability of MAIRCA solutions at varying criteria weights and degrees of preference

The results of MCDM methods largely depend on the relative importance we assign to individual criteria. The sensitivity analysis is presented under 14 scenarios (Table 11). In the first eight, certain criteria were favoured, while the preference for all the alternatives was the same ($P_{A_i} = 0.125$). In scenarios S9, S10, S11 and S12, the criteria weights remained unchanged, but the preferences for alternatives were changed. In other words, under scenarios S9, S10, S11 and S12 certain alternatives were favoured to determine the advantage a favoured alternative has over the next one.

The preference for a favoured alternative P_{A_α} is calculated using Equation (25):

$$P_{A_\alpha} = \frac{1 - \alpha_{A_i}}{m - \alpha_{A_i}} \tag{25}$$

where α_{A_i} is the degree of preference for the favoured alternative and m is the total number of alternatives.

The preferences for the alternatives that have not been favoured are defined by Eq. (26):

$$P_{A_i} = \frac{1 - P_{A_\alpha}}{m - 1} \tag{26}$$

where P_{A_α} is the preference for the favoured alternative and m is the total number of alternatives.

The resulting rankings are given in Table 12. The results show that assigning different weights to the criteria changes the rank of alternatives. In addition, varying preferences for individual alternatives have also changed the alternative rankings. The conclusion is that the model is sensitive to any change of preference for alternatives and to varying criteria weights. A comparison between the top-ranked alternatives under Scenarios 1–12 and the results displayed in Table 10 shows that the two first-ranked alternatives do not change under most of the scenarios. Slight changes occur under Scenarios 6, 7 and 10. Besides, Scenario 10 shows that the first-ranked alternative (LC 5) is better than the second-ranked alternative (LC 6) by 30%. The analysis can serve to confirm the ranks obtained in Table 10, and for the selection of the optimal alternative (LC 5).

Table 11. Scenarios with varying criteria weights and preferences for certain alternatives.

	CRITERION WEIGHTS										
SCENARIOS	CMT	EID	EI	CSPPEGS	GITU	RC	AADCE	DBULC	TS	RRF	EQTAIT
Scenario 1 $w_1 = w_2 = \ldots w_{11}$	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Scenario 2 $w_1 > w_2 = \ldots w_{11}$	0.350	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065
Scenario 3 $w_2 > w_1 = \ldots w_{11}$	0.068	0.320	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068
Scenario 4 $w_3, w_4 > w_1 = \ldots w_{11}$	0.067	0.067	0.200	0.200	0.067	0.067	0.067	0.067	0.066	0.066	0.066
Scenario 5 $w_5, w_6 > w_1 = \ldots w_{11}$	0.056	0.056	0.056	0.056	0.250	0.250	0.056	0.055	0.055	0.055	0.055
Scenario 6 $w_7, w_8 > w_1 = \ldots w_{11}$	0.067	0.067	0.067	0.067	0.067	0.067	0.200	0.200	0.066	0.066	0.066
Scenario 7 $w_9, w_{10} > w_1 = \ldots w_{11}$	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.350	0.200	0.050
Scenario 8 $w_{11} > w_1 = \ldots w_{10}$	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.350
Advantage of the alternative LC 6 – 29% ($\alpha_{LC4} = 0.29$)	0.109	0.105	0.101	0.097	0.094	0.094	0.093	0.088	0.084	0.071	0.063
Advantage of the alternative LC 6 – 30% ($\alpha_{LC4} = 0.30$)	0.109	0.105	0.101	0.097	0.094	0.094	0.093	0.088	0.084	0.071	0.063
Advantage of the alternative LC 7 – 3.2% ($\alpha_{LC4} = 0.032$)	0.109	0.105	0.101	0.097	0.094	0.094	0.093	0.088	0.084	0.071	0.063
Advantage of the alternative LC 2 – 1.4% ($\alpha_{LC4} = 0.014$)	0.109	0.105	0.101	0.097	0.094	0.094	0.093	0.088	0.084	0.071	0.063

Source: Provided by authors - from calculations.

Table 12. Alternative rankings under different scenarios.

	SCENARIOS/RANK											
ALTERNATIVE	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
LC 1	8	6	8	8	6	7	7	7	8	8	8	8
LC 2	4	4	2	4	4	1	2	4	4	4	4	4
LC 3	5	5	6	6	5	5	4	8	5	5	5	5
LC 4	7	8	7	5	8	8	8	6	7	7	7	7
LC 5	1	1	1	1	1	2	3	1	1	2	1	1
LC 6	3	3	3	2	2	3	5	3	2	1	3	2
LC 7	2	2	4	3	3	4	1	2	3	3	2	3
LC 8	6	7	5	7	7	6	6	5	6	6	6	6

Source: Provided by authors - from calculations.

Table 13. Scales S1 and S2.

NO.	LINGUISTIC TERMS	S1	S2
1.	Very good (VG)	(4.5,5,5)	(8,9,9)
2.	Good (G)	(3.5,4,4.5)	(6,7,8)
3.	Fair (F)	(2.5,3,3.5)	(4,5,6)
4.	Poor (P)	(1.5,2,2.5)	(2,3,4)
5.	Very poor (VP)	(1,1,1)	(1,1,1)

Source: Provided by authors.

On the other hand, the sensitivity of MCDM methods to varying criterion weights does not provide sufficient information to decide how reliable the MCDM method results are. The literature (Anojkumar, Ilangkumaran, & Sasirekha, 2014) offers comparative analyses by the authors trying to detect the characteristics of the selection problem that generate the equality of, or differences in, the solutions of individual MCDM methods. However, the same choice suggested by different methods cannot guarantee the rationality and quality of the given solution.

The next section deals with the problem of objective assessment of the solutions resulting from the COPRAS, MOORA, PROMETHEE, TOPSIS, ELECTRE and MAIRCA methods, using two conditions the sensitivity analysis is based on. One is the analysis of consistency of results of the above-listed MCDM methods, depending on a varying unit of measurement in which the values of individual criteria are expressed. The other condition is the analysis of the consistency of results, depending on the formulation of criteria, if the same criterion can be expressed in two normatively equivalent ways. Illustrative examples show that some of the methods cannot meet these requirements.

Phase 2. Independence of value scale

The independence of value scale (IVS) criterion has been applied in the normative theory of decision-making under risk and uncertainty (French, 1988). In this paper the IVS condition is adjusted to the analysis of the consistency of solutions resulting from the assorted MCDM methods (COPRAS, MOORA, PROMETHEE, TOPSIS and MAIRCA).

The IVS of the results of an MCDM method means that the results we obtained from an MCDM method do not depend on the unit of measurement in which we have expressed the value of any criterion, on condition that the different units of measurement of the given criteria are interconnected by a linear transformation or a positive affine transformation. For the purposes of this analysis, the initial scale (Table 5) has been modified, generating another scale (Scale 2), linked with Scale 1

Table 14. IVS – rankings of alternatives.

ALTERNATIVE	COPRAS				TOPSIS				MOORA				PROMETHEE				MAIRCA			
	S1		S2		S1		S2		S1		S2		S1		S2		S1		S2	
LC 1	81.26	8	79.89	7	0.3871	7	0.4141	7	0.1824	8	0.1819	7	−0.4198	8	−0.4198	8	0.0889	8	0.0889	8
LC 2	97.74	3	96.70	3	0.6328	2	0.6230	3	0.2450	2	0.2465	3	0.1920	4	0.1920	4	0.0417	4	0.0417	4
LC 3	85.98	5	84.63	5	0.4339	6	0.4550	5	0.2005	5	0.2003	5	−0.2164	5	−0.2164	5	0.0698	5	0.0698	5
LC 4	81.57	7	79.46	8	0.3796	8	0.3823	8	0.1836	7	0.1805	8	−0.3529	7	−0.3529	7	0.0849	7	0.0849	7
LC 5	100.0	1	100.0	1	0.6039	3	0.6252	2	0.2528	1	0.2575	1	0.5097	1	0.5097	1	0.0281	1	0.0281	1
LC 6	97.96	2	97.34	2	0.6329	1	0.6340	1	0.2445	3	0.2467	2	0.2844	2	0.2844	2	0.0398	2	0.0398	2
LC 7	95.19	4	94.15	4	0.5567	4	0.5607	4	0.2359	4	0.2375	4	0.2370	3	0.2370	3	0.0411	3	0.0411	3
LC 8	85.76	6	83.88	6	0.4350	5	0.4247	6	0.1973	6	0.1945	6	−0.2339	6	−0.2339	6	0.0743	6	0.0743	6

Source: Provided by authors - from calculations.

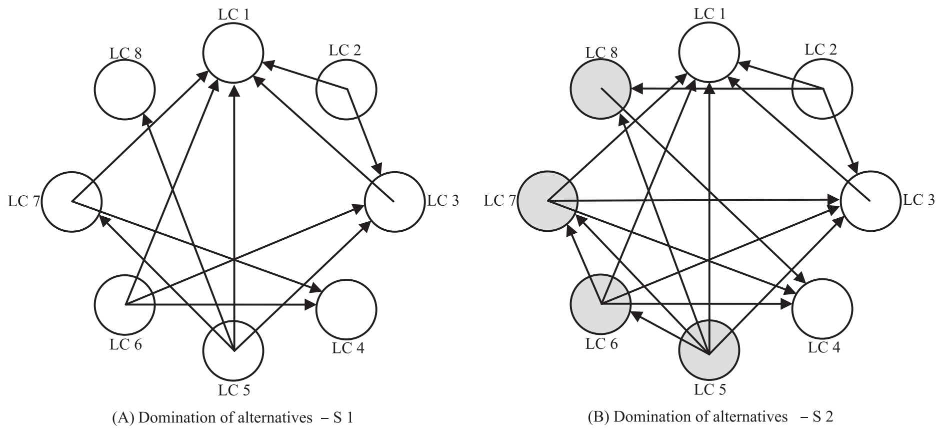

Figure 2. IVS – ELECTRE method. Source: Provided by authors - from calculations.

with a positive affine transformation ($y = 2x-1$). Scale 1 (S1) and Scale 2 (S2) are shown in Table 13.

Scale S2 is used to describe the qualitative criteria CMT, EI, CSPPEGS, DBULC, TS and EQTAIT. A comparison was then made between the results of the MCDM methods (rankings of the alternatives) that were obtained using S1 and S2. The criteria weights were not changed. The sensitivity (consistency) of the alternative rankings to a varying value scale is shown in Table 14. The consistency of rankings by the ELECTRE method is displayed in Figure 2.

The analysis of the results presented in Table 14 and Figure 2 shows that the methods COPRAS, TOPSIS, MOORA and ELECTRE do not give consistent solutions. These methods demonstrate inconsistency of the rankings, i.e., dependence of the final alternative rankings on a change to the value scale. The methods PROMETHEE and MAIRCA provide for consistent solutions. The method ELECTRE demonstrates a change in domination at four alternatives (LC 5, LC 6, LC 7 and LC 8). In Figure 2b the grey colour marks the alternatives that recorded change in domination under the ELECTRE method.

The results indicate that the methods COPRAS, TOPSIS, MOORA and ELECTRE do not satisfy the IVS condition. On the other hand, the results of the PROMETHEE and MAIRCA methods do not change if the value scale changes.

Phase 3. Independence of criteria formulation

The independence of criteria formulation (ICF) condition is modelled after the descriptive invariability condition, which in the behavioural theory of decision-making is defined as the rationality of choice by an individual decision-maker (Kahneman & Tversky, 1981). If there is more than one way to present the alternatives, and if these ways are normatively equivalent, a rational individual's preferences to these alternatives should not depend on the selected formulation, i.e., they should be independent of the so-called frame.

If this level of rationality is required from the individual decision-maker, it is only logical that the MCDM methods we use to support rational decision-making should satisfy the same condition. As some criteria can be presented in both frames (benefit-and cost-related), the benefit formulation (benefit-type criteria) will be treated as the 'positive frame' and the cost formulation (cost-type criteria) as the 'negative frame'. In addition, the results of an MCDM method should be resistant to the changes in the formulation of these criteria.

This research has identified three criteria that can be presented in two normatively equivalent ways, i.e., as benefit-type and cost-type criteria. These are EID, RC and RRF.

The EID is expressed in the percentages describing the estimated levels of infrastructure development. Accordingly, the EID can be expressed as a benefit-type criterion (a degree of infrastructure development expressed as a percentage, X^{+}) and as a cost-type criterion (a degree of infrastructure underdevelopment expressed as a percentage, X^{-}). As the percentages of infrastructure development and infrastructure underdevelopment add to 100% ($X^{+} + X^{-} = 100\%$), the two formulations are normatively equivalent.

The RC criterion can be expressed as a benefit-type criterion (the maximum number of ITUs that can be reloaded within an hour, ITU/h), and as a cost-type criterion (the time needed for ITU reload). The numerical values of the two formulations are connected with the function $X^{-} = 60/X^{+}$, where X^{+} is the maximum number of ITUs that can be reloaded within an hour (ITU/h), while $X^{-}$is the time needed to reload one ITU (min/ITU).

The RRF criterion. The maximum required length of a railway reload front is 720 m. Based on this information, the RRF can be expressed as a benefit-type criterion (the existing length of the railway reload front, X^{+}), and as a cost-type criterion (the missing length of the railway reload front, X^{-}). As the existing length of the railway reload front and the missing length of the railway reload front add up to 720 ($X^{+} + X^{-} = 720$).

As shown, the EID and RRF criteria can be observed as special cases of the affine transformation. As these are the special cases of the affine transformation explained in the previous section (*Phase 2. independence of value scale*) the change of EID and RRF criteria formulation won't be considered independently. Scenario 1 will focus on the independent effect of different formulations of the RC criteria on the consistency of the results provided by MCDM methods. Scenarios 2, 4 and 6 will address the impact of changes of the RC criteria formulations on the consistency of the MCDM method results with the simultaneous change of EID or RRF criteria formulation.

Seven scenarios have been considered in this analysis. The description and results of the scenarios are presented in the following part of the paper.

Scenario 1. MCDM results were compared when the RC criterion was presented as a benefit-type criterion (Scale 1, S1), and as a cost-type criterion (Scale 1, S1). The values of the other criteria remained unchanged (Table 6). The results of the consistency of the MCDM methods based on the condition from Scenario 1 are presented in Table 15.

Scenario 2. The MCDM results were compared when the EID and RC criteria were presented as cost-type criteria (Scale 2, S2). The values of the other criteria remained unchanged (Table 6). The results were compared to those obtained when the EID and RC criteria were presented as benefit-type criteria (Scale 1, S1). The consistency results under the Scenario 2 are presented in Table 16.

Table 15. ICF Scenario 1 – rankings of alternatives.

ALTERNATIVE	COPRAS S1		COPRAS S2		TOPSIS S1		TOPSIS S2		MOORA S1		MOORA S2		PROMETHEE S1		PROMETHEE S2		MAIRCA S1		MAIRCA S2	
LC 1	81.26	8	81.27	8	0.3871	7	0.3920	7	0.1824	8	0.1171	8	−0,4198	8	−0,4198	8	0.0889	8	0.0821	8
LC 2	97.74	3	97.73	3	0.6328	2	0.6366	1	0.2450	2	0.1796	2	0,1920	4	0,1920	4	0.0417	4	0.0379	4
LC 3	85.98	5	85.91	5	0.4339	6	0.4362	5	0.2005	5	0.1347	5	−0,2164	5	−0,2164	5	0.0698	5	0.0645	5
LC 4	81.57	7	81.50	7	0.3796	8	0.3855	8	0.1836	7	0.1182	7	−0,3529	7	−0,3529	7	0.0849	7	0.0786	7
LC 5	100.0	1	100.0	1	0.6039	3	0.6053	3	0.2528	1	0.1863	1	0,5097	1	0,5097	1	0.0281	1	0.0263	1
LC 6	97.96	2	97.96	2	0.6329	1	0.6350	2	0.2445	3	0.1784	3	0,2844	2	0,2844	2	0.0398	2	0.0370	2
LC 7	95.19	4	95.14	4	0.5567	4	0.5616	4	0.2359	4	0.1705	4	0,2370	3	0,2370	3	0.0411	3	0.0376	3
LC 8	85.76	6	85.74	6	0.4350	5	0.4331	6	0.1973	6	0.1301	6	−0,2339	6	−0,2339	6	0.0743	6	0.0696	6

Source: Provided by authors - from calculations.

Table 16. ICF Scenario 2 – rankings of alternatives.

ALTERNATIVE	COPRAS S1		COPRAS S2		TOPSIS S1		TOPSIS S2		MOORA S1		MOORA S2		PROMETHEE S1		PROMETHEE S2		MAIRCA S1		MAIRCA S2	
LC 1	81.26	8	76.74	8	0.3871	7	0.3922	7	0.1824	8	0.0333	8	−0,4198	8	−0,4198	8	0.0889	8	0.0877	8
LC 2	97.74	3	97.60	2	0.6328	2	0.6486	1	0.2450	2	0.1154	2	0,1920	4	0,1920	4	0.0417	4	0.0405	4
LC 3	85.98	5	82.71	6	0.4339	6	0.4491	6	0.2005	5	0.0575	6	−0,2164	5	−0,2164	5	0.0698	5	0.0689	5
LC 4	81.57	7	77.05	7	0.3796	8	0.3750	8	0.1836	7	0.0355	7	−0,3529	7	−0,3529	7	0.0849	7	0.0838	7
LC 5	100.0	1	100.0	1	0.6039	3	0.6380	3	0.2528	1	0.1215	1	0,5097	1	0,5097	1	0.0281	1	0.0281	1
LC 6	97.96	2	96.87	3	0.6329	1	0.6423	2	0.2445	3	0.1099	3	0,2844	2	0,2844	2	0.0398	2	0.0395	2
LC 7	95.19	4	93.29	4	0.5567	4	0.5724	4	0.2359	4	0.1001	4	0,2370	3	0,2370	3	0.0411	3	0.0401	3
LC 8	85.76	6	83.20	5	0.4350	5	0.4572	5	0.1973	6	0.0578	5	−0,2339	6	−0,2339	6	0.0743	6	0.0743	6

Source: Provided by authors - from calculations.

Table 17. ICF Scenario 3 – rankings of alternatives.

ALTERNATIVE	COPRAS S1		COPRAS S2		TOPSIS S1		TOPSIS S2		MOORA S1		MOORA S2		PROMETHEE S1		PROMETHEE S2		MAIRCA S1		MAIRCA S2	
LC 1	81.26	8	75.68	7	0.3871	7	0.3995	6	0.1824	8	0.0615	7	−0,4198	8	−0,4198	8	0.0889	8	0.0877	8
LC 2	97.74	3	94.22	3	0.6328	2	0.6302	3	0.2450	2	0.1350	3	0,1920	4	0,1920	4	0.0417	4	0.0405	4
LC 3	85.98	5	84.08	5	0.4339	6	0.5042	5	0.2005	5	0.0943	5	−0,2164	5	−0,2164	5	0.0698	5	0.0689	5
LC 4	81.57	7	74.74	8	0.3796	8	0.3613	8	0.1836	7	0.0568	8	−0,3529	7	−0,3529	7	0.0849	7	0.0838	7
LC 5	100.0	1	100.0	1	0.6039	3	0.6508	1	0.2528	1	0.1503	1	0,5097	1	0,5097	1	0.0281	1	0.0281	1
LC 6	97.96	2	95.57	2	0.6329	1	0.6477	2	0.2445	3	0.1362	2	0,2844	2	0,2844	2	0.0398	2	0.0395	2
LC 7	95.19	4	93.15	4	0.5567	4	0.6009	4	0.2359	4	0.1308	4	0,2370	3	0,2370	3	0.0411	3	0.0401	3
LC 8	85.76	6	79.93	6	0.4350	5	0.3942	7	0.1973	6	0.0705	6	−0,2339	6	−0,2339	6	0.0743	6	0.0743	6

Source:Provided by authors - from calculations.

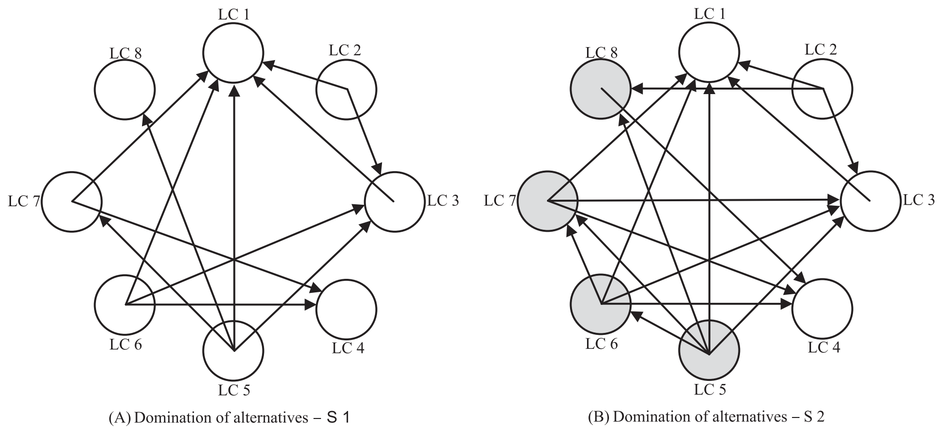

Figure 3. ICF Scenario 2 – ELECTRE method. Sources: Provided by authors - from calculations.

Table 18. Analysis of sensitivity of methods to the change of value scale and criteria formulation.

SCENARIO	COPRAS	TOPSIS	MOORA	PROMETHEE	MAIRCA	ELECTRE
IVS	x	x	x	✓	✓	x
ICF Scenario 1	✓	x	✓	✓	✓	✓
ICF Scenario 2	x	x	x	✓	✓	x
ICF Scenario 3	x	x	x	✓	✓	✓

Sources: Provided by authors - from calculations.

Scenario 3. The MCDM results were compared when the RC and RRF criteria were presented as cost-type criteria (Scale 2, S2). The values of the other criteria, just like under the previous scenarios, remained unchanged (Table 6). The results were compared to those obtained when the RC and RRF criteria were presented as benefit-type criteria (Scale 1, S1). The consistency results under the Scenario 3 terms are presented in Table 17.

The analyses presented in Tables 15–17 show that some methods do not retain consistency of results if the criteria are formulated in two normatively equivalent ways. The shaded parts of Tables 15–17 mark the inconsistent rankings.

Under Scenario 1 (Table 15), only the TOPSIS method shows inconsistency of rankings, while the other methods maintain consistency. In this scenario, a change in the sequence of top-ranked alternatives is recorded in the TOPSIS method. In addition to the top-ranked alternatives, the rankings of alternatives LC 3 and LC 8 also changed when the TOPSIS method is used. Under Scenario 1, aside from the TOPSIS method, all the others showed consistency of rankings.

Under Scenario 2 (Table 16), inconsistency of rankings occurred when the methods COPRAS, TOPSIS, MOORA and ELECTRE were used. The COPRAS method is the most inconsistent (displaying inconsistency in four rankings), whereas the MOORA and TOPSIS methods had two inconsistent rankings each. The other methods (PROMETHEE and MAIRCA) proved to be stable and maintained stability under this scenario.

Unlike the first three scenarios, where the ELECTRE method demonstrated stability, the same method showed changes in the domination of alternatives under

Scenario 2 (Figures 3a and 3b). The changes in the domination of alternatives that occurred under Scenario 2 are the same as in Phase 2 (Figures 2a and 2b).

Under Scenario 3 (Table 17), the TOPSIS method is the most inconsistent one (showed inconsistency of six rankings). Under this scenario the rankings of the top three alternatives changed when TOPSIS was used. This shows that the TOPSIS method considerably violates the consistency of rankings as the formulation of criteria changes.

It is noteworthy, however, that no change was recorded to the first-ranked alternative LC 5 under this scenario, when the COPRAS and MOORA methods were used. The methods PROMETHEE, ELECTRE and MAIRCA demonstrated stability of the solutions under Scenario 3.

The conclusion is that the methods COPRAS, TOPSIS, MOORA and ELECTRE are sensitive to a change to the criteria formulation (do not satisfy the ICF condition), whereas the PROMETHEE and MAIRCA do satisfy the ICF condition. Based on the presented analyses, the results were systematised as follows (Table 18).

In Table 18, symbol '*x*' indicates that the method does not satisfy the defined conditions of sensibility and symbol '✓' that it does.

Based on the results of the sensitivity analysis (Table 18), the solutions resulting from the MAIRCA and PROMETHEE methods are proven to be stable. Both methods recommend the first-ranked alternative LC 5.

The method ELECTRE demonstrates sensitivity to a change to the value scale under the ICF Scenario 2. However, the inconsistency of solutions that occurs when the ELECTRE method is used (Figures 2b and 3b) affects only the increasing dominance of first-ranked alternatives over the others. Such changes do not affect the change of an initial solution (Figures 2a and 3a), but confirm additionally the domination of first-ranked alternatives (LC 5 and LC 6) over the others.

The COPRAS and MOORA methods demonstrate sensitivity to a varying value scale and to the changing formulation of attributes. Inconsistency was recorded in seven of eight cases (Table 18). The inconsistency, however, didn't change the first-ranked alternative. In all cases, LC 5 was the first-ranked alternative.

When the TOPSIS method was used, the top-ranked alternatives changed in six of eight cases. It proves that TOPSIS significantly violates the consistency of rankings. Owing to this problem, the sequence of alternatives suggested by the TOPSIS method was not considered while making a final choice of the LC location.

As LC 5 was the first-ranked alternative when, MOORA, MAIRCA, ELECTRE and PROMETHEE were used, we can conclude that LC 5 is the optimal alternative.

5. Conclusion

This paper presents the application of the hybrid DEMATEL–MAIRCA model in a decision-making process aimed to select the location of a multimodal logistics centre (LC) by the Danube River (Transportation Corridor IX). The DEMATEL method was used to specify the weights of criteria, and a new multi-criteria method, MAIRCA, to value the alternatives and select the LC location. The application of the two methods was presented in consecutive steps and illustrated by examples.

After the MAIRCA method was applied, a sensitivity analysis was performed in three phases. In Phase 1, the stability of MAIRCA solutions was analysed, depending on varying criteria weights preferences for individual alternatives. In Phases 2 and 3, a consistency analysis was carried out and the results of several MCDM methods (COPRAS, TOPSIS, MOORA, PROMETHEE and ELECTRE) were compared. The results of these MCDM methods were compared to the results obtained when the MAIRCA method was used. Two conditions to provide for the rationality of a MCDM choice were made based on the consistency of final results. One is the consistency of MCDM results depending on changing the unit of measurement in which the values of individual criteria was expressed. The other is the analysis of consistency of the results depending on the formulation of criteria, if the same criteria can be presented in two normatively equivalent ways – as benefit- and cost-type criteria. Based on these results, COPRAS, TOPSIS, MOORA and ELECTRE were found not to satisfy between one and all five conditions, whereas MAIRCA and PROMETHEE showed consistency in all cases.

According to the results of the sensitivity analysis presented in this paper, it can be concluded that MAIRCA has a stable and well-structured analytical framework for ranking the alternatives. Relaying the presented application of MAIRCA method and sensitivity analysis that was conducted, the following advantages of MAIRCA can be singled out: (1) the method's mathematical framework remains the same regardless of the number of alternatives and criteria; (2) the possibility of MAIRCA application in a case of a large number of alternatives and criteria; (3) the clearly defined alternative rank presented by numerical value, enabling easier comprehension of results; (4) applicability to qualitative and quantitative criteria type; (5) the method takes into account the distance between ideal and anti-ideal solutions; and (6) the method gives stable solutions regardless of changes in the qualitative criteria measurement scale and changes in quantitative criteria formulation.

Apart from the application in LC location selection, MAIRCA can be used in other problems involving multi-criteria decision-making. The principal recommendation for further use of this method is a simple mathematical apparatus, consistency of solutions and the possibility of combining it with other methods, especially when criteria weights are to be specified.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

Anojkumar, L., Ilangkumaran, M., & Sasirekha, V. (2014). Comparative analysis of MCDM methods for pipe material selection in sugar industry. *Expert Systems with Applications*, *41*, 2964–2980.

Badi I., & Ballem, M. (2018). Supplier selection using rough BWM-MAIRCA model: A case study in pharmaceutical supplying in Libya. *Decision Making: Applications in Management and Engineering*, *1*(2), 15–32. doi:10.31181/dmame1802016b

Brimberg, J., Drezner, Z., Mladenović, N., & Salhi, S. (2014). A new local search for continuous location problems. *European Journal of Operational Research*, *232*(2), 256–265.

Camparo, J. (2013). A geometrical approach to the ordinal data of Likert scaling and attitude measurements: The density matrix in psychology. *Journal of Mathematical Psychology*, *57*, 29–42.

Chen S., & Liu, X. (2006). Factors and a method of selecting a site for a logistical centre. *Journal of Weinan Teachers College*, 3.

Dalalah, D., Hayajneh, M., & Batieha, F. (2011). A fuzzy multi-criteria decision making model for supplier selection. *Expert Systems with Applications*, *38*, 8384–8391.

Erlenkotter, D. (1978). A dual-based procedure for uncapacitated facility location. *Operations Research*, *26*(6), 992–1009.

French, S. (1988). *Decision theory - an introduction to the mathematics of rationality*. Chrichster: Ellis Horwood Ltd.

Han H, Li B, Wang K.F., & Shi Z (2016). Exploiting structural similarity of log files in fault diagnosis for web service composition. *CAAI Transactions on Intelligence Technology*, *1*(1), 61–71.

Janáček, J., & Buzna, L. (2008). An acceleration of Erlenkotter–Körkel's algorithms for the uncapacitated facility location problem. *Annals of Operations Research*, *164*(1), 97–109.

Ji, W., Tang, L., Li, D., Yang, W., & Liao, Q. (2016). Video-based construction vehicles detection and its application in intelligent monitoring system. *CAAI Transactions on Intelligence Technology*, *1*(2), 162–172.

Kahneman, D., & Tversky, A. (1981). The framing of decisions and the psychology of choice. *Science*, *211*(4481), 453–458.

Kannan G., Noorul Haq, P., & Sasikumar, P. (2008). An application of the analytical hierarchy process and Fuzzy analytical hierarchy process in the selection of collecting centre location for the reverse logistics multi-criteria decision-making supply chain model. *International Journal of Management and Decision Making*, *9*(4), 350–365.

Kracka, M., Brauers, W. K. M., & Zavadskas, E. K. (2010). Ranking heating losses in a building by applying the MULTIMOORA. *Inzinerine Ekonomika-Engineering Economics*, *21*(4), 352–359.

Li, Q. (2013). A novel Likert scale based on fuzzy sets theory. *Expert Systems with Applications*, *40*, 1609–1618.

Liu, Z., Wang, W., & Jin, Q. (2016c). Manifold alignment using discrete surface Ricci flow. *CAAI Transactions on Intelligence Technology*, *1*(3), 285–292.

Milosavljevic, M., Bursać, M. & Tričković, G. (2018). The selection of the railroad container terminal in Serbia based on multi criteria decision making methods. *Decision Making: Applications in Management and Engineering*, *1*(2), 1–14.

Mladenović, N., Brimberg, J., Hansen, P., & Moreno-Pérez, J. A. (2017). The p-median problem: A survey of metaheuristic approaches. *European Journal of Operational Research*, *179*(3), 927–939.

Ou, C.-W., & Chou, S.-Y. (2009). International distribution centre selection from a foreign market perspective using a weighted fuzzy factor rating system. *Expert System with Applications*, 36(2), 1773–1782.

Pamučar, D., & Ćirović, Y. (2015). The selection of transport and handling resources in logistics centres using Multi-Attributive Border Approximation area Comparison (MABAC). *Expert Systems with Applications*, *42*, 3016–3028. doi: 10.1016/j.eswa.2014.11.057

Petrović, I., & Kankaraš, M. (2018). DEMATEL-AHP multi-criteria decision making model for the selection and evaluation of criteria for selecting an aircraft for the protection of air traffic. *Decision Making: Applications in Management and Engineering*, 1(2), 91–108. doi: 10.31181/dmame1802091p

Qazi, K., Lam, H.K., Xiao, B., Ouyang, G., Yin, X. (2016). Classification of epilepsy using computational intelligence techniques. *CAAI Transactions on Intelligence Technology*, *1*(2), 137–149.

Rezaeiniya, N., Zolfani, S. H., & Zavadskas, E. K. (2012). Greenhouse locating based on ANP-COPRAS-G methods - an empirical study based on Iran. *International Journal of Strategic Property Management*, *16*(2), 188–200.

Sirikijpanichkul, A., & Ferreira, L. (2006). Modeling intermodal freight hub location decisions. 2006 IEEE International Conference on Systems,Man and Cybernetics, Oct. 8-11, Taipei, Taiwan.

Turskis, Z., Zavadskas, E. K., Antucheviciene, J., Kosareva, N. (2015). A Hybrid Model Based on Fuzzy AHP and Fuzzy WASPAS for Construction Site Selection. *International Journal of Computers Communications & Control*, 10(6), 873–888.

Vasiljevic, M., Fazlollahtabar, H., Stevic, Z., & Veskovic, S. (2018). A rough multicriteria approach for evaluation of the supplier criteria in automotive industry. *Decision Making: Applications in Management and Engineering*, *1*(1), 82–96. doi:10.31181/dmame180182v

Wan, L., Huang, Z., & Li, Z. (2007). Research of optimal Dijkstra algorithm in logistic center location based on GIS. *Application Research of Computers*, *8*(24), 289–291.

Wang, X., Li, L., Yuan, Y., Ye, P., & Wang, F. Y. (2016b). ACP-based social computing and parallel intelligence: Societies 5.0 and beyond. *CAAI Transactions on Intelligence Technology*, *1*(4), 377–393.

Xu, X., Law, R., Chen, W. & Tang, L. (2016a). Forecasting tourism demand by extracting fuzzy Takagi-Sugeno rules from trained SVMs. *CAAI Transactions on Intelligence Technology*, *1*(1), 30–42. http://dx.doi.org/10.1016/j.trit.2016.03.004

Xu, Y., Dong, J., Zhang, B., & Xu, D. (2016b). Background modeling methods in video analysis: A review and comparative evaluation. *CAAI Transactions on Intelligence Technology*, *1*(1), 43–60.

Yang, J., & Lee, H. (1997). An AHP decision model for facility location selection. *Facilities*, *15*(9/10), 241–254.

Yang, W., Sun, X., Deng, W., Zhang, C., Liao, Q. (2016). Fourier locally linear soft constrained MACE for facial landmark localization. *CAAI Transactions on Intelligence Technology*, *1*(3), 241–248.

Zavadskas, E.K., Turskis, Z., Bagočius, V. (2015). Multi-criteria selection of a deep-water port in the Eastern Baltic Sea. *Applied Soft Computing*, 26, 180–192.

Zecevic, S. (2006). *Cargo Terminals and Cargo Transport Centers, Faculty of Transportation*, Belgrade University.

Zhang, Q., Xie, Q., Wang, G. (2016). A survey on rough set theory and its applications. *CAAI Transactions on Intelligence Technology*, 1(4), 323–333.