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Evaluating the performance of suppliers based on using the R'AMATEL-MAIRCA method for green supply chain implementation in electronics industry

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A B S T R A C T

Green supply chain management (GSCM) practitioners striving to create a healthier environment should first identify the key criteria pertinent to the process of implementing the appropriate sustainable policies, particularly in the most rapidly growing electronics sector. Since the decision to adopt GSCM in electronics industry is associated with the use of a multi-dimensional approach involving a number of qualitative criteria, the paper examines GSCM based on fifteen criteria expressed in five dimensions and proposes a multi-criteria evaluation framework for selecting suitable green suppliers. In real life, the assessment of this decision is based on vague information or imprecise data of the expert's subjective judgements, including the feedback from the criteria and their interdependence. Thus to treat this uncertainty in multi-criteria decision making (MCDM) process, rough number (RN) is applied here using only the internal knowledge in the operative data available to the decision-makers. In this way objective imprecisions and uncertainties are used and there is no need to rely on models of assumptions. Instead of different external parameters in the application of RN, the structure of the given data is used. Therefore, the identified components are incorporated into a rough DEMATEL-ANP (R'AMATEL) method, combining the Decision Making Trial and Evaluation Laboratory Model (DEMATEL) and the Analytical Network Process (ANP) in a rough context. In group decision making, a rough number-based approach aggregates individual judgements and handles imprecision. The structure of the relationships between the criteria expressed in different dimensions is determined by using the rough DEMATEL (R'DAMETEL) method and building an influential network relation mapping, based on which the rough ANP (R'ANP) method is implemented to obtain the respective criteria weights. Then, the rough multi-attribute Ideal-Real Comparative Analysis (R'MAIRCA) is used to evaluate the environmental performance of suppliers for each evaluation criterion. Sensitivity analysis is performed to determine the impact of the weights of criteria and the influence of the decision maker's preferences on the final evaluation results. Applying the Spearman's rank correlation coefficient and other ranking methods, the stability of the alternative rankings based on the variation in the criteria weights is checked. The results obtained in the study show that the proposed method significantly increases the objectivity of supplier assessment in a subjective environment.

1. Introduction

In recent decades, manufacturing companies have been shifting their purchasing trends towards green suppliers, following the environmental standards and regulations proposed by the government, as well as the environmental protection perceptions among consumers, thus keeping only low cost-based high quality products (Genovese et al., 2010). This means that a green supplier assessment system is required for an industry to maintain its sustainability in the global market, while green supplier performance evaluation is one of the crucial issues for purchasing managers that still needs to be further explored (Shen et al., 2013; Kannan et al.,

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2014; Liu and Zhang, 2011). A number of literature reviews and research papers on GSCM have been published in recent years to facilitate effective green supplier selection and identify the gaps in the previous works (Buyukozkan and Cifci, 2012; Tsui and Wen. 2014; Govindan et al., 2015a; Fahimnia et al., 2015). The green suppliers are chosen to satisfy a company's expectations and objectives, to minimize negative environmental effects, to maximize economic performance and to improve its green skills (Chen et al., 2016). Since the multi-criteria decision making (MCDM) methods are the supportive tools increasing flexibility in decision making, GSCM implements various MCDM methods for selecting among the alternative suppliers with respect to a predetermined set of criteria (Çelikbilek and Tüysüz, 2016; Yazdani et al., 2017).

The present research work aims to achieve the objective, mentioned as -—evaluating and prioritizing suppliers in green supply chain management perspectives. To resolve this difficulty in implementing green aspect in business, this research raises the following questions:

1. What are the factors (criteria) need to be considered in a successful implementation of GSCM?
2. How the causal relations among the identified factors in successful adoption and implementation of GSCM be determined?
3. What is the novelty and present contribution of multi-criteria decision making approach?
4. What methodology or technique be presented in prioritizing green suppliers in GSCM sector?

Taking into account the causal relationship between the GSC criteria for supplier selection, it may be stated that the DEMATEL methodology can support decision making by deriving a visual graph showing the degree of their influence on the final result (Hsu et al., 2013). In more realistic conditions, the analytical network process (ANP) is also capable of handling interdependencies between the criteria, but it assumes an equal cluster weight to obtain the weighted supermatrix (Govindan et al., 2014; Hashemi et al., 2015). To overcome this shortcoming, DANP (DEMATEL-ANP) is applied to find the influential weights of the criteria based on the network relationship map (NRM) (Yang and Tzeng, 2011). The ANP technique is used to determine the weights of the performance criteria based on the total relation matrix formed by the DEMATEL, thus avoiding pairwise comparisons of the criteria required for ANP analysis (Kuo et al., 2015). Calculating the relative weights of criteria using traditional ANP means that the levels of interdependence of the factors are treated as reciprocal values. In contrast, in using the DEMATEL method, the levels of interdependence of factors do not have reciprocal values, which is closer to real circumstances (Yang and Tzeng, 2011). Because all of the above, implementation DEMATEL method in ANP model gives more objective insight into weight coefficient values.

Traditionally, the information in green supplier selection is presented in the form of linguistic descriptions relying on subjective expert's assumptions, which are lacking objectivity and generalization. Inappropriate human judgements and imprecise information increase the vagueness in a decision making process. Therefore, to manipulate it, researchers have introduced fuzzy logic into the DANP algorithm by using the membership function (Uygun and Dede, 2016; Wu et al., 2015). Besides, the fuzzy set theory and the grey set theory can also handle situations with incomplete data sets and unknown sample distribution, avoiding subjective perceptions (Çelikbilek and Tüysüz, 2016). Recently, a rough set-based algorithm has been developed in decision-making to determine the criteria weights, ignoring the vagueness by utilizing incomplete information in a more genuine way in the poor data environments (Bai and Sarkis, 2010). As the rough set theory fails to deal with more alternatives in MCDM, the rough number approach based on the principle of rough sets and integrated with fuzzy arithmetic operations, has been applied in the work of Zhu et al. (2015) to fully reflect the subjectivity, relying only on the original data.

Thus the central objective of this paper is to seek out the following:

1. What are the main advantage of rough numbers in place of traditional fuzzy and interval numbers?
2. Can rough numbers be successfully used to develop appropriate group decision-making model in order to provide a rational and inclusive operational solution in the process of supplier selection?
3. Are operational processes and outcomes in the decision-making model significantly improved by using rough numbers?

Unlike fuzzy theory, grey theory and other interval valued approaches, rough set theory, is a very convenient tool for the treatment of imprecisions and uncertainty without the impact of subjectivism (Zhai et al., 2009). In the rough approach, the borders are determined on the basis of border approximation areas and the uncertainty that governs them. While in traditional fuzzy theory and probability theory the degree of uncertainty is defined on the basis of assumptions, in the rough approach uncertainty is determined on the basis of approximation, which is the basic concept of rough numbers (Song et al., 2014).

- The rough approach uses exclusively internal knowledge, i.e., operative data, and there is no need to rely on assumption models.
- In other words, in the application of rough numbers, instead of different additional/external parameters, only the structure of the given data is used. This leads to the objective indicators contained in the data.
- The basic logic of rough numbers (RN) is that the actual data should speak for themselves.
- RN eliminate the shortcomings of the traditional fuzzy approach relating to the interval borders, since for every rating of the expert unique interval borders are formed.
- This means that the interval borders do not depend on subjective assessment, but rather are defined on the basis of uncertainty and imprecisions in the data.

Within the recently used decision-making framework, different ranking results have been obtained by applying various MCDM methods to support the alternative selection process (Keshavarz Ghorabaee et al., 2016; Liu and Wang, 2017; Liu, 2017). Thus, it implies that not only the criteria weights, but also the applied MCDM models play an important role in the final selection of an alternative (Pamučar and Ćirović, 2015; Liu et al., 2017). Recently, various MCDM models have been used in ranking the alternative green suppliers taking into account various environmental and management criteria, viz. fuzzy ELECTRE (Kumar et al., 2016) and fuzzy VIKOR (Rostamzadeh et al., 2015). The present paper explores and extends the recently developed MAIRCA approach (Pamučar et al., 2014; Gigović et al., 2016a) in a rough domain. The MAIRCA technique is more stable than TOPSIS or ELECTRE because it is based on using a different linear normalization method characterized by a simple mathematical apparatus and solution stability (Gigović et al., 2016b). With rough numbers unified in structure, it is expected to help decision-makers make reasonable decisions in a subjective environment. Moreover, there are only a few papers discussing green supplier selection based on using the integrated methods in crisp, fuzzy and grey domains, viz. DANP-VIKOR (Kuo et al., 2015; Yang et al., 2013), DANP-PROMETHEE (Govindan et al., 2014), fuzzy-based DANP-TOPSIS (Buyukozkan and Cifci, 2012; Uygun and Dede, 2016) and grey-based DANP-VIKOR (Çelikbilek and Tüysüz, 2016).

Thus the main question arising in this paper is:

Q1: How this present methodology aid in prioritizing green suppliers in GSCM sector and the main advantage behind it?

Taking into account the above information as well as the investigated literature and judgements of both academic and industrial experts, the authors of the present paper propose a rough number-based framework of DEMATEL-ANP and MAIRCA (R'AMATEL-MAIRCA) approaches for determining the criteria weights and performing the ranking of the alternatives, which provides deeper insights into decision-makers' perceptions in GSCM perspective. For the purpose of accepting the imprecisions and subjectivity in the collective decision making process, this paper modifies the DEMATEL and ANP methods by applying rough numbers. Therefore, the main goal of this research paper is to explore an effective procedure for selecting green suppliers by employing GSCM, using a rough number-based MCDM approach. Finally, a Taiwanese electronics manufacturing company is considered as a case study to validate the suggested framework for selecting the appropriate green suppliers. The case company wished to incorporate environmental management into its GSC supplier evaluation. In recent years, several GSCM studies have been proposed to help companies reduce the environmental burden of both manufacturing and product disposal, thus increasing their competitive edge, particularly in the electronics sector (Kannan et al., 2014; Tsui and Wen, 2014; Kuo et al., 2015). The above mentioned studies provide a scientific approaches to the decision-making process under environmental management perspective.

Thus the main contribution and novelty of this study are as follows:

1. This paper introduce hybrid R'AMATEL-MAIRCA MCDM model that provides more objective expert evaluation of criteria in a subjective environment.
2. The improved MCDM methodology suggested provides purchasing managers with another tool for selecting suitable suppliers and helps successfully reduce the gaps in the green performance of various companies.
3. The present methodology enable the evaluation of alternative solutions despite dilemmas in the decision making process and lack of quantitative information.
4. The environmental indicators are provide a critical analysis of empirical research content in GSCM, that serves as a useful reference for researchers in GSCM or other operations fields.

The remaining part of this paper is arranged as follows: Section 2 presents a brief review of the available literature on GSC supplier evaluation and the application of the described methods with present research gaps. Section 3 introduce the proposed methodology, which combines rough number, DEMATEL-ANP and MAIRCA methods. Section 4 applies the proposed approach to a real case study in an electronics company along with comparative study and sensitivity analysis as assigned by expert decision-makers. Managerial implications is addressed in Section 5, for analysing and discussion of methodology. Finally, the conclusions with the outlined future research area are provided in Section 6.

2. A brief review of the literature on the considered problem

This section presents a brief review of the literature on the criteria and methods of green supplier selection. Over the last two decades, various decision-making methods were proposed to address green supplier selection problems. This study provides an empirical investigation on GSCM practices, and conducts a literature survey to fill the gap on identification of crucial factors for GSCM implementation in electronics industry. This paper aims to answer the following research questions (RQs) in literature:

RQ1: What multiple criteria decision making trends recently develop in green supply chain management (GSCM)?
RQ2: What are the relevant criteria and sub-criteria generally considered in green supply chain management (GSCM)?
RQ3: What are the recent works in electronics sector supply chain management (SCM) related to GSCM?

To answer these questions, we analyze academic peer-reviewed articles, published recently from 2012 to 2017. In this work, a search for papers on the considered problem is conducted and the papers from the Thomson Reuters ISI Web of Science are selected. Based on the previous studies, the *approaches* employed in GSCM (section 2.1), as well as the *criteria taken* for the analysis of the GSC supplier selection problem (section 2.2), and the *application* of this system in electronics industry (section 2.3) have been classified and presented there forth. In section 2.4, we discuss our findings critically and state current research gaps as well possible future trends in GSCM.

2.1. GSCM practices using the DEMATEL and ANP and the integrated approaches

Since the integration of the MCDM methods yields different approaches, researchers combine and extend various MCDM methods for specific purposes and prerequisite perspectives (Mardani et al., 2015; Liu and Shi, 2017). Moreover, the papers published on the topic present DANP models along with their integrated approaches for solving green supplier selection, which consider the interaction between the dimensions and supplier selection criteria. Hsu et al. (2013) have utilized the DEMATEL methodology to build causal relationships between the influential GSC criteria for improving the global performance of suppliers. Wu et al. (2015) proposed Fuzzy-DEMATEL to explore the effect of each factor inside GSCM for a Vietnamese automobile manufacturing industry. Wu and Chang (2015) have identified the critical dimensions and factors suitable for Taiwanese electronics industry and constructed digraphs to show causal relationships between them in GSCM. Govindan et al. (2015b) have used the IF- DEMATEL method for developing green practices and environmental performances in an automobile industry.

As concerns the ANP method, Akman and Piskin (2013) have evaluated the green performances of suppliers of an automobile company using the ANP and TOPSIS MCDM model. Dou et al. (2014) have introduced a grey ANP model to focus on the interrelationship between the green supplier development model and green supplier involvement propensity for improving supplier performances. Hashemi et al. (2015) have used both economic and environmental criteria to propose the ANP-GRA model to address the uncertainties inherent in green supplier selection in the automotive industry. Wu and Barnes (2016) presented a green partner selection model combining ANP and multi-objective programming (MOP) methods to diminish a negative environmental effect produced by the Chinese electrical appliance supply chain.

In recent years, hybrid DANP MCDM models have been widely used to solve performance evaluation problems. Buyukozkan and Cifci (2012) have examined the GSC management principles to propose a multi-criteria approach based on the conflicting and uncertain evaluation framework for green suppliers, combining

DANP and TOPSIS in a fuzzy context for an automobile company. Bakeshlou et al. (2014) have developed a fuzzy multi-objective linear programming (MOLP) model for solving the GSC selection problem, using a fuzzy DANP model considering the interrelation between the criteria. Govindan et al. (2014) have selected the best green manufacturing process based on a multi-criteria approach combining the DANP with PROMETHEE framework for rubber industry. Uygun and Dede (2016) have proposed a model based on the integrated fuzzy DANP-TOPSIS model for performance evaluation of GSCM.

2.2. The related works on the criteria used in GSCM

In addition to the ample literature on green performance measurement of suppliers, a large number of papers describing the analysis of the GSC criteria can be found. Shen et al. (2013) presented a literature review on green supplier selection criteria, describing the environmental performance of suppliers. Kannan et al. (2015) have offered a systematic approach considering 26 traditional and 72 environmental criteria from a comprehensive review for selecting green suppliers by using the Affinity Diagram methodology. Rostamzadeh et al. (2015) have explored the relationship between individual practices and performance assessments and presented a summary of previous researches on green supplier criteria. Kuo et al. (2015) have listed the environmental criteria from the EICC Code of Conduct to consider the recent developments in electronics industry in the CSR sector. Govindan et al. (2015a) have listed and summarized the papers investigating the green practices and initiatives aimed at achieving green supply chain management. Recently, Kumar et al. (2016) have considered a total of 38 criteria in rating the suppliers in GSCM that are grouped into six main clusters such as cost, quality, flexibility, service, green practices, environmental management, and pollution control. Chen et al. (2016) have presented the criteria used in the past works to evaluate the environmental aspects and economic performance of green supplier selection.

2.3. GSCM in the electronics sector

The suppliers of the global brand name companies are mainly from Taiwan, the home of the majority of electronic equipment manufacturers in the Asia-Pacific region (Kuo et al., 2015). For effective performance appraisal of suppliers in the electronics sector, the environmental criteria given in the EICC code of conduct (*related to customer requests and social responsibility*) were adopted (Kuo et al., 2015). Some of the latest findings confirm the significance of GSCM for companies' success. For example, Chiou et al. (2008) categorized GSC criteria to explore the relative difference in supplier selection among multi-national electronics companies in China. Chen et al. (2012) have proposed the ANP network model to develop GSCM strategies for a Taiwanese electronics company to effectively direct its business activities and outline its green management perspective. Kannan et al. (2014) suggested a GSCM framework to select green suppliers using the fuzzy TOPSIS for a Brazilian electronics company. Considering the environmental criteria, Tsui and Wen (2014) have developed a green supplier selection procedure for TFT-LCD industry in Taiwan, using the hybrid AHP-entropy-ELECTRE III and a linear assignment method. Rostamzadeh et al. (2015) have pursued to evaluate the uncertainty of GSCM indicators for a Malaysia-based laptop manufacturer, applying the intuitionistic fuzzy VIKOR-based MCDM model. Liou et al. (2016) have proposed a novel DANP-based COPRAS-G method for improving and selecting green suppliers in GSCM for a Taiwanese electronics company. Freeman and Chen (2015) have applied the AHP-entropy-TOPSIS methodology to develop a green supplier selection model for a Chinese electronics manufacturer. Kuo et al. (2015) have proposed a hybrid DANP-VIKOR MCDM method to evaluate green suppliers for an electronics company, choosing the criteria both from the environmental and managerial perspectives.

2.4. Research gaps in the present study

In this section we will discuss research gaps (limitations) of our literature study, summarize the findings of the earlier sections and derive possible trends of MCDM applications in SCM.

- Regarding limitations of our study (literature survey), the review was restricted to academic peer-reviewed articles. Textbooks, master theses and doctoral dissertations were thus not selected; furthermore, only articles in English were considered.
- Moreover, our investigation is based on keyword search in the database ISI Web of Science. Hence, it is possible that some relevant articles did not match our search terms or were not listed in searched databases.
- This review has applications rather than theoretical orientation, and integrates many techniques in a simplified framework.
- Hence there is a gap in the literature on applications of MCDM in GSCM in recent years, specifically focusing on empirical challenges and the pros and cons of alternative MCDM techniques.
- Currently, both environmental and economic factors play a vital role for long term success of GSCM. In the present study, only environmental factor is considered as current literature address this factor considered by the decision makers for supplier selection and evaluation.

3. Methodology

3.1. Rough numbers and operations on them

In group decision making problems, the priorities are defined based on the aggregated decision of multiple experts and decisions based on subjective expert evaluations. Rough numbers, consisting of the upper, lower and boundary intervals, respectively, determine the intervals of their evaluations without requiring any additional information and relying only on the original data (Zhai et al., 2008). Hence, the obtained decision makers' (DMs') preferences objectively represent and improve the decision making process. The definition of rough numbers according to Zhai et al. (2009) is given below.

Let U be a universe containing all the objects and X be a random object from U. Then, it is assumed that there exists a set of k classes which represents a DM's preferences, $R = (J_1, J_2, \ldots, J_k)$ with the condition $J_1 < J_2 < , \ldots, < J_k$ Then for every $X \in U, J_q \in R, 1 \leq q \leq k$, the lower approximation $\underline{Apr}(J_q)$, the upper approximation $\overline{Apr}(J_q)$ and the boundary interval $Bnd(J_q)$ are determined as follows:

$$\underline{Apr}\left(J_q\right) = \cup\left\{X \in U / R(X) \leq J_q\right\} \tag{1}$$

$$\overline{Apr}\left(J_q\right) = \cup\left\{X \in U / R(X) \geq J_q\right\} \tag{2}$$

$$\begin{aligned} Bnd\left(J_q\right) &= \cup\left\{X \in U / R(X) \neq J_q\right\} \\ &= \left\{X \in U / R(X) > J_q\right\} \cup \left\{X \in U / R(X) < J_q\right\} \end{aligned} \tag{3}$$

The object can be represented by a rough number with the lower limit $\underline{Lim}(J_q)$ and the upper limit $\overline{Lim}(J_q)$ in Eqns. (4)–(5).

$$\underline{Lim}\left(J_q\right) = \frac{1}{M_L}\sum R(X)|X\in\underline{Apr}\left(J_q\right) \tag{4}$$

$$\overline{Lim}\left(J_q\right) = \frac{1}{M_U}\sum R(X)|X\in\overline{Apr}\left(J_q\right) \tag{5}$$

where M_L and M_U represent the sum of objects given in the lower and upper object approximations of J_q respectively. For object J_q, the rough boundary interval ($IRBnd(J_q)$) is the interval between the lower and upper limits:

$$IRBnd\left(J_q\right) = \overline{Lim}\left(J_q\right) - \underline{Lim}\left(J_q\right) \tag{6}$$

The rough boundary interval presents a measure of uncertainty. A bigger $IRBnd(J_q)$ value shows that the variations in experts' preferences exist, while smaller values show that experts' opinions do not differ considerably. All the objects between the lower limit $\underline{Lim}(J_q)$ and the upper limit $\overline{Lim}(J_q)$ of the rough number $RN(J_q)$ are included in $IRBnd(J_q)$. This means that $RN(J_q)$ can be presented using $\underline{Lim}(J_q)$ and $\overline{Lim}(J_q)$ as follows:

$$RN\left(J_q\right) = \left[\underline{Lim}\left(J_q\right), \overline{Lim}\left(J_q\right)\right] \tag{7}$$

3.1.1. The operations on rough numbers

Since rough numbers belong to a group of interval numbers, arithmetic operations applied to interval numbers are also appropriate for rough numbers (Zhu et al., 2015). If P and Q represent two rough numbers $RN(P) = \left[\underline{Lim}(P), \overline{Lim}(P)\right]$ and $RN(Q) = \left[\underline{Lim}(Q), \overline{Lim}(Q)\right]$, k denotes a constant, $k > 0$ then, the arithmetic operations with $RN(A)$, $RN(B)$ and k are as follows:

1. The addition ("+") of rough numbers $RN(P)$ *and* $RN(Q)$:

$$RN(P)\times RN(Q) = \left[\underline{Lim}(P), \overline{Lim}(P)\right] \times \left[\underline{Lim}(Q), \overline{Lim}(Q)\right] = \left[\underline{Lim}(P)\times\underline{Lim}(Q), \overline{Lim}(P)\times\overline{Lim}(Q)\right] \tag{8}$$

2. The subtraction ("−") of rough numbers $RN(P)$*and* $RN(Q)$:

$$RN(P) - RN(Q) = \left[\underline{Lim}(P), \overline{Lim}(P)\right] - \left[\underline{Lim}(Q), \overline{Lim}(Q)\right] = \left[\underline{Lim}(P) - \overline{Lim}(Q), \overline{Lim}(P) - \underline{Lim}(Q)\right] \tag{9}$$

3. The multiplication ("×") of rough numbers $RN(P)$ *and* $RN(Q)$:

$$RN(A)\times RN(B) = \left[\underline{Lim}(A), \overline{Lim}(A)\right] \times \left[\underline{Lim}(B), \overline{Lim}(B)\right] = \left[\underline{Lim}(A)\times\underline{Lim}(B), \overline{Lim}(A)\times\overline{Lim}(B)\right] \tag{10}$$

4. The division ("/") of rough numbers $RN(P)$*and* $RN(Q)$:

$$RN(P)/RN(Q) = \left[\underline{Lim}(P), \overline{Lim}(P)\right] \Big/ \left[\underline{Lim}(Q), \overline{Lim}(Q)\right] = \left[\underline{Lim}(P) \Big/ \overline{Lim}(Q), \overline{Lim}(P)/\underline{Lim}(Q)\right] \tag{11}$$

5. The scalar multiplication of a rough number $RN(A)$, where $k > 0$:

$$k\times RN(P) = k\times\left[\underline{Lim}(P), \overline{Lim}(P)\right] = \left[k\times\underline{Lim}(P), k\times\overline{Lim}(P)\right] \tag{12}$$

3.1.2. Ranking rule of rough numbers

For any two rough numbers, $RN(P) = \left[\underline{Lim}(P), \overline{Lim}(P)\right]$ and $RN(Q) = \left[\underline{Lim}(Q), \overline{Lim}(Q)\right]$, where $\underline{Lim}(P)$ and $\underline{Lim}(Q)$ are the lower limits, while $\overline{Lim}(P)$ and $\overline{Lim}(Q)$ are the upper limits. The ranking rule for rough numbers is described as follows (Zhu et al., 2015):

1. If the rough boundary interval of a rough number is not strictly bound by another, then the ranking order is easily determined:

$$(\mathrm{a})\begin{cases} If\,\underline{Lim}(P) \geq \underline{Lim}(Q) and \overline{Lim}(P) > \overline{Lim}(Q) \\ If\,\underline{Lim}(P) > \underline{Lim}(Q) and \overline{Lim}(P) \geq \overline{Lim}(Q) \end{cases} : then\ RN(P) > RN(Q) \tag{13}$$

$$(\mathrm{b}) If\,\underline{Lim}(P) = \underline{Lim}(Q)\text{and } \overline{Lim}(P) = \overline{Lim}(Q)\text{then } RN(P) = RN(Q) \tag{14}$$

2. If the rough boundary interval of a rough number is strictly bound by another, then ranking becomes complicated, and the medians $M(P)$ and $M(Q)$ of $RN(P)$ and $RN(Q)$ respectively, are used in this process:

$$(\mathrm{a})\text{If } \underline{Lim}(Q) > \underline{Lim}(P)\text{and } \overline{Lim}(Q) < \overline{Lim}(P) : \begin{cases} if\ M(P) \leq M(Q) then\ RN(P) < RN(Q) \\ if\ M(P) > M(Q) then\ RN(P) > RN(Q) \end{cases} \tag{15}$$

(b)Similar rules can be derived if $\underline{Lim}(P) > \underline{Lim}(Q)$and $\overline{Lim}(P) < \overline{Lim}(Q)$.

3.2. The hybrid rough DEMATEL-ANP method (R'AMATEL)

The criteria do not have the same implications in problem solving processes, therefore, the experts (DMs) should define the significance of each criterion using an adequate weighting method. A hybrid rough DEMATEL-ANP method (R'AMATEL model) is used for calculating the normalized criteria weights and subsequently using a rough MAIRCA method for ranking the available alternatives based on the above criteria weights.

3.2.1. The R'DEMATEL method for determining the interrelationships between the criteria

The modification of the DEMATEL has so far been performed by using numerous models treating uncertainty such as fuzzy theory

(Gigović et al., 2017), D number theory (Zhou et al., 2017) and grey theory (Su et al., 2016; Shao et al., 2016). For more comprehensive appreciation of the subjectivity characteristic of group decision-making, the rough number-based DEMATEL (*R'DEMATEL*) method and the *R'ANP* method for expert evaluation of the criteria weights are proposed in this subsection. The implementation of the *R'DEMATEL method* is described by the following steps:

Step 1: The analysis of the experts' response matrices

Assuming that there exists a group of d experts and n criteria, each expert should determine the degree of mutual influence of criteria i *and* $j(\forall\ i,j\in n)$. For this purpose, a pairwise comparative analysis of the i^{th} and j^{th} criteria sets for k^{th} expert is made and denoted by the values $x_{ij}^k(i,j=1,2,\ldots,n;k=1,2,\ldots d)$, which were scored on the integer scale from 0 to 4 (0 – no influence, 1 – low influence, 2 – medium influence, 3 – high influence and 4 – very high influence) (Kuo et al., 2015). Moreover, for each k^{th} expert, the $n\times n$ non-negative matrix X_k was constructed (with n denoting the number of criteria). The pairwise response matrix X_k of the k-th expert $(k=1,2,\ldots d)$ as per Eqn. (17) is as follows:

$$X_k=\begin{bmatrix} 0 & x_{12}^k & \cdots & x_{1n}^k \\ x_{21}^k & 0 & \cdots & x_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1}^k & x_{n2}^k & \cdots & 0 \end{bmatrix}_{n\times n} \quad where\ x_{ij}^k=0 \quad \forall i=j \tag{17}$$

Assuming that n criteria were categorised under m dimensions (factors), the same calculation procedure could also be applicable, which resulted in $m\times m$ pairwise response matrices $\widehat{X}_k$ as follows:

$$\widehat{X}_k=\left[\widehat{x}_{ij}^k\right]_{m\times m} where\ \widehat{x}_{ij}^k=0 \quad \forall i=j,\ \ k=1,2,\ldots,d \tag{18}$$

Step 2: Determination of experts' weight coefficients (w_i)

The experts' weight coefficients were determined using three parameters: the *objective expert's* evaluation (w_o), which was determined on the basis of the expert's experience in the field of research; *mutual experts*' evaluation (w_u) which was determined based on mutual assessment of the experts participating in the study; and *subjective experts*' evaluation (w_s), which was determined based on experts' assessment of their own competence for participation in the study. All three weight parameters (w_o,w_u,w_s) were scored on a predefined linguistic scale as defined in Pamučar and Ćirović (2015).

The weighting coefficient (w_i) was calculated from the score representing the sum of individual assessment parameters (w_o,w_u,w_s). Since the requirement $\sum_{i=1}^d w_i=1$ had to be satisfied, the final w_i values were calculated by Eqn. (19), where $W_i=w_{o_i}+w_{u_i}+w_{s_i}(i=1,2,\ldots,d)$ are the weight coefficients of d experts:

$$w_i=\frac{W_i}{\sum\limits_{i=1}^{d}W_i} \tag{19}$$

Step 3: Determining the matrices of experts' average response

Using the response matrix $X_k=[x_{ij}^k]_{n\times n}(i,j=1,2,\ldots,n;$ $k=1,2,\ldots,d)$ obtained from all d experts and aggregating the experts' estimates, the integrated rough direct relation matrix X^* was constructed, as shown in Eqn. (20):

$$X^*=\begin{bmatrix} x_{11}^1,x_{11}^2,\ldots,x_{11}^d & x_{12}^1;x_{12}^2;\ldots;x_{12}^d, & \ldots, & x_{1n}^1;x_{1n}^2,\ldots,x_{1n}^d \\ x_{21}^1,x_{21}^2,\ldots,x_{21}^d & x_{22}^1;x_{22}^2;\ldots;x_{22}^d, & \ldots, & x_{2n}^1;x_{2n}^2,\ldots,x_{2n}^d \\ \ldots & \ldots & \ldots, & \ldots \\ x_{n1}^1,x_{n1}^2,\ldots,x_{n1}^d & x_{n2}^1;x_{n2}^2;\ldots;x_{n2}^d, & \ldots, & x_{nn}^1;x_{nn}^2,\ldots,x_{nn}^d \end{bmatrix} \tag{20}$$

where $x_{ij}=\{x_{ij}^1,x_{ij}^2,\ldots,x_{ij}^d\}$ is the sequence of relative importance of criterion i on criterion j. The element $x_{ij}^k(k=1,2,\ldots,d)$ were translated into rough number $RN(x_{ij}^k)=\left[\underline{Lim}(x_{ij}^k),\overline{Lim}(x_{ij}^k)\right]$ using Eqns. (1)–(6), where $\underline{Lim}(x_{ij}^k)$ and $\overline{Lim}(x_{ij}^k)$ are the lower and upper limit of $RN(x_{ij}^k)$ respectively. The rough sequence $RN(x_{ij})$ is thus represented in Eqn. (21), with the respective direct rough relation matrix X_C^k in Eqn. (22).

$$RN(x_{ij})=\left\{\left[\underline{Lim}\left(x_{ij}^1\right),\overline{Lim}\left(x_{ij}^1\right)\right],\left[\underline{Lim}\left(x_{ij}^2\right),\overline{Lim}\left(x_{ij}^2\right)\right],\ldots,\left[\underline{Lim}\left(x_{ij}^d\right),\overline{Lim}\left(x_{ij}^d\right)\right]\right\} \tag{21}$$

$$X_C^k=\left[RN\left(x_{ij}^k\right)\right]_{n\times n}=\begin{bmatrix} [0,0] & RN\left(x_{12}^k\right) & \cdots & RN\left(x_{1n}^k\right) \\ RN\left(x_{21}^k\right) & [0,0] & \cdots & RN\left(x_{2n}^k\right) \\ \vdots & \vdots & \ddots & \vdots \\ RN\left(x_{n1}^k\right) & RN\left(x_{n2}^k\right) & \cdots & [0,0] \end{bmatrix}_{n\times n} \tag{22}$$

$RN(x_{ij}^k)=[0,0]\ \forall i=j$. It was further transformed into an average rough number $RN(z_{ij})$ by applying a rough operation, as defined in Eqn. (23), as follows:

$$RN(z_{ij})=RN\left(z_{ij}^1,z_{ij}^2,\ldots,z_{ij}^d\right)=\begin{cases}\underline{Lim}(z_{ij})=\prod_{k=1}^d\left(\underline{Lim}\left(x_{ij}^k\right)\right)^{w_k} \\ \overline{Lim}(z_{ij})=\prod_{k=1}^d\left(\overline{Lim}\left(x_{ij}^k\right)\right)^{w_k}\end{cases} \tag{23}$$

where $w_k(k=1,2,...,d)$ denotes the weight coefficient of k-th expert $(k=1,2,\ldots,d)$, whereas $\underline{Lim}(z_{ij})$ and $\overline{Lim}(z_{ij})$ denote lower and upper rough number limit of $RN(z_{ij})$, respectively. Finally, the initial average rough direct-relation matrix, Z_C was obtained, as per Eqn. (24), as follows:

$$Z_C=\left[RN(z_{ij})\right]_{n\times n}=\begin{bmatrix} [0,0] & RN(z_{12}) & \cdots & RN(z_{1n}) \\ RN(z_{21}) & [0,0] & \cdots & RN(z_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ RN(z_{n1}) & RN(z_{n2}) & \cdots & [0,0] \end{bmatrix}_{n\times n} \tag{24}$$

where each $RN(z_{ij})=\left[\underline{Lim}(z_{ij}),\overline{Lim}(z_{ij})\right]$ for every $i,j=1,2,\ldots,n$ and $RN(z_{ij})=[0,0]$ when $i=j$.

The matrix Z_C shows the initial effects produced by the use of a particular criterion, as well as the initial effects produced by the application of other criteria. The sum of each i-th matrix row Z_C represents the total direct effect which criterion i produced on other criteria, and the sum of each j-th column of the matrix Z_C represents the total direct effect which criterion j experienced due to the influence of other criteria.

Applying the same calculation procedure to m dimensions ($m<n$) as defined in Eqn. (20)–(24) for n criteria, the average rough direct-relation matrix Z_D was obtained as follows:

$$Z_D = \left[RN\left(\hat{z}_{ij}\right)\right]_{m\times m} = \begin{bmatrix} [0,0] & RN(\hat{z}_{12}) & \cdots & RN(\hat{z}_{1m}) \\ RN(\hat{z}_{21}) & [0,0] & \cdots & RN(z_{2m}) \\ \vdots & \vdots & \ddots & \vdots \\ RN(\hat{z}_{m1}) & RN(\hat{z}_{m2}) & \cdots & [0,0] \end{bmatrix}_{m\times m}. \tag{25}$$

where each $RN(\hat{z}_{ij}) = \left[\underline{Lim}(\hat{z}_{ij}), \overline{Lim}(\hat{z}_{ij})\right]$ *for every* $i,j = 1,2,\ldots,$ m *and* $RN(\hat{z}_{ij}) = [0,0] \quad \forall\ i=j$

Step 4: Calculating the normalized rough direct relation matrices

Based on Eqn. (24), the normalized rough direct-relation matrix $D_C = [RN(d_{ij})]_{n\times n}$ for n criteria was obtained by normalizing each matrix element, i.e. by dividing each element $RN(z_{ij})$ of the matrix Z_C by a rough number $RN(s)$, as shown in Eqn. (26).

$$D_C = \begin{bmatrix} 0 & RN(d_{12}) & \cdots & RN(d_{1n}) \\ RN(d_{21}) & 0 & \cdots & RN(d_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ RN(d_{n1}) & RN(d_{n2}) & \cdots & 0 \end{bmatrix} \tag{26}$$

where each $RN(d_{ij}) = \left[\underline{Lim}(d_{ij}), \overline{Lim}(d_{ij})\right]$ was calculated using Eqns. (27)–(28):

$$RN(d_{ij}) = \frac{RN(z_{ij})}{RN(s)} = RN\left(\frac{\underline{Lim}(z_{ij})}{\overline{Lim}(s)}, \frac{\overline{Lim}(z_{ij})}{\underline{Lim}(s)}\right) \tag{27}$$

where

$$\begin{aligned} RN(s) &= \max\left(\sum_{j=1}^{n} RN(z_{ij})\right) \\ &= \max\left(\sum_{j=1}^{n} \underline{Lim}(z_{ij}), \sum_{j=1}^{n} \overline{Lim}(z_{ij})\right) \\ &= \left[\max\left(\sum_{j=1}^{n} \underline{Lim}(z_{ij})\right), \max\left(\sum_{j=1}^{n} \overline{Lim}(z_{ij})\right)\right] \end{aligned} \tag{28}$$

Similarly, applying the same procedure, *which is given in* Eqns. (26)–(28), the normalized rough direct-relation matrix D_D for m dimensions was derived as shown in Eqn. (29), where

$$D_D = \left[RN\left(\hat{d}_{ij}\right)\right]_{m\times m} \textit{where} \quad RN\left(\hat{d}_{ij}\right) = [0,0] \quad \forall\ i=j \tag{29}$$

Step 5: Determining the rough number-based total relation matrices

Using Eqns. (30)–(32), the total influence matrix $T_C = [RN(t_{ij})]_{n\times n}$ for n criteria was obtained, where I denotes the $n\times n$ identity matrix. If the element $RN(t_{ij})$ denotes the indirect effects of criterion i on criterion j, then, the matrix T_C shows the total relationship between each set of i^{th} and j^{th} criteria $(i,j = 1,2,\ldots,n)$. The initial normalized direct-relation rough matrix $D_C = [RN(d_{ij})]_{n\times n}$ was partitioned into discrete sub-matrices $D_C = (D_L,\ D_U)$, where $D_L = [\underline{Lim}(d_{ij})]_{n\times n}$ *and* $D_U = [\overline{Lim}(d_{ij})]_{n\times n}$. Besides, $\lim_{m\to\infty}(D_L)^m = O$ *and* $\lim_{m\to\infty}(D_U)^m = O$, with O denoting the zero matrix.

$$\left.\begin{aligned} &\lim_{m\to\infty}\left(I + D_L + D_L^2 + \ldots + D_L^m\right) = (I-D_L)^{-1} \\ &\textit{and} \\ &\lim_{m\to\infty}\left(I + D_U + D_U^2 + \ldots + D_U^m\right) = (I-D_U)^{-1} \end{aligned}\right\} \tag{30}$$

Hence, the total relation rough matrix T_C was obtained by computing the subsequent terms, where $D_L = [\underline{Lim}(d_{ij})]_{n\times n}$ *and* $D_U = [\overline{Lim}(d_{ij})]_{n\times n}$:

$$\left.\begin{aligned} &T_L = \lim_{m\to\infty}\left(D_L + D_L^2 + \ldots + D_L^m\right) = D_L(I-D_L)^{-1} = \left[\underline{Lim}(t_{ij})\right]_{n\times n} \\ &\text{and} \\ &T_U = \lim_{m\to\infty}\left(D + D_U^2 + \ldots + D_U^m\right) = D_U(I-D_U)^{-1} = \left[\overline{Lim}(t_{ij})\right]_{n\times n} \end{aligned}\right\} \tag{31}$$

The sub-matrices T_L and T_U were combined to form the rough total relation matrix $T_C = (T_L, T_U)$ presented as follows:

$$T_C = \begin{bmatrix} RN(t_{11}) & RN(t_{12}) & \cdots & RN(t_{1n}) \\ RN(t_{21}) & RN(t_{22}) & \cdots & RN(t_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ RN(t_{n1}) & RN(t_{n2}) & \cdots & RN(t_{nn}) \end{bmatrix}_{n\times n} \tag{32}$$

where $RN(t_{ij}) = \left[\underline{Lim}(t_{ij}), \overline{Lim}(t_{ij})\right]$ is the overall influence rating of the experts for each criteria i on criteria j, thus reflecting their mutual dependence on each other.

Similarly, the rough total relation matrix $T_D = (\hat{T}_L, \hat{T}_U)$ was obtained for m dimensions, where $[RN(\hat{t}_{ij})] = (\hat{T}_L, \hat{T}_U) = \left[\underline{Lim}(\hat{t}_{ij}), \overline{Lim}(\hat{t}_{ij})\right]$ for every $i,j = 1,2,\ldots,m$:

$$T_D = \begin{bmatrix} RN(\hat{t}_{11}) & RN(\hat{t}_{12}) & \cdots & RN(\hat{t}_{1m}) \\ RN(\hat{t}_{21}) & RN(\hat{t}_{22}) & \cdots & RN(\hat{t}_{2m}) \\ \vdots & \vdots & \ddots & \vdots \\ RN(\hat{t}_{m1}) & RN(\hat{t}_{m2}) & \cdots & RN(\hat{t}_{mm}) \end{bmatrix}_{m\times m} \tag{33}$$

Step 6: Compute the sum of rows and columns of the total relation matrices

In the total relation matrix T_C, the sum of rows and columns was represented, respectively, by the vectors R and S of rank $n\times 1$ (in the rough domain) as shown in Eqns. (34)–(35):

$$\begin{aligned} R &= \left[\sum_{j=1}^{n} RN(t_{ij})\right]_{n\times 1} = \left[\sum_{j=1}^{n} \underline{Lim}(t_{ij}), \sum_{j=1}^{n} \overline{Lim}(t_{ij})\right]_{n\times 1} \\ &= \left[\underline{Lim}(t_{i.}), \overline{Lim}(t_{i.})\right]_{n\times 1} \end{aligned} \tag{34}$$

$$\begin{aligned} S &= \left[\sum_{i=1}^{n} RN(t_{ij})\right]'_{n\times 1} = \left[\sum_{i=1}^{n} \underline{Lim}(t_{ij}), \sum_{i=1}^{n} \overline{Lim}(t_{ij})\right]_{1\times n} \\ &= \left[\underline{Lim}(t_{j}), \overline{Lim}(t_{j})\right]_{1\times n} \end{aligned} \tag{35}$$

The value R represents the sum of values from the i-th row of T_C and shows the total direct and indirect effects that criteria i have on other criteria. The value S represents the sum of values from the j-th column of T_C and shows the total direct and indirect effects produced by other criteria on j. In the case when $j=i$, $(R+S)$ denotes the criterion significance and $(R-S)$ denotes the intensity of the criterion influence with respect to that of other criteria. Similarly, assuming $T_D = (\hat{T}_L, \hat{T}_U) = \left[\underline{Lim}(\hat{t}_{ij}), \overline{Lim}(\hat{t}_{ij})\right]$, the sum of rows and columns for the dimensions were also calculated using the vectors R and S of rank $m \times 1$ in the rough domain.

Step 7: Determining the threshold value (α) *and creating a cause-effect relationship diagram.*

The cause-effect relationship diagram (CERD) was created to visualize complex relationships and to provide information allowing the authors to identify the most important factors (dimensions) and their mutual influence. Using Eqn. (36), the threshold value $RN(\alpha)$ for m dimensions was computed by taking the average value of the elements in $m \times m$ matrix T_D, where N denotes the total number of the elements in the above matrix:

$$RN(\alpha) = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m}\left[\underline{Lim}\left(\widehat{t}_{ij}\right), \overline{Lim}\left(\widehat{t}_{ij}\right)\right]}{N} \tag{36}$$

Based on $RN(\alpha)$, the cause and effect relationship diagram for m dimensions was constructed. The dimensions' values $RN(\widehat{t}_{ij})$ larger than the threshold value $RN(\alpha)$ were extracted and stored in the causal diagram, with x-axis $(D+R)$ and y-axis $(D-R)$ respectively representing the relationship between the two factors. The arrow of the causal relationship is pointed from the factor with a value smaller than $RN(\alpha)$ towards the element with a larger value. Similarly, taking the threshold value for every group of criteria on the basis of affiliation to dimensions, the CERD diagram was constructed.

When the diagram of the cause and effect relationship was drawn, the second phase embracing the calculation of the weight coefficients of the criteria based on using the rough ANP followed.

3.2.2. Using the rough ANP for determining the criteria weights based on the R'DEMATEL method

Unlike the hierarchically structured method, the approach based on the analytical network process (ANP) was created to replace the feedback hierarchy found within the AHP, using the network with frequently occurring loops which connect groups (Saaty and Vargas, 2012). The matrices which, in the case of a network, describe these dependencies, are called super matrices and must possess the column stochastic trait (implying that the *sum of the elements per column is equal to one*).

The levels of interdependences of the criteria and dimensions are treated as reciprocal values by using the Rough ANP method for calculating the relative weight coefficients. On the contrary, in the R'DEMATEL method, the levels of interdependences of criteria do not have any reciprocal values, which makes them closer to the real systems.

This *sub-section* presents the implementation of the rough DEMATEL in the ANP network relation method. The incorporation of the rough DEMATEL in the ANP method (R'AMATEL) was realized through the following steps:

Step 1. Developing the unweighted supermatrix.

In this step, before developing an unweighted supermatrix, a *R'ANP*-based network model, using the total influence matrix $T_c = [t_{ij}]_{n\times n}$ from the criteria and $T_D = [t_{ij}^D]_{m\times m}$ using the dimensions (clusters) from T_c, were defined. Then, the supermatrix T_c for the *R'ANP* weights of dimensions was normalized using the influence matrix T_D:

$$T_c = \begin{array}{cc} & \begin{array}{ccccc} D_1 & D_2 & & D_m \\ c_{11}c_{12}\ldots c_{1(n_1)} & c_{21}c_{22}\ldots c_{2(n_2)} & \cdots & c_{m1}c_{m2}\ldots c_{m(n_m)} \end{array} \\ \begin{array}{cc} D_1 & \begin{array}{c} c_{11} \\ c_{12} \\ \mathrm{M} \\ c_{1(n_1)} \end{array} \\ D_2 & \begin{array}{c} c_{21} \\ c_{22} \\ \mathrm{M} \\ c_{2(n_2)} \end{array} \\ D_m & \begin{array}{c} c_{m1} \\ c_{m2} \\ \mathrm{M} \\ c_{m(n_m)} \end{array} \end{array} & \begin{bmatrix} T_c^{11} & T_c^{12} & \cdots & T_c^{1m} \\ T_c^{21} & T_c^{22} & \cdots & T_c^{2m} \\ \vdots & \vdots & \ddots & \vdots \\ T_c^{m1} & T_c^{m2} & \cdots & T_c^{mm} \end{bmatrix} \end{array} \quad where \sum_{j=1}^{m}(n_j)=n \tag{37}$$

where matrix T_c^{11} contains the criteria from the dimension (cluster) D_1 and the values of influences on these criteria. The matrix T_c^{12}(Eqn. (38)) contains the criteria from the dimension D_2 and the values of influences on these criteria, etc.:

$$T_c^{12} = \begin{bmatrix} RN\left(t_{c^{11}}^{12}\right) & \cdots & RN\left(t_{c^{1j}}^{12}\right) & \cdots & RN\left(t_{c^{1(n_2)}}^{12}\right) \\ \vdots & & \vdots & \cdots & \vdots \\ RN\left(t_{c^{i1}}^{12}\right) & \cdots & RN\left(t_{c^{ij}}^{12}\right) & \cdots & RN\left(t_{c^{i(n_2)}}^{12}\right) \\ \vdots & & \vdots & & \vdots \\ RN\left(t_{c^{(n_1)1}}^{12}\right) & \cdots & RN\left(t_{c^{(n_1)j}}^{12}\right) & \cdots & RN\left(t_{c^{(n_1)(n_2)}}^{12}\right) \end{bmatrix} \tag{38}$$

Then, by normalizing the total influence matrix T_c using the dimensions (clusters), a new matrix T_c^{α} was developed as shown in Eqn. (39):

$$T_c^{\alpha} = \begin{array}{cc} & \begin{array}{ccccc} D_1 & D_2 & & D_m \\ c_{11}c_{12}\ldots c_{1(n_1)} & c_{21}c_{22}\ldots c_{2(n_2)} & \cdots & c_{n1}c_{n2}\ldots c_{n(n_m)} \end{array} \\ \begin{array}{cc} D_1 & \begin{array}{c} c_{11} \\ c_{12} \\ \mathrm{M} \\ c_{1(n_1)} \end{array} \\ D_2 & \begin{array}{c} c_{21} \\ c_{22} \\ \mathrm{M} \\ c_{2(n_2)} \end{array} \\ D_m & \begin{array}{c} c_{n1} \\ c_{n2} \\ \mathrm{M} \\ c_{m(n_m)} \end{array} \end{array} & \begin{bmatrix} T_c^{\alpha 11} & T_c^{\alpha 12} & \cdots & T_c^{\alpha 1m} \\ T_c^{\alpha 21} & T_c^{\alpha 22} & \cdots & T_c^{\alpha 2m} \\ \vdots & \vdots & \ddots & \vdots \\ T_c^{\alpha m1} & T_c^{\alpha m2} & \cdots & T_c^{\alpha mm} \end{bmatrix} \end{array} \tag{39}$$

Thus, normalization of $T_c^{\alpha 11}$ for criteria $c_{1j}(j = 1, 2, ..., (m_1))$ in the dimension D_1 was performed by using Eqn. (40).

$$T_c^{\alpha 11} = \begin{bmatrix} RN\left(t_{c^{11}}^{11}\right)\Big/RN\left(d_{c^1}^{11}\right) & \cdots & RN\left(t_{c^{1j}}^{11}\right)\Big/RN\left(d_{c1}^{11}\right) & \cdots & RN\left(t_{c^{1n_1}}^{11}\right)\Big/RN\left(d_{c^1}^{11}\right) \\ \vdots & & \vdots & \cdots & \vdots \\ RN\left(t_{c^{i1}}^{11}\right)\Big/RN\left(d_{c^i}^{11}\right) & \cdots & RN\left(t_{c^{ij}}^{11}\right)\Big/RN\left(d_{c^i}^{11}\right) & \cdots & RN\left(t_{c^{in_1}}^{11}\right)\Big/RN\left(d_{c^i}^{11}\right) \\ \vdots & & \vdots & & \vdots \\ RN\left(t_{c^{n_1 1}}^{11}\right)\Big/RN\left(d_{c^{n_1}}^{11}\right) & \cdots & RN\left(t_{c^{n_1 j}}^{11}\right)\Big/RN\left(d_{c^{n_1}}^{11}\right) & \cdots & RN\left(t_{c^{n_1 n_1}}^{12}\right)\Big/RN\left(d_{c^{n_1}}^{11}\right) \end{bmatrix}; \tag{40}$$

where $RN(d_{c^i}^{11}) = \sum_{j=1}^{(n_1)} RN(t_{c^{ij}}^{11})$ and $RN(t_{cj}^{11})$ denote the values of the criteria influences $c_{1j}(j = 1, 2, \ldots, n_1)$ with respect to the criteria from the dimension D_1, while the elements $RN(t_{c^{11}}^{\alpha 11})$ denote their normalized values. The remaining matrices $T_c^{\alpha mm}$ within the matrix T_c^{α}(*in* Eqn. (35)) were calculated in the same way.

Then, the cluster elements $RN(t_D^{\alpha ij})$ of the normalized total influence matrix T_D^{α}(*given in* Eqn. (42)) were used together with the *cluster* elements $W^{ij}(i,j = 1, 2, \ldots m)$ of the supermatrix W in Eqn. (41) to obtain the weighted supermatrix W^{α} as shown in Eqn. (44)

$$W^{\alpha} = T_D^{\alpha} \times W = \begin{bmatrix} RN\left(t_D^{\alpha 11}\right) \times W^{11} & \ldots & RN\left(t_D^{\alpha 1j}\right) \times W^{1j} & \ldots & RN\left(t_D^{\alpha 1m}\right) \times W^{1m} \\ \vdots & & \vdots & \cdots & \vdots \\ RN\left(t_D^{\alpha i1}\right) \times W^{i1} & \ldots & RN\left(t_D^{\alpha ij}\right) \times W^{ij} & \ldots & RN\left(t_D^{\alpha im}\right) \times W^{im} \\ \vdots & & \vdots & & \vdots \\ RN\left(t_D^{\alpha m1}\right) \times W^{m1} & \ldots & RN\left(t_D^{\alpha mj}\right) \times W^{mj} & \ldots & RN\left(t_D^{\alpha mm}\right) \times W^{mm} \end{bmatrix} \quad (44)$$

By transposing the normalized influence matrix T_c^{α} from Eqn. (39), the *unweighted supermatrix* $W = (T_c^{\alpha})'$ was obtained in Eqn. (41), where matrix $W^{ij}(i,j = 1, 2, \ldots m)$ denotes the values of criteria influences from dimensions (*clusters*) $D_i(i = 1, 2, \ldots, m)$ in relation to the criteria from its group:

$$W = (T_c^{\alpha})' = \begin{array}{cc} & \begin{array}{cccc} D_1 & D_2 & \cdots & D_m \\ c_{11}c_{12}\cdots c_{1(n_1)} & c_{21}c_{22}\cdots c_{2(n_2)} & \cdots & c_{m1}c_{m2}\cdots c_{m(n_m)} \end{array} \\ \begin{array}{c} D_1 \begin{array}{c} c_{11} \\ c_{12} \\ \mathrm{M} \\ c_{1(n_1)} \end{array} \\ D_2 \begin{array}{c} c_{21} \\ c_{22} \\ \mathrm{M} \\ c_{2(n_2)} \end{array} \\ D_m \begin{array}{c} c_{m1} \\ c_{m2} \\ \mathrm{M} \\ c_{m(n_m)} \end{array} \end{array} & \begin{bmatrix} W^{11} & W^{12} & \cdots & W^{1m} \\ W^{21} & W^{22} & \cdots & W^{2m} \\ \vdots & \vdots & \ddots & \vdots \\ W^{m1} & W^{m2} & \cdots & W^{mm} \end{bmatrix} \end{array} \quad (41)$$

Step 2. Determining the elements of the weighted supermatrix (W^{α})

First, the elements of the total influence matrix $T_D = [RN(t_D^{ij})]_{m \times m}(i,j = 1, 2, \ldots, m)$ were normalized, and a new matrix $T_D^{\alpha} = [RN(t_D^{\alpha ij})]_{m \times m}$ was obtained, as shown in Eqn. (42):

$$T_D^{\alpha} = \begin{bmatrix} RN\left(t_D^{\alpha 11}\right) & \ldots & RN\left(t_D^{\alpha 1j}\right) & \ldots & RN\left(t_D^{\alpha 1m}\right) \\ \vdots & & \vdots & \cdots & \vdots \\ RN\left(t_D^{\alpha i1}\right) & \ldots & RN\left(t_D^{\alpha ij}\right) & \ldots & RN\left(t_D^{\alpha im}\right) \\ \vdots & & \vdots & & \vdots \\ RN\left(t_D^{\alpha m1}\right) & \ldots & RN\left(t_D^{\alpha mj}\right) & \ldots & RN\left(t_D^{\alpha mm}\right) \end{bmatrix} \quad i,j = 1, 2, \ldots, m \quad (42)$$

where

$$\begin{cases} RN(t_D^{\alpha ij}) = \left(\dfrac{RN(t_D^{ij})}{RN(d_i)}\right) \\ RN(d_i) = \displaystyle\sum_{j=1}^{m} RN\left(t_D^{ij}\right), \quad i = 1, 2, \ldots, m \end{cases} \quad (43)$$

Step 3. Limiting the weighted supermatrix

Calculate the limited weighted supermatrix $\widehat{W}$ by raising the rough weighted supermatrix (W^{α}) (*in* Eqn. (44)) to a power of ρ with $\rho \to \infty$ $(i.e.\ \lim_{\rho \to \infty}(W^{\alpha})^{\rho})$ until it converge to long term stable matrix, as shown *in* Eqn. (45).

$$\widehat{W} = \lim_{\rho \to \infty}(W^{\alpha})^{\rho} = \left[RN(w_{ij})\right]_{n \times n} \quad \forall\ i,j = 1, 2, \ldots, n \quad (45)$$

All the n column vectors are same in this rough limit supermatrix $(\widehat{W})$. The influential weight coefficients $(\tilde{w}_i)$ for each criterion $C_i(i = 1, 2, \ldots, n)$ are derived by taking any column of $(\widehat{W})$.

$$\tilde{w}_i = [RN(w_{i.})]_{n \times 1} = [RN(w_{1.}), \quad RN(w_{2.}), \ldots, RN(w_{n.})]^T \quad \forall\ i = 1, 2, \ldots, n \quad (46)$$

Each row elements $RN(w_{i.})(i = 1, 2, \ldots, n)$ in Eqn. (46) represents the global priority weight $\tilde{w}_i(i = 1, 2, \ldots, n)$ for each criterion $C_i(i = 1, 2, \ldots, n)$, while the sum of every group of criteria (*taken on the basis of affiliation to dimensions*) represented the weight $\widehat{w}_i(i = 1, 2, \ldots, m)$ of each dimension $D_i(i = 1, 2, \ldots, m)$.

3.3. The rough MAIRCA method

The default setting for the MAIRCA method was found in determining the gap between the ideal and the empirical assessments (Gigović et al., 2016a, b). The summation of the gaps for each criterion values gave the total gap for each observed alternative and the highest ranked alternative was the one with the lowest value for the total gap. The alternative with the lowest total gap had the majority of criteria with the values that were closest to the ideal estimates (ideal value criteria). Based on the criteria weights (Eqn. (46) *in step 3 of sub*-section 3.2) calculated by *R'AMETAL* and the proposed rough *MAIRCA* method, distinct priorities were aggregated and the appropriate alternatives were selected. The suggested steps are given below:

Step 1. Forming the initial rough decision matrix $(\tilde{Y})$

For each expert $E_k(k = 1, 2, \ldots, d)$, the group decision-making matrix $Y_k(k = 1, 2, \ldots, d)$ was constructed by identifying the alternatives $A_i(i = 1, 2, \ldots, l)$ with respect to each criterion $C_j(j = 1, 2, \ldots, n)$:

$$Y_k = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_l \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} y_{11}^k & y_{12}^k & \cdots & y_{1n}^k \\ y_{21}^k & y_{22}^k & \cdots & y_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ y_{l1}^k & y_{l2}^k & \cdots & y_{ln}^k \end{bmatrix}_{l\times n} \end{array} \tag{47}$$

Each element $y_{ij}^k (i = 1,2,\ldots,l;\ j = 1,2,\ldots,n)$ of $Y_k = [y_{ij}^k]_{l\times n}$ was first aggregated to $Y^* = [y_{ij}]_{l\times n}$, where each $y_{ij} = \{y_{ij}^1, y_{ij}^2, \ldots, y_{ij}^d\}$ was then converted to a rough number,$RN(y_{ij}^k)$ using Eqns. (1)–(7). Applying the same procedure as described in section 3.2 (Eqns. (20)–(24)), the initial average rough decision matrix $\tilde{Y} = [RN(y_{ij})]_{l\ \times n}$ was constructed (*using* Eqn. (47)), where the observed alternative $A_i = (RN(y_{i1}), RN(y_{i2}), \ldots, RN(y_{in}))$ are defined, as follows:

$$\tilde{Y} = \begin{array}{c} \\ A_1 \\ A_2 \\ \ldots \\ A_l \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{bmatrix} RN(y_{11}) & RN(y_{12}) & \ldots & RN(y_{1n}) \\ RN(y_{21}) & RN(y_{22}) & & RN(y_{2n}) \\ \ldots & \ldots & \ldots & \ldots \\ RN(y_{l1}) & RN(y_{l2}) & \ldots & RN(y_{ln}) \end{bmatrix}_{l\times n} \end{array} \tag{48}$$

where $RN(y_{ij}) = \left[\underline{Lim}(y_{ij}), \overline{Lim}(y_{ij})\right]$ denotes the value of the i-th alternative for the j-th criterion $(i = 1,2,\ldots,l;\ j = 1,2,\ldots,n)$. The matrix elements $RN(y_{ij})$ in Eqn. (48) are rough numbers (RNs) determined by the DMs or by using the aggregation of the experts' decisions.

Step 2. Determining the preferences P_{A_i} according to the alternative selection.

The Experts $E_k (k = 1,2,\ldots,d)$ are neutral with respect to the alternatives $A_i (i = 1,2,\ldots,l)$ during alternative selection and do not have any preferences. All the alternatives are considered and selected with equal probability. Therefore, the process of selecting one alternative from among l alternatives is as follows:

$$\begin{cases} P_{A_i} = \dfrac{1}{l} \qquad (i = 1,2,\ldots,l) \\ \displaystyle\sum_{i=1}^{l} P_{A_i} = 1 \end{cases} \tag{49}$$

Step 3. Calculating the matrix elements of theoretical estimates (T_p)

Theoretical estimates matrix $T_p = [RN(b_{ij})]_{l\times n}$ of the format $l \times n$ (*with n being the number of the criteria and l the number of the alternatives, respectively*) is created and shown by Eqn. (50).

$$T_p = \begin{array}{c} \\ A_1 \\ A_2 \\ \ldots \\ A_l \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{bmatrix} RN(b_{11}) & RN(b_{12}) & \ldots & RN(b_{1n}) \\ RN(b_{21}) & RN(b_{22}) & & RN(b_{2n}) \\ \ldots & \ldots & \ldots & \ldots \\ RN(b_{l1}) & RN(b_{l2}) & \ldots & RN(b_{ln}) \end{bmatrix}_{l\times n} \end{array} \tag{50}$$

The elements $RN(b_{ij}) (i = 1,2,\ldots,l;\ j = 1,2,\ldots,n)$ of theoretical estimate (T_p) were calculated by multiplying the preferences $P_{A_i} (i = 1,2,\ldots,l)$(*in* Eqn. (49)) for the each alternative $A_i (i = 1,2,\ldots,l)$ with the weight coefficients $\tilde{w}_i (i = 1,2,\ldots,n)$ (*in* Eqn. (46)) for criterion $C_j (j = 1,2,\ldots,n)$. The details shown in Eqn. (51).

$$T_p = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_l \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} P_{A_1} \cdot \tilde{w}_1 & P_{A_1} \cdot \tilde{w}_2 & \cdots & P_{A_1} \cdot \tilde{w}_n \\ P_{A_2} \cdot \tilde{w}_1 & P_{A_2} \cdot \tilde{w}_2 & \cdots & P_{A_2} \cdot \tilde{w}_n \\ \vdots & \vdots & \ddots & \vdots \\ P_{A_l} \cdot \tilde{w}_1 & P_{A_l} \cdot \tilde{w}_2 & \cdots & P_{A_l} \cdot \tilde{w}_n \end{bmatrix}_{l\times n} \end{array} \tag{51}$$

Since the DMs are neutral towards the initial alternative selection, the preferences $P_{A_i} (i = 1,2,\ldots,l)$ are equal for all the alternatives $A_i (i = 1,2,\ldots,l)$.

$$P_{A_1} = P_{A_2} = \ldots = P_{A_l} \tag{52}$$

Subsequently, the matrix $T_p = [RN(b_{ij})]_{l\times n}$ in Eqn. (50) can also be shown as per Eqn. (53):

$$T_p = A_i \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{bmatrix} RN(b_{i1}) & RN(b_{i2}) & \ldots & RN(b_{in}) \end{bmatrix}_{1\times n} \end{array} \tag{53}$$

Step 4. Determining the matrix elements for the real assessment (T_r)

The calculation of the matrix elements $RN(v_{ij})$ for the real assessment (T_r) (*in* Eqn. (54)) was done by multiplying the matrix elements $RN(b_{ij})$ for the theoretical assessment (T_p) (*in* Eqn. (50)) and the elements $RN(y_{ij})$ of the initial decision matrix $\tilde{Y}$, according to the expression given *in* Eqn. (55)–(57), as follows:

$$T_r = \begin{array}{c} \\ A_1 \\ A_2 \\ \ldots \\ A_l \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{bmatrix} RN(v_{11}) & RN(v_{12}) & \ldots & RN(v_{1n}) \\ RN(v_{21}) & RN(v_{22}) & & RN(v_{2n}) \\ \ldots & \ldots & \ldots & \ldots \\ RN(v_{l1}) & RN(v_{l2}) & \ldots & RN(v_{ln}) \end{bmatrix}_{l\times n} \end{array} \tag{54}$$

(a) For the criteria type "benefit" (larger criteria values preferred):

$$RN(v_{ij}) = \left[\underline{Lim}(b_{ij}) \cdot \left(\frac{\underline{Lim}\left(y_{ij}\right) - y_i^-}{y_i^+ - y_i^-}\right), \overline{Lim}(b_{ij}) \cdot \left(\frac{\overline{Lim}\left(y_{ij}\right) - y_i^-}{y_i^+ - y_i^-}\right)\right]; \tag{55}$$

(b) For the criteria type "*cost*" (*smaller criteria value preferred*)

$$RN(v_{ij}) = \left[\underline{Lim}(b_{ij}) \cdot \left(\frac{\underline{Lim}\left(y_{ij}\right) - y_i^+}{y_i^- - y_i^+}\right), \overline{Lim}(b_{ij}) \cdot \left(\frac{\overline{Lim}\left(y_{ij}\right) - y_i^+}{y_i^- - y_i^+}\right)\right], \tag{56}$$

where y_i^- and y_i^+ are the minimum and maximum values of the considered criterion limit intervals, respectively:

$$\begin{cases} y_i^- = \min\limits_i \left\{ \underline{Lim}\left(y_{ij}\right) \right\} \\ y_i^+ = \max\limits_i \left\{ \overline{Lim}\left(y_{ij}\right) \right\} \end{cases} \tag{57}$$

Step 5. Calculating the total gap matrix (G)

The elements of the matrix G were calculated based on the difference (*gap*) between the theoretical assessment $RN(b_{ij})$ and real assessment $RN(v_{ij})$, or by subtracting the matrix (T_r) elements from the (T_p) matrix elements:

$$G = T_p - T_r = \begin{bmatrix} RN(g_{11}) & RN(g_{12}) & \dots & RN(g_{1n}) \\ RN(g_{21}) & RN(g_{22}) & \dots & RN(g_{2n}) \\ \dots & \dots & \dots & \dots \\ RN(g_{l1}) & RN(g_{l2}) & \dots & RN(g_{ln}) \end{bmatrix}_{l \times n} \tag{58}$$

where, the calculated gap $RN(g_{ij})$ of the alternative i for the criterion j, was calculated as per Eqn. (59):

$$\begin{aligned} RN\left(g_{ij}\right) &= RN(b_{ij}) - RN(v_{ij}) \\ &= \left[\underline{Lim}(b_{ij}) - \overline{Lim}(v_{ij}), \overline{Lim}(b_{ij}) - \underline{Lim}(v_{ij})\right]. \end{aligned} \tag{59}$$

The value of $RN(g_{ij})$ had to be close to zero $(RN(g_{ij}) \to 0)$ because the alternative with the least difference between $RN(b_{ij})$ and $RN(v_{ij})$ was chosen. If the alternative A_i for the criterion C_i has the value of theoretical assessment equal to the value of real assessment $(RN(b_{ij}) \approx RN(v_{ij}))$, then the gap for the alternative $A_i (i = 1, 2, \dots, l)$ for the criterion $C_j (j = 1, 2, \dots, n)$ is close to zero. Therefore, the alternative A_i for the criterion C_i is the best (*ideal*) alternative.

If the alternative A_i for the criterion C_j has the value of theoretical assessment $RN(b_{ij})$, while the value of real assessment $RN(v_{ij})$ is striving to zero, then the gap for the alternative A_i for the criterion C_i is $RN(g_{ij}) \approx RN(b_{ij})$. This means that the alternative A_i for the criterion C_i is the worst (*anti-ideal*) alternative.

Step 6. Calculating the initial value of the criterion function (Q_i) *for the alternatives.*

The values of the criterion function were calculated by summing up the gaps from the matrix in Eqn. (58) for each alternative A_i according to the evaluation criteria C_i or by summing up the matrix (G) elements in the columns, shown in Eqn. (60):

$$RN(Q_i) = \sum_{j=1}^{n} RN\left(g_{ij}\right), i = 1, 2, \dots, l \tag{60}$$

Ranking the alternatives can be performed by applying the rules for ranking rough numbers described in *sub-section* 3.1.2. The conversion of rough number $RN(Q_i) = \left[\underline{Lim}(Q_i), \overline{Lim}(Q_i)\right]$ into real number Q_i is enabled by applying Eqns. (61) and (63).

$$RN\left(\widehat{Q}_i\right) = \begin{cases} \underline{Lim}\left(\widehat{Q}_i\right) = \dfrac{\underline{Lim}(Q_i) - \min\limits_i\{\underline{Lim}(Q_i)\}}{\max\limits_i\left\{\overline{Lim}(Q_i)\right\} - \min\limits_i\{\underline{Lim}(Q_i)\}} \\ \overline{Lim}\left(\widehat{Q}_i\right) = \dfrac{\overline{Lim}(Q_i) - \min\limits_i\{\underline{Lim}(Q_i)\}}{\max\limits_i\left\{\overline{Lim}(Q_i)\right\} - \min\limits_i\{\underline{Lim}(Q_i)\}} \end{cases} \tag{61}$$

where $\underline{Lim}(Q_i)$ and $\overline{Lim}(Q_i)$ represent the lower limit and upper limit of the rough number $RN(Q_i)$, respectively; $\underline{Lim}(\widehat{Q}_i)$ and $\overline{Lim}(\widehat{Q}_i)$ are the normalized forms of $\underline{Lim}(Q_i)$.

After normalization, we obtain a total normalized crisp value:

$$\beta_i = \frac{\underline{Lim}\left(\widehat{Q}_i\right) \cdot \left\{1 - \underline{Lim}\left(\widehat{Q}_i\right)\right\} + \overline{Lim}\left(\widehat{Q}_i\right) \cdot \overline{Lim}\left(\widehat{Q}_i\right)}{1 - \underline{Lim}\left(\widehat{Q}_i\right) + \overline{Lim}\left(\widehat{Q}_i\right)} \tag{62}$$

Finally crisp form Q_i^{crisp} for $RN(Q_i)$ is obtained by applying Eqn. (63):

$$Q_i^{crisp} = \min_i\{\underline{Lim}(Q_i)\} + \beta_i \cdot \left[\max_i\left\{\overline{Lim}(Q_i)\right\} - \min_i\{\underline{Lim}(Q_i)\}\right] \tag{63}$$

Step 7. Defining the dominance index $(A_{D,1-j})$ *of the best-ranked alternative and final rank of alternatives.*

The dominance index of the best-ranked alternative defines its advantage in relation to the other alternatives, and determined here by applying Eqn. (64).

$$A_{D,1-j} = \left| \frac{|Q_j| - |Q_1|}{|Q_n|} \right|, j = 2, 3, \dots, m \tag{64}$$

where Q_1 denotes the criterion function of the best-ranked alternative, Q_n denotes the criterion function of the last ranked alternative, Q_j denotes the criterion function of the alternative which is compared to the best-ranked alternative, and m denotes the number of alternatives.

Once the dominance index is determined, the dominance threshold I_D is determined by applying Eqn. (65)

$$I_D = \frac{m-1}{m^2} \tag{65}$$

where m denotes the number of alternatives.

Provided that the dominance index $A_{D,1-j}$ is greater or equal to dominance threshold I_D $(A_{D,1-j} \ge I_D)$, the obtained rank will be retained. However, if the dominance index $A_{D,1-j}$ is smaller than the dominance threshold I_D $(A_{D,1-j} < I_D)$, then it cannot be said with certainty that the first ranked alternatives have an advantage over the alternative being analyzed. The said restrictions can be shown by applying the following Eqn. (66)

$$R_{final,j} = \begin{cases} A_{D,1-j} \ge I_D \Rightarrow R_{final,j} = R_{initial,j} \\ A_{D,1-j} < I_D \Rightarrow R_{final,j} = R_{initial,1} \end{cases} \tag{66}$$

where $R_{initial,j}$ and $R_{final,j}$ denotes the initial and final rank of the alternative, respectively, that is compared with the best-ranked alternative, I_D denotes the dominance threshold, and $A_{D,1-j}$

denotes the dominance index of the best-ranked alternative in relation to the alternative.

Provided that criterion $A_{D,1-j} < I_D$ is satisfied, then the rank of the alternative that is compared to the best-ranked alternative will be corrected and then treated as the best-ranked alternative and assigned the value "1*". In this way it is emphasized that the best-ranked alternative is characterized by a smaller advantage than the one specified in Eqn. (65).

Assume, for example, that the best-ranked alternative is compared to the second-ranked alternative and that the criterion $A_{D,1-2} < I_D$ is satisfied. Then the second-ranked alternative will be assigned rank "1*". The comparison may proceed with the third-ranked alternative. If for the third-ranked alternative criterion $A_{D,1-3} < I_D$ is satisfied, then the third-ranked alternative will be assigned rank "1**" and so on, until reaching the last alternative.

Finally, correction of the initial ranks ($R_{initial}$) is carried out for all alternatives satisfying criterion $A_{D,1-j} < I_D$, while the ranks of alternatives satisfying the criterion $A_{D,1-j} \geq I_D$ remain unchanged. Therefore, the final rank of alternatives (R_{final}) which is presented simultaneously with the initial rank of alternatives ($R_{initial}$) is obtained.

4. Case study: GSCM in the electronics industry

An empirical study of the performance evaluation of suppliers based on GSC criteria and dimensions in the Electronics GSC was performed to demonstrate the viability of the suggested algorithmic approach.

4.1. The background and problem description

Although many businesses realize the significance of GSCM secured by the state law and show their commitment to GSCM practices, it is still a new concept in the electronics sector. In the proposed study, a Taiwanese *electronics company* (referred to as XYZ, a pseudonym), a global leader in electronics and computing product development, is chosen as a case study for implementing green practices at all levels of production to improve ecological efficiency, including the selection of the alternative suppliers. The company has strong R&D capability with strong supply chain networks. The company was selected because the rapidly changing environment of the electronics sector forcing firm to develop ongoing sustainable capabilities and to respond to the uncertain environment. Various papers related to supplier selection on Taiwanese electronics companies are proposed in recent years (Chen et al., 2012; Tsui and Wen, 2014; Liou et al., 2016). Since suppliers largely determine the manufacturer's performance in the entire green supply chain, the performance evaluation of its five major alternative suppliers based on using the sustainable GSC criteria was made. The rating scale was pre-determined by experts.

4.2. The criteria of supplier performance evaluation

The GSCM is a complex process characterized by various interdependent dimensions and described by various criteria used for selecting green suppliers in the electronics sector. For the case study analysed, 15 criteria in five dimensions were selected based on the GSCM system (see Table 1).

To assess the identified GSC indicators based on the literature sources and the judgements of highly skilled and experienced experts in electronics sector industries of the country, a questionnaire survey including a face-to-face interview with the expert panel was conducted to gauge the importance levels of the indicators (criteria) used in decision-making. This study began by consulting with four senior decision experts and referring to prior studies. In this study, some specific expertise requirements for the qualification of expert panelists were introduced, which are detailed in Table 2.

The questionnaire was structured for conducting a face-to-face interview with professionals (*contractor, client and consultant companies*), which would help to understand their ideas and check the compatibility of the indicators with the specific conditions in Taiwan. The questionnaire was distributed among the professionals and experts, including the stakeholders like the contractor, the client, and consultant companies (*with at least five years of working*

Table 1
Dimensions and criteria of the GSCM.

Dimensions	Criteria	References
Green design (D_1)	Increasing innovation capabilities (C_1)	Govindan et al. (2014); Buyukozkan and Cifci (2012)
	Abstaining from toxic substances (C_2)	Chen et al. (2012); Liou et al. (2016)
	Saving Energy (C_3)	Kumar et al. (2016); Govindan et al. (2015a)
Green purchasing (D_2)	Green Image (C_4)	Govindan et al. (2014); Kannan et al. (2014)
	Green management abilities (C_5)	Shen et al. (2013); Keshavarz Ghorabaee et al. (2016)
	Green competencies (C_6)	Chen et al. (2012, 2016); Govindan et al. (2015b)
Green production (D_3)	Green recycling and lean production (C_7)	Kumar et al. (2016); Rostamzadeh et al. (2015)
	Cleaner production technologies (C_8)	Liou et al. (2016); Govindan et al. (2015a)
	Decrease Scrap rate (C_9)	Keshavarz Ghorabaee et al. (2016); Uygun and Dede (2016)
Green Warehousing (D_4)	Eco-packaging (C_{10})	Kannan et al. (2014); Keshavarz Ghorabaee et al. (2016)
	Decrease Inventory Levels (C_{11})	Rostamzadeh et al. (2015); Liou et al. (2016)
	Sale of excess capital equipment (C_{12})	Uygun and Dede (2016)
Green Transportation (D_5)	Use Green fuels (Low sulfur content) (C_{13})	Rostamzadeh et al. (2015)
	Reverse logistics (C_{14})	Uygun and Dede (2016); Govindan et al. (2015b)
	Environmental friendly distribution (C_{15})	Rostamzadeh et al. (2015); Kannan et al. (2014)

Table 2
Demographic characteristics of the expert decision makers (DMs).

Decision makers (Experts)	Gender	Age	Education background	Service tenure	Occupational background	Job title
Expert 1	Male	45	Masters	>18	Governmental	Purchasing manager
Expert 2	Male	51	Master	>23	Industrial	Production Engineer
Expert 3	Male	43	Master	>17	Industrial	Design analyst
Expert 4	Female	39	Master	>12	Industrial.	Legal advisor (Green Tribunal)

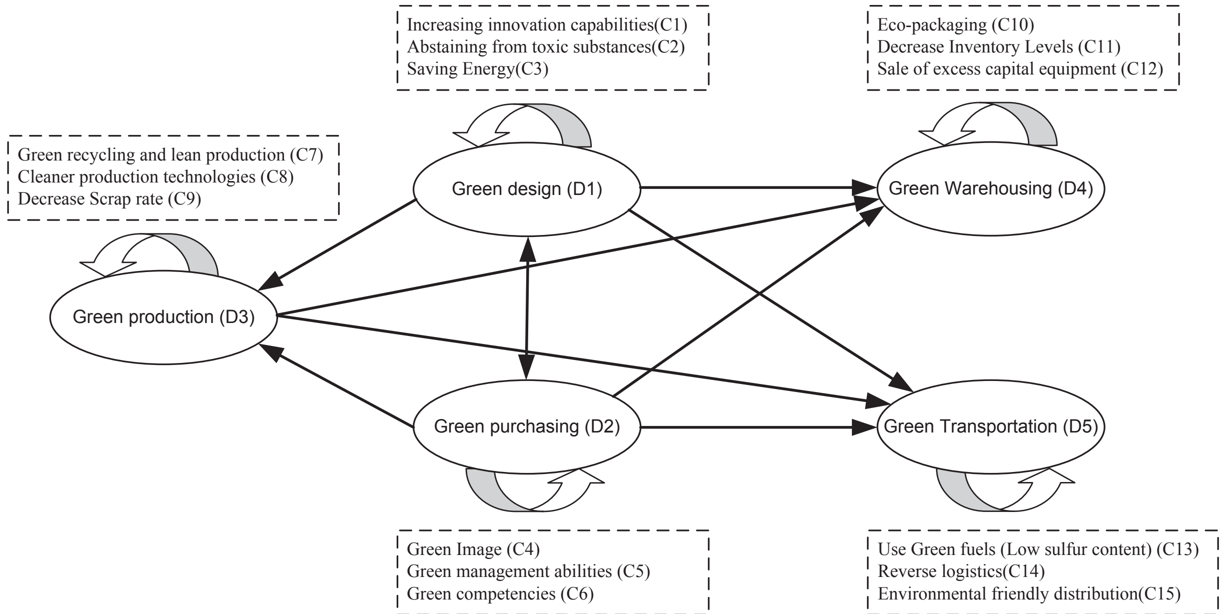

Fig. 1. Map of network relationships - Rough ANP model.

experience) and used in feasibility studies of the electronics sector in Taiwan.

4.3. The analysis of the map of network relations between dimensions and criteria based on using R'DEMATEL method

The rough DEMATEL technique introduced in *sub-section* 3.2.1 was used to analyze the interrelationships between fifteen criteria and five dimensions (Table 1) summarized based on the various literature sources. Details shown in Fig. 1.

Step 1: Four experts $E_k (k = 1, 2, \ldots, 4)$ were asked to determine the degree of influence for each of the relationships between the dimensions (clusters) and the criteria, using a five point scale ranging from 0 (no influence) to 4 (very high influence). Applying Eqns. (17)–(18), four response matrices $X_k = [x_{ij}^k]_{15\times15} (k = 1, 2, \ldots, 4)$ (Table 4) and $\widehat{X}_k = [\widehat{X}_{ij}^k]_{5\times5}$ $(k = 1, 2, \ldots, 4)$ (Table 5) were calculated for the criteria $C_j (j = 1, 2, \ldots, 15)$ and the dimensions $D_j (j = 1, 2, \ldots, 5)$, respectively.
Step 2: The weight coefficients $w_j (j = 1, 2, \ldots, 4)$ for expert $E_k (k = 1, 2, \ldots, 4)$ were calculated using Eqn. (19) and given in Table 3.
Step 3: Applying Eqns. (20)–(22) to the results presented in Tables 4 and 5, object classes were determined and rough number intervals were defined in matrices $X_C^k = [RN(x_{ij}^k)]_{15\times15}$ (Table 6) and $\widehat{X}_D^k = [RN(\widehat{X}_{ij}^k)]_{5\times5}$(Table 7), respectively.

Table 3
Experts weight coefficient of expert $E_j (j = 1, 2, \ldots, 4)$.

	Expert 1	Expert 2	Expert 3	Expert 4
w_0	5.00	5.00	4.00	5.00
w_u	4.25	4.75	4.00	4.75
w_s	5.00	5.00	4.00	5.00
$\sum$	14.25	14.75	12	14.75
w	0.2556	0.2646	0.2152	0.2646

Using Eqns. (23)–(25), the average rough number was calculated for the criteria and used as an element in the average rough matrix $Z_C = [RN(z_{ij})]_{15\times15}$ (Table 8). The same calculations were made with the dimensions and the expert analysis of the dimensions $Z_D = [RN(z_{ij})]_{5\times5}$ (see Table 9).
Step 4: The initial normalized direct-relation matrix $D_c = [RN(d_{ij})]_{15\times15}$ was calculated for the criteria based on the matrix Z_c, which is given in Table 10. The matrix D_C was obtained by dividing each element $RN(z_{ij})$ of the matrix Z_D by the rough number $RN(s)$ as shown in Eqns. (26)–(28). The initial direct-relation matrix D_D for dimensions was also calculated in the same way and presented in Table 11.
Step 5: The elements of the total relation matrices $T_C = [RN(t_{ij})]_{15\times15}$(Table 12) and $T_D = [RN(\widehat{t}_{ij})]_{5\times5}$(Table 13) respectively, were calculated by Eqns. (32)–(33).
Step 6: The values of the matrix (T_C) were summed up using the vectors *R and S*, as defined in Eqns. (34)–(35). Details shown in Table 14. Similarly, the sums of the row and column vectors were calculated for dimensions also (see Table 14).
Step 7: Based on the results given in Tables 12–14 and Eqn. (36), the diagram of cause and effect relationship (CERD) (Fig. 2) was drawn, which demonstrated the interdependence between the dimensions and the impact of the criteria on each other within the observed dimension.

The CERD was obtained as a result of data processing at the first stage, based on using the rough DEMATEL method, and served as the basis for implementing the rough ANP method and for better understanding of the relationship between the clusters (criteria).

4.4. Determining the dimensions and the criteria weights using R'ANP

Step 1: The total influence matrix T_C was included in the *R'ANP* model, and the *unweighted supermatrix* $W = (T_C^\alpha)'$ was obtained using Eqns. (37) – (41) and shown in Table 15.
Step 2: Using Eqns. (42)–(44), the elements of the *weighted supermatrix* were calculated (Table 16).

Table 4
Expert analysis $X_k = [x_{ij}^k]_{15\times15}(k = 1, 2, 3, 4)$ of the criteria $C_j(j = 1, 2, \ldots, 15)$.

Expert 1

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1	0	3	2	3	2	3	2	3	2	1	4	3	5	2	1
C_2	4	0	4	2	2	3	5	4	3	3	4	5	4	2	3
C_3	4	3	0	3	3	4	2	4	3	3	4	3	3	2	3
C_4	4	3	5	0	2	3	3	3	4	3	4	5	4	2	2
C_5	5	4	5	4	0	4	5	5	3	5	4	5	5	1	2
C_6	4	4	3	3	1	0	2	4	4	4	4	3	3	2	3
C_7	4	4	3	4	2	4	0	5	5	4	5	5	5	1	1
C_8	3	3	4	2	1	2	2	0	3	4	4	3	4	2	2
C_9	3	3	4	2	2	2	3	3	0	3	4	4	3	2	2
C_{10}	4	4	5	5	4	2	3	2	2	0	4	4	4	2	2
C_{11}	2	2	1	2	1	1	2	2	1	1	0	3	3	1	1
C_{12}	3	3	1	2	2	1	2	3	2	2	3	0	3	2	2
C_{13}	1	2	1	3	1	1	3	1	2	2	3	3	0	1	1
C_{14}	5	5	3	4	5	4	5	5	5	5	5	5	5	0	4
C_{15}	5	5	5	4	4	5	4	5	5	5	5	5	5	3	0

Expert 2

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1	0	4	3	4	1	5	2	4	1	2	5	2	4	2	2
C_2	4	0	4	4	1	5	5	3	3	3	4	3	4	3	4
C_3	4	1	0	5	3	5	3	4	3	2	3	4	3	3	3
C_4	4	2	5	0	2	5	3	3	4	2	4	5	5	3	2
C_5	5	3	5	5	0	5	5	5	3	4	3	4	4	2	3
C_6	4	2	4	4	1	0	2	4	4	5	3	4	4	3	2
C_7	4	2	4	5	2	5	0	5	5	5	4	4	4	2	2
C_8	4	2	5	4	1	4	2	0	3	4	4	4	5	3	3
C_9	3	1	4	3	2	4	3	3	0	4	5	5	4	3	3
C_{10}	5	3	5	4	4	3	4	2	2	0	4	5	5	3	3
C_{11}	2	1	1	3	1	3	3	2	1	2	0	3	3	2	2
C_{12}	2	1	2	2	1	2	2	3	2	3	4	0	3	3	3
C_{13}	2	1	2	3	1	3	1	1	1	2	2	2	0	2	2
C_{14}	5	3	3	5	4	3	5	5	5	4	4	4	4	0	3
C_{15}	5	4	5	5	4	4	4	5	5	4	4	4	4	4	0

Expert 3

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1	0	4	3	3	2	5	3	3	2	5	4	4	4	5	3
C_2	4	0	3	5	1	3	4	3	3	5	5	4	4	4	3
C_3	5	5	0	5	4	3	2	3	3	5	4	4	4	4	4
C_4	3	4	5	0	3	4	3	3	4	5	4	5	5	5	2
C_5	3	5	5	4	0	3	5	3	4	4	3	4	4	3	3
C_6	4	5	3	4	2	0	2	3	5	3	3	4	5	4	2
C_7	5	4	3	4	2	3	0	3	5	5	4	4	3	4	2
C_8	4	4	4	4	1	3	2	0	4	3	3	3	4	4	2
C_9	3	4	5	5	1	3	4	5	0	5	5	3	4	3	3
C_{10}	5	4	4	5	5	5	4	5	2	0	4	3	3	3	2
C_{11}	1	3	2	5	2	4	3	3	2	5	0	3	4	5	2
C_{12}	2	3	2	3	2	5	3	3	2	3	4	0	4	5	2
C_{13}	2	5	1	3	1	3	2	5	2	5	3	5	0	5	1
C_{14}	3	5	2	4	5	3	4	3	5	3	5	4	4	0	3
C_{15}	4	3	5	4	4	4	4	3	3	3	4	4	5	4	0

Expert 4

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1	0	5	2	5	1	4	2	5	1	4	4	3	3	3	2
C_2	3	0	3	4	1	5	4	4	2	4	4	5	3	5	3
C_3	4	3	0	4	3	5	2	4	2	3	3	5	3	5	3
C_4	3	3	4	0	2	5	3	4	4	4	4	4	5	4	2
C_5	5	4	4	5	0	5	4	4	3	5	2	5	3	4	3
C_6	3	3	3	5	1	0	2	4	4	4	3	5	4	5	2
C_7	4	3	3	5	2	4	0	5	4	4	4	5	3	3	1
C_8	3	3	4	5	1	5	1	0	3	5	3	4	4	5	2
C_9	2	3	4	4	1	5	3	4	0	4	4	4	4	4	2
C_{10}	4	5	4	4	4	4	4	4	1	0	3	4	5	4	2
C_{11}	1	2	1	4	1	5	2	4	1	4	0	4	3	4	1
C_{12}	1	2	1	4	1	3	2	5	1	4	4	0	3	4	2
C_{13}	1	3	1	4	1	4	1	3	1	4	2	3	0	3	1
C_{14}	5	4	2	5	4	4	4	4	5	4	4	5	4	0	2
C_{15}	4	5	4	5	3	5	4	5	5	4	4	5	4	5	0

Step 3: At the final stage of the ANP application, using Eqn. (45)–(46), the elements of the *limited supermatrix* were determined (Table 17), whose vectors elements $RN(w_{i.})(i = 1, 2, \ldots, 15)$ represented the weight coefficients $\tilde{w}_i(i = 1, 2, \ldots, 15)$ (global weights) of the criteria taken (Table 18). The coefficient weights $\widehat{w}_i = RN(\overline{w}_{i.})(i = 1, 2, \ldots, 5)$ for each dimension $D_i(i = 1, 2, \ldots, 5)$ represent the sum of criteria (clusters) based on their affiliation with corresponding dimensions. Details shown in Table 18.

4.5. Evaluating the performance of GSC suppliers using R'MAIRCA

Step 1: In the initial decision matrix $(\tilde{Y})$, the vectors $A_i = (RN(y_{i1}), RN(y_{i2}), \ldots, RN(y_{i(15)}))$ were determined using Eqns. (47)–(48). Individual experts' evaluations of the alternatives are shown in Table 19. The matrix elements were determined in rough numbers for $(\tilde{Y})$(Table 20), based on the aggregation of experts'$E_k(k = 1, 2, \ldots, 4)$ decisions.
Step 2: Using the data from Table 20 and Eqn. (49), the preferences $P_{A_i}(i = 1, 2, \ldots, 5)$ were calculated for the alternatives $A_i(i = 1, 2, \ldots, 5)$ as follows:$P_{A_i} = \frac{1}{m} = \frac{1}{5} = 0.2$ (*where m is the number of the alternatives*). In the considered case, $P_{A_1} = P_{A_2} = \ldots = P_{A_5} = 0.2$ (*assuming equal preferences*).
Step 3: Following Eqns. (50)–(51), the elements of the theoretical estimate matrix T_p were calculated and presented in Table 21.
Step 4: Applying Eqns. (54)–(57), the elements $RN(v_{ij})(i = 1, 2, \ldots, l; j = 1, 2, \ldots, n)$ of the real assessment matrix (T_r) are obtained and the results shown in Table 22.

Table 5
Expert analysis $\widehat{X}_k = [\widehat{x}_{ij}^k]_{5\times5}(k = 1, 2, 3, 4)$ of dimensions $D_j(j = 1, 2, \ldots, 5)$.

Dimen.	D_1	D_2	D_3	D_4	D_5	Dimen.	D_1	D_2	D_3	D_4	D_5
	Expert 1						Expert 3				
D_1	0	4	5	4	4	D_1	0	5	4	3	5
D_2	5	0	4	5	4	D_2	5	0	3	4	5
D_3	1	3	0	4	3	D_3	3	2	0	5	4
D_4	2	2	3	0	3	D_4	3	3	3	0	3
D_5	1	1	3	1	0	D_5	2	1	2	1	0
	Expert 2						Expert 4				
D_1	0	3	4	5	3	D_1	0	4	5	5	5
D_2	4	0	3	4	5	D_2	5	0	4	4	4
D_3	2	1	0	4	3	D_3	2	3	0	4	4
D_4	2	3	4	0	4	D_4	3	3	3	0	4
D_5	2	2	2	1	0	D_5	2	1	3	2	0

Step 5: The total gap matrix elements were derived from Eqns. (58)–(59) and shown in Table 23. It was desirable that g_{ij} would have the values close to zero $(g_{ij} \to 0)$ because the alternative with the smallest difference between (t_{pij}) and the real assessments (t_{rij}) had to be chosen.
Step 6: The values of the criterion function were calculated by summing up the gaps from Table 23 (*using* Eqn. (60)) for each alternative according to the evaluation criteria. The results are given in Table 24.

The initially best-ranked alternative is the one with the smallest total gap value, i.e., A3. In order to define the total gap of the final ranked alternatives presented by RN, they are transferred into crisp values by applying Eqns. (62)–(63). The dominance index of the

Table 6
Rough matrix of the criteria $C_j (j = 1, 2, \ldots, 15)$.

Criteria	C_1		C_2		C_3		C_4		C_5		C_6		C_7		C_8		C_9		…	C_{15}	
	Expert 1																				
C_1	0.00	0.00	3.00	4.00	2.00	2.50	3.00	3.75	1.50	2.00	3.00	4.25	2.00	2.25	3.00	3.75	1.50	2.00		1.00	2.00
C_2	4.00	3.75	0.00	0.00	3.50	4.00	2.00	3.75	1.25	2.00	3.00	4.00	4.50	5.00	3.50	4.00	2.75	3.00		3.00	3.25
C_3	4.00	4.25	2.33	3.67	0.00	0.00	3.00	4.25	3.00	3.25	3.50	4.67	2.00	2.25	3.75	4.00	2.75	3.00		3.00	3.25
C_4	3.50	4.00	2.67	3.33	4.75	5.00	0.00	0.00	2.00	2.25	3.00	4.25	3.00	3.00	3.00	3.25	4.00	4.00		2.00	2.00
C_5	4.50	5.00	3.67	4.33	4.75	5.00	4.00	4.50	0.00	0.00	3.50	4.67	4.75	5.00	4.25	5.00	3.00	3.25		2.00	2.75
C_6	3.75	4.00	3.00	4.50	3.00	3.25	3.00	4.00	1.00	1.25	0.00	0.00	2.00	2.00	3.75	4.00	4.00	4.25		2.25	3.00
C_7	4.00	4.25	3.25	4.00	3.00	3.25	4.00	4.50	2.00	2.00	3.67	4.33	0.00	0.00	4.50	5.00	4.75	5.00		1.00	1.50
C_8	3.00	3.50	2.67	3.33	4.00	4.25	2.00	3.75	1.00	1.00	2.00	3.50	1.75	2.00	0.00	0.00	3.00	3.25		2.00	2.25
C_9	2.75	3.00	2.33	3.33	4.00	4.25	2.00	3.50	1.50	2.00	2.00	3.50	3.00	3.25	3.00	3.75	0.00	0.00		2.00	2.50
C_{10}	4.00	4.50	3.67	4.33	4.50	5.00	4.50	5.00	4.00	4.25	2.00	3.50	3.00	3.75	2.00	3.25	1.75	2.00	…	2.00	2.25
C_{11}	1.50	2.00	1.67	2.33	1.00	1.25	2.00	3.50	1.00	1.25	1.00	3.25	2.00	2.50	2.00	2.75	1.00	1.25		1.00	1.50
C_{12}	2.00	3.00	2.25	3.00	1.00	1.50	2.00	2.75	1.50	2.00	1.00	2.75	2.00	2.25	3.00	3.50	1.75	2.00		2.00	2.25
C_{13}	1.00	1.50	1.50	3.33	1.00	1.25	3.00	3.25	1.00	1.00	1.00	2.75	1.75	3.00	1.00	2.50	1.50	2.00		1.00	1.25
C_{14}	4.50	5.00	4.25	5.00	2.50	3.00	4.00	4.50	4.50	5.00	3.50	4.00	4.50	5.00	4.25	5.00	5.00	5.00		3.00	4.00
C_{15}	4.50	5.00	4.25	5.00	4.75	5.00	4.00	4.50	3.75	4.00	4.50	5.00	4.00	4.00	4.50	5.00	4.50	5.00		0.00	0.00
…																					
	Expert 4																				
C_1	0.00	0.00	4.00	5.00	2.00	2.50	3.75	5.00	1.00	1.50	3.50	4.67	2.00	2.25	3.75	5.00	1.00	1.50		1.67	2.33
C_2	3.00	3.75	0.00	0.00	3.00	3.50	3.33	4.33	1.00	1.25	4.00	5.00	4.00	4.50	3.50	4.00	2.00	2.75		3.00	3.25
C_3	4.00	4.25	2.33	3.67	0.00	0.00	3.50	4.67	3.00	3.25	4.25	5.00	2.00	2.25	3.75	4.00	2.00	2.75		3.00	3.25
C_4	3.00	3.50	2.67	3.33	4.00	4.75	0.00	0.00	2.00	2.25	4.25	5.00	3.00	3.00	3.25	4.00	4.00	4.00		2.00	2.00
C_5	4.50	5.00	3.67	4.33	4.00	4.75	4.50	5.00	0.00	0.00	4.25	5.00	4.00	4.75	3.50	4.67	3.00	3.25		2.75	3.00
C_6	3.00	3.75	2.50	4.00	3.00	3.25	4.00	5.00	1.00	1.25	0.00	0.00	2.00	2.00	3.75	4.00	4.00	4.25		2.00	2.25
C_7	4.00	4.25	2.50	3.67	3.00	3.25	4.50	5.00	2.00	2.00	3.67	4.33	0.00	0.00	4.50	5.00	4.00	4.75		1.00	1.50
C_8	3.00	3.50	2.67	3.33	4.00	4.25	3.75	5.00	1.00	1.00	3.50	5.00	1.00	1.75	0.00	0.00	3.00	3.25		2.00	2.25
C_9	2.00	2.75	2.33	3.33	4.00	4.25	3.00	4.50	1.00	1.50	3.50	5.00	3.00	3.25	3.33	4.50	0.00	0.00		2.00	2.50
C_{10}	4.00	4.50	4.00	5.00	4.00	4.50	4.00	4.50	4.00	4.25	3.00	4.50	3.75	4.00	2.67	4.50	1.00	1.75	…	2.00	2.25
C_{11}	1.00	1.50	1.67	2.33	1.00	1.25	3.00	4.50	1.00	1.25	3.25	5.00	2.00	2.50	2.75	4.00	1.00	1.25		1.00	1.50
C_{12}	1.00	2.00	1.50	2.67	1.00	1.50	2.75	4.00	1.00	1.50	2.00	4.00	2.00	2.25	3.50	5.00	1.00	1.75		2.00	2.25
C_{13}	1.00	1.50	2.00	4.00	1.00	1.25	3.25	4.00	1.00	1.00	2.75	4.00	1.00	1.75	1.67	4.00	1.00	1.50		1.00	1.25
C_{14}	4.50	5.00	3.50	4.67	2.00	2.50	4.50	5.00	4.00	4.50	3.50	4.00	4.00	4.50	3.50	4.67	5.00	5.00		2.00	3.00
C_{15}	4.00	4.50	4.25	5.00	4.00	4.75	4.50	5.00	3.00	3.75	4.50	5.00	4.00	4.00	4.50	5.00	4.50	5.00		0.00	0.00

Table 7
Rough matrix of the dimensions $D_j (j = 1, 2, \ldots, 5)$.

Dimensions	D_1		D_2		D_3		D_4		D_5	
	Expert 1									
D_1	0.00	0.00	3.67	4.33	4.50	5.00	3.50	4.67	3.50	4.67
D_2	4.75	5.00	0.00	0.00	3.50	4.00	4.25	5.00	4.00	4.50
D_3	1.00	2.00	2.25	3.00	0.00	0.00	4.00	4.25	3.00	3.50
D_4	2.00	2.50	2.00	2.75	3.00	3.25	0.00	0.00	3.00	3.50
D_5	1.00	1.75	1.00	1.25	2.50	3.00	1.00	1.25	0.00	0.00
…										
	Expert 4									
D_1	0.00	0.00	3.67	4.33	4.50	5.00	4.25	5.00	4.25	5.00
D_2	4.75	5.00	0.00	0.00	3.50	4.00	4.00	4.25	4.00	4.50
D_3	1.67	2.33	2.25	3.00	0.00	0.00	4.00	4.25	3.50	4.00
D_4	2.50	3.00	2.75	3.00	3.00	3.25	0.00	0.00	3.50	4.00
D_5	1.75	2.00	1.00	1.25	2.50	3.00	1.25	2.00	0.00	0.00

best-ranked alternative in relation to other alternatives is defined by applying Eqn. (64) as shown in Table 24.

- If the dominance index $A_{D,1\text{-}j}$ of the best-ranked alternative in relation to all other alternatives is higher than or equal to the dominance threshold I_D, as stated in Eqn. (65), then the initial rank will be taken as final.
- However, if the dominance index $A_{D,1\text{-}j}$ for any other alternative is smaller than I_D we cannot say that the best-ranked alternative has enough advantage and therefore it will be assigned a rank "1*".

In our example, the dominance threshold is $I_D = 0.160$. Since the dominance index of alternative A_3 in relation to alternative A_2 (initially the second-ranked alternative) is smaller than I_D we conclude that A_3 does not have enough advantage in relation to A_2, and thus alternative A_2 will be assigned the corrected rank "1*". The other values $A_{D,1\text{-}j}$ are higher than I_D so the initial rank is retained for the other alternatives.

4.6. A comparative analysis of the alternative ranking methods

Many papers have proposed analytical models as aids in conflict management situations. The managerial level defines the goals, and chooses the final optimal alternative. The multi-criteria nature of decisions is emphasized at this managerial level, at which decision makers have the power to accept or reject the solution proposed by the engineering level. In some cases, the preference structure is based on political rather than only technical criteria. In that situations, a system analyst can aid the decision making process by making a comprehensive analysis and by listing the important properties of non-inferior and or compromise solutions (Zeleny, 1982).

A compromise solution for a problem with conflicting criteria can help the decision makers to reach a final decision. The foundation for compromise solution was established by Zeleny (1982). The compromise solution is a feasible solution, which is the closest to the ideal, and a compromise means an agreement established by mutual concessions.

Since the MAIRCA model (like TOPSIS, COPRAS and VIKOR models) is based on an aggregating function representing closeness to the ideal solution, in this section the discussion of the results is

Table 8
Average rough matrix (Criteria) - Z_C matrix.

Criteria	C_1		C_2		C_3		C_4		C_5		C_6		C_7		C_8		C_9		…	C_{15}	
C_1	0.00	0.00	3.56	4.41	2.23	2.73	3.27	4.25	1.21	1.72	3.69	4.71	2.05	2.39	3.27	4.25	1.21	1.72		1.52	2.37
C_2	3.71	3.75	0.00	0.00	3.25	3.75	3.00	4.31	1.06	1.41	3.49	4.50	4.25	4.75	3.25	3.75	2.53	2.93		3.06	3.43
C_3	4.05	4.40	1.97	3.72	0.00	0.00	3.69	4.71	3.05	3.40	3.75	4.74	2.06	2.43	3.57	3.94	2.53	2.93		3.05	3.40
C_4	3.25	3.75	2.53	3.37	4.54	4.93	0.00	0.00	2.05	2.39	3.73	4.73	3.00	3.00	3.06	3.43	4.00	4.00		2.00	2.00
C_5	4.12	4.89	3.54	4.38	4.54	4.93	4.26	4.76	0.00	0.00	3.75	4.74	4.54	4.93	3.75	4.74	3.05	3.40		2.54	2.93
C_6	3.54	3.93	2.65	4.17	3.06	3.43	3.56	4.41	1.05	1.38	0.00	0.00	2.00	2.00	3.57	3.94	4.05	4.40		2.06	2.42
C_7	4.05	4.40	2.67	3.70	3.06	3.43	4.26	4.76	0.00	2.00	3.59	4.42	0.00	0.00	4.12	4.89	4.54	4.93		1.21	1.72
C_8	3.23	3.73	2.53	3.37	4.06	4.44	3.02	4.34	1.00	1.00	2.71	4.23	1.51	1.93	0.00	0.00	3.05	3.40		2.06	2.43
C_9	2.53	2.93	1.93	3.29	4.05	4.40	2.66	4.18	1.23	1.74	2.71	4.23	3.05	3.40	3.24	4.19	0.00	0.00		2.23	2.73
C_{10}	4.23	4.73	3.56	4.41	4.25	4.75	4.23	4.73	4.05	4.40	2.66	4.18	3.54	3.93	2.40	3.89	1.51	1.93		2.06	2.43
C_{11}	1.23	1.74	1.51	2.36	1.05	1.38	2.66	4.18	1.05	1.38	2.03	4.13	2.23	2.73	2.25	3.20	1.05	1.38		1.21	1.72
C_{12}	1.53	2.39	1.63	2.69	1.21	1.72	2.25	3.20	1.21	1.72	1.66	3.63	2.05	2.39	3.12	3.85	1.51	1.93		2.06	2.43
C_{13}	1.21	1.72	1.66	3.63	1.06	1.42	3.06	3.43	1.00	1.00	1.96	3.33	1.23	2.17	1.39	3.29	1.21	1.72		1.06	1.42
C_{14}	4.12	4.89	3.68	4.70	2.25	2.75	4.26	4.76	4.23	4.73	3.25	3.75	4.25	4.75	3.75	4.74	5.00	5.00		2.55	3.40
C_{15}	4.25	4.75	3.75	4.74	4.54	4.93	4.26	4.76	3.54	3.93	4.25	4.75	4.00	4.00	4.12	4.89	4.12	4.89		0.00	0.00

Table 9
Average rough matrix (Dimensions) - Z_D matrix.

Dimensions	D_1		D_2		D_3		D_4		D_5	
D_1	0.000	0.000	3.543	4.375	4.253	4.754	3.752	4.744	3.688	4.706
D_2	4.539	4.933	0.000	0.000	3.250	3.752	4.062	4.430	4.233	4.733
D_3	1.521	2.368	1.664	2.711	0.000	0.000	4.053	4.401	3.230	3.732
D_4	2.226	2.729	2.535	2.934	3.064	3.434	0.000	0.000	3.255	3.756
D_5	1.517	1.933	1.061	1.416	2.246	2.749	1.061	1.416	0.000	0.000

Table 10
Normalized rough direct-relation matrix $D_C = [RN(d_{ij})]_{15\times15}$ for criteria.

Criteria	C_1		C_2		C_3		C_4		C_5		C_6		C_7		C_8		C_9		…	C_{15}	
C_1	0.000	0.000	0.055	0.078	0.035	0.048	0.051	0.075	0.019	0.030	0.057	0.083	0.032	0.042	0.051	0.075	0.019	0.030		0.024	0.042
C_2	0.058	0.066	0.000	0.000	0.050	0.066	0.047	0.076	0.016	0.025	0.054	0.080	0.066	0.084	0.050	0.066	0.039	0.052		0.048	0.061
C_3	0.063	0.078	0.031	0.066	0.000	0.000	0.057	0.083	0.047	0.060	0.058	0.084	0.032	0.043	0.056	0.070	0.039	0.052		0.047	0.060
C_4	0.050	0.066	0.039	0.060	0.070	0.087	0.000	0.000	0.032	0.042	0.058	0.084	0.047	0.053	0.048	0.061	0.062	0.071		0.031	0.035
C_5	0.064	0.086	0.055	0.077	0.070	0.087	0.066	0.084	0.000	0.000	0.058	0.084	0.070	0.087	0.058	0.084	0.047	0.060		0.039	0.052
C_6	0.055	0.070	0.041	0.074	0.048	0.061	0.055	0.078	0.016	0.024	0.000	0.000	0.031	0.035	0.056	0.070	0.063	0.078		0.032	0.043
C_7	0.063	0.078	0.041	0.065	0.048	0.061	0.066	0.084	0.000	0.035	0.056	0.078	0.000	0.000	0.064	0.086	0.070	0.087		0.019	0.030
C_8	0.050	0.066	0.039	0.060	0.063	0.078	0.047	0.077	0.016	0.018	0.042	0.075	0.023	0.034	0.000	0.000	0.047	0.060		0.032	0.043
C_9	0.039	0.052	0.030	0.058	0.063	0.078	0.041	0.074	0.019	0.031	0.042	0.075	0.047	0.060	0.050	0.074	0.000	0.000		0.035	0.048
C_{10}	0.066	0.084	0.055	0.078	0.066	0.084	0.066	0.084	0.063	0.078	0.041	0.074	0.055	0.070	0.037	0.069	0.023	0.034		0.032	0.043
C_{11}	0.019	0.031	0.024	0.042	0.016	0.024	0.041	0.074	0.016	0.024	0.031	0.073	0.035	0.048	0.035	0.057	0.016	0.024		0.019	0.030
C_{12}	0.024	0.042	0.025	0.048	0.019	0.030	0.035	0.057	0.019	0.030	0.026	0.064	0.032	0.042	0.049	0.068	0.023	0.034		0.032	0.043
C_{13}	0.019	0.030	0.026	0.064	0.016	0.025	0.048	0.061	0.016	0.018	0.030	0.059	0.019	0.038	0.022	0.058	0.019	0.030		0.016	0.025
C_{14}	0.064	0.086	0.057	0.083	0.035	0.049	0.066	0.084	0.066	0.084	0.050	0.066	0.066	0.084	0.058	0.084	0.078	0.088		0.040	0.060
C_{15}	0.066	0.084	0.058	0.084	0.070	0.087	0.066	0.084	0.055	0.070	0.066	0.084	0.062	0.071	0.064	0.086	0.064	0.086		0.000	0.000

Table 11
Normalized rough direct-relation matrix $D_D = [RN(\hat{d}_{ij})]_{5\times5}$ for dimensions.

Dimensions	D_1		D_2		D_3		D_4		D_5	
D_1	0.000	0.000	0.191	0.272	0.229	0.296	0.202	0.295	0.199	0.293
D_2	0.244	0.307	0.000	0.000	0.175	0.233	0.219	0.275	0.228	0.294
D_3	0.082	0.147	0.090	0.169	0.000	0.000	0.218	0.274	0.174	0.232
D_4	0.120	0.170	0.136	0.182	0.165	0.213	0.000	0.000	0.175	0.234
D_5	0.082	0.120	0.057	0.088	0.121	0.171	0.057	0.088	0.000	0.000

shown through the application of these four models (rough TOPSIS, rough COPRAS, rough MAIRCA and rough VIKOR). The rankings based on using rough TOPSIS, rough COPRAS, rough MAIRCA and rough VIKOR methods were showed in Table 25. In order to better understand results of these four methods, in Table 25 are presented crisp values of the calculations.

- The Rough VIKOR (R'VIKOR) method introduces an aggregating function representing the distance from the ideal solution. This ranking index is an aggregation of all criteria, the relative importance of the criteria, and a balance between total and individual satisfaction (Opricovic, 1998). R'VIKOR method focuses on ranking and selecting from a set of alternatives in the presence of conflicting criteria. It introduces the multi-criteria ranking index based on the particular measure of closeness to the ideal solution (Opricovic and Tzeng, 2002; Zhu et al., 2015)
- R'MAIRCA method defines the ideal and anti-ideal alternative and measures the gap between observed alternative and

Table 12
Total relation matrix T_C for criteria.

	C_1		C_2		C_3		C_4		C_5		C_6		C_7		C_8		C_9		…	C_{15}	
C_1	0.0678	0.5210	0.1090	0.6090	0.0984	0.5351	0.1228	0.6812	0.0578	0.3601	0.1202	0.6817	0.0906	0.4904	0.1174	0.6412	0.0788	0.4785		0.0685	0.4002
C_2	0.1399	0.6464	0.0709	0.6011	0.1284	0.6103	0.1377	0.7560	0.0653	0.3967	0.1337	0.7521	0.1366	0.5820	0.1339	0.7032	0.1120	0.5537		0.1014	0.4606
C_3	0.1418	0.6539	0.0993	0.6597	0.0792	0.5462	0.1436	0.7577	0.0931	0.4259	0.1349	0.7515	0.1032	0.5430	0.1366	0.7025	0.1096	0.5500		0.0991	0.4580
C_4	0.1337	0.6393	0.1092	0.6511	0.1481	0.6223	0.0944	0.6776	0.0812	0.4076	0.1387	0.7479	0.1203	0.5487	0.1337	0.6914	0.1340	0.5634		0.0874	0.4335
C_5	0.1573	0.7301	0.1324	0.7402	0.1589	0.6918	0.1670	0.8396	0.0554	0.4123	0.1485	0.8318	0.1500	0.6411	0.1524	0.7907	0.1287	0.6163		0.1009	0.4980
C_6	0.1316	0.6156	0.1058	0.6356	0.1224	0.5749	0.1388	0.7180	0.0631	0.3743	0.0770	0.6389	0.0999	0.5099	0.1335	0.6693	0.1287	0.5462		0.0837	0.4221
C_7	0.1420	0.6642	0.1083	0.6700	0.1257	0.6143	0.1524	0.7725	0.0491	0.4092	0.1334	0.7601	0.0719	0.5106	0.1445	0.7293	0.1378	0.5900		0.0738	0.4385
C_8	0.1230	0.5963	0.1005	0.6068	0.1316	0.5744	0.1273	0.6984	0.0614	0.3592	0.1134	0.6900	0.0889	0.4944	0.0761	0.5860	0.1101	0.5165		0.0812	0.4108
C_9	0.1149	0.6095	0.0936	0.6307	0.1332	0.5988	0.1241	0.7261	0.0647	0.3865	0.1151	0.7199	0.1125	0.5396	0.1260	0.6834	0.0673	0.4824		0.0848	0.4326
C_{10}	0.1506	0.6827	0.1259	0.6945	0.1462	0.6456	0.1583	0.7865	0.1109	0.4561	0.1253	0.7706	0.1299	0.5874	0.1248	0.7276	0.0993	0.5536		0.0890	0.4587
C_{11}	0.0677	0.4595	0.0644	0.4817	0.0629	0.4269	0.0931	0.5715	0.0442	0.2968	0.0774	0.5648	0.0768	0.4159	0.0835	0.5239	0.0595	0.3944		0.0510	0.3249
C_{12}	0.0810	0.4892	0.0728	0.5077	0.0740	0.4509	0.0970	0.5802	0.0529	0.3149	0.0810	0.5803	0.0818	0.4281	0.1047	0.5559	0.0732	0.4204		0.0686	0.3509
C_{13}	0.0648	0.4388	0.0638	0.4809	0.0603	0.4094	0.0960	0.5370	0.0432	0.2786	0.0735	0.5298	0.0597	0.3905	0.0681	0.5032	0.0592	0.3822		0.0463	0.3075
C_{14}	0.1617	0.7451	0.1389	0.7614	0.1319	0.6733	0.1727	0.8582	0.1206	0.5000	0.1460	0.8345	0.1523	0.6537	0.1577	0.8083	0.1620	0.6547		0.1051	0.5159
C_{15}	0.1699	0.7715	0.1446	0.7911	0.1691	0.7327	0.1792	0.8907	0.1148	0.5059	0.1666	0.8823	0.1531	0.6653	0.1693	0.8403	0.1546	0.6771		0.0709	0.4792

extreme points. This method focuses on ranking and selecting from a set of alternatives in the presence of conflicting criteria. It is desirable for an alternative to have the smallest possible gap between the theoretical and real evaluations, and therefore the initially best-ranked alternative is the one with the smallest total gap value. The dominance index of the best-ranked alternative in relation to other alternatives is defined by applying equation (64) (See section 3.3). If the dominance index $A_{D,1-j}$ of the best-ranked alternative in relation to all other alternatives is higher than or equal to the dominance threshold I_D, then the initial rank will be taken as final. if the dominance index $A_{D,1-j}$ for any other alternative is smaller than I_D we cannot say that the best-ranked alternative has enough advantage and therefore it will be assigned a rank “1*”.

- The Rough TOPSIS (R'TOPSIS) method introduces the ranking index including the distances from the ideal point and from the negative-ideal point (Hwang and Yoon, 1981; Petković et al., 2017). These distances in R'TOPSIS are simply summed without considering their relative importance. However, the reference point could be a major concern in decision making, and to be as close as possible to the ideal is the rationale of human choice. Being far away from a nadir point could be a goal only in a particular situation, and the relative importance remains an open question. The similar problems (like in R'TOPSIS) method may appear in R'COPRAS method. The R'TOPSIS method uses n-dimensional Euclidean distance that by itself could represent some balance between total and individual satisfaction, but uses it in a different way than R'VIKOR, R'COPRAS and R'MAIRCA.
- Rough COPRAS (R'COPRAS) method, compared to previous methods, has slightly more complex aggregation procedure, but it does not require transformation of cost to benefit type criteria. The overall ranking index, of each alternative, is calculated using proportional assessment procedure. R'COPRAS method can show the inherent inconsistency. For example if the value of the most important alternative of a minimizing criterion is the smallest and the largest criterion weight w_j matches it. Then the sum of these weighted values is in the denominator of the aggregation function. This may lead to incorrect evaluation of the alternatives.

Besides that these four MCDM methods use different kinds of normalization to eliminate the units of criterion functions: the R'VIKOR and R'MAIRCA method uses linear normalization, R'COPRAS method use linear transformation - Sum method and the R'TOPSIS method uses vector normalization. In MCDM models with linear normalization the normalized value does not depend on the evaluation unit of a criterion (Opricovic and Tzeng, 2004). Pamučar and Ćirović (2015) showed that in models with vector normalization the normalized value could be different for different evaluation unit of a particular criterion. The main difference between these four methods appears in the aggregation approaches.

A comparison of the results given in Table 25 shows that the alternative ranking results yielded by R'MAIRCA, R'COPRAS and R'VIKOR are similar. R'MAIRCA and R'COPRAS has the same ranks $A_3 > A_2 > A_1 > A_4 > A_5$. The ranking obtained by the R'TOPSIS method is slightly different ($A_2 > A_3 > A_4 > A_5 > A_1$), but all methods gave preference to the alternatives A_3 and A_2. The alternative A_3 was ranked first in the R'MAIRCA, R'COPRAS and R'VIKOR methods and second in the R'TOPSIS method. The results indicate the set {A_3, A_2} as good alternatives.

The highest ranked alternative by R'VIKOR, R'COPRAS and R'MAIRCA is the closest to the ideal solution. However, the highest ranked alternative by R'TOPSIS is the best in terms of the ranking

Table 13
Total relation matrix T_D for dimensions.

Dimensions	D_1		D_2		D_3		D_4		D_5	
D_1	0.2248	1.0529	0.3679	1.2311	0.4804	1.4985	0.4607	1.5010	0.4918	1.6623
D_2	0.4373	1.2647	0.2210	0.9934	0.4581	1.4273	0.4858	1.4557	0.5301	1.6284
D_3	0.2288	0.9021	0.2242	0.8906	0.1989	0.9321	0.3778	1.1499	0.3714	1.2435
D_4	0.2737	0.9098	0.2721	0.8914	0.3582	1.0974	0.2153	0.9227	0.3915	1.2332
D_5	0.1686	0.5920	0.1424	0.5539	0.2310	0.7324	0.1805	0.6740	0.1378	0.6639

Table 14
The sums of given and received impact among the dimensions/criteria.

Dimensions/criteria	R		S		$R+S$		$R-S$	
D_1	**2.026**	**6.946**	**1.333**	**4.721**	**3.359**	**11.667**	**−2.696**	**5.613**
C_1	1.4967	8.6515	1.8476	9.263	3.3443	17.915	−7.766	6.8039
C_2	1.8574	9.6936	1.5397	9.5215	3.3971	19.215	−7.664	8.154
C_3	1.792	9.6287	1.7701	8.7069	3.5621	18.336	−6.915	7.8586
D_2	**2.132**	**6.769**	**1.228**	**4.560**	**3.360**	**11.330**	**−2.428**	**5.542**
C_4	1.9027	9.5892	2.0044	10.851	3.907	20.44	−8.948	7.5849
C_5	2.0916	10.775	1.0778	5.8842	3.1694	16.659	−3.793	9.6967
C_6	1.7441	9.1386	1.7847	10.736	3.5288	19.875	−8.992	7.3539
D_3	**1.401**	**5.118**	**1.727**	**5.688**	**3.128**	**10.806**	**−4.287**	**3.392**
C_7	1.8318	9.8347	1.6276	8.0006	3.4594	17.835	−6.169	8.2071
C_8	1.6564	8.87	1.8624	10.156	3.5189	19.026	−8.5	7.0076
C_9	1.6983	9.297	1.615	7.9793	3.3133	17.276	−6.281	7.6821
D_4	**1.511**	**5.055**	**1.720**	**5.703**	**3.231**	**10.758**	**−4.193**	**3.334**
C_{10}	1.9144	10.026	1.7921	10.543	3.7065	20.569	−8.629	8.2337
C_{11}	1.0815	7.1114	2.0961	10.104	3.1776	17.215	−9.022	5.0153
C_{12}	1.2631	7.4445	2.1134	10.847	3.3765	18.292	−9.584	5.331
D_5	**0.860**	**3.216**	**1.923**	**6.431**	**2.783**	**9.647**	**−5.571**	**1.294**
C_{13}	1.0093	6.7877	2.1185	10.577	3.1277	17.364	−9.567	4.6692
C_{14}	2.2148	11.039	1.433	9.8239	3.6478	20.863	−7.609	9.6065
C_{15}	2.3401	11.498	1.2118	6.3912	3.5519	17.889	−4.051	10.286

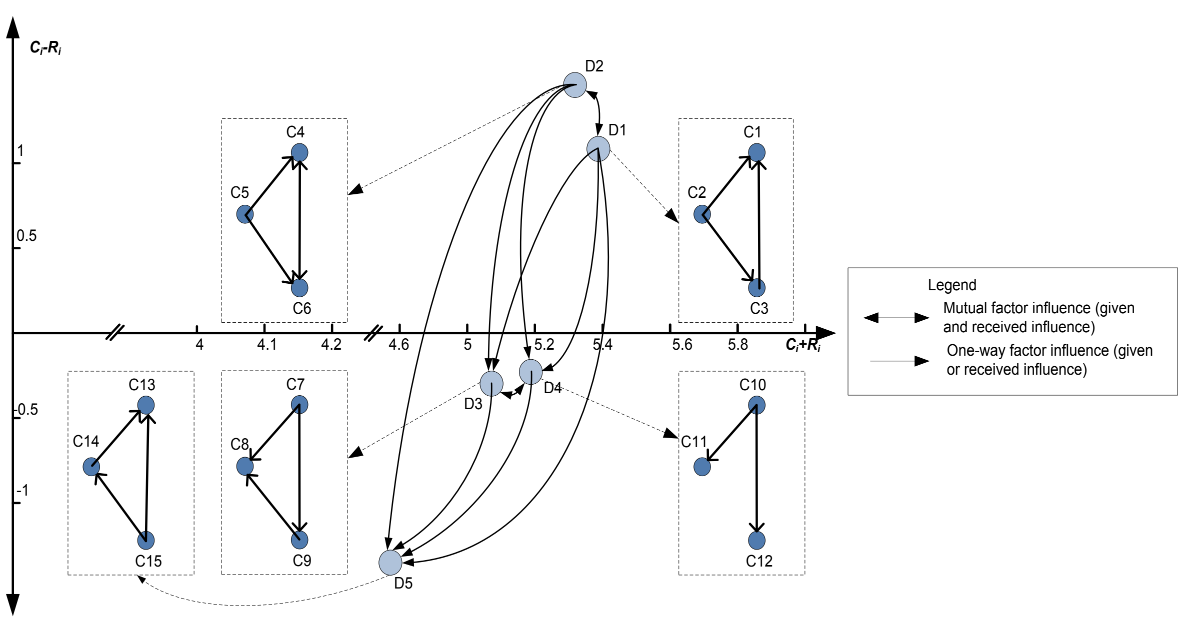

Fig. 2. Cause and effect relationship diagram among dimensions and criteria.

index, which does not mean that it is always the closest to the ideal solution. Alternatives A_2 and A_3 are top ranked by R'TOPSIS, and they are very close to each other. Some results by R'TOPSIS are different from the results by R'VIKOR, R'COPRAS and R'MAIRCA, and the solution by R'TOPSIS is not always the closest to the ideal. For certain weights, the alternative ranked highest by R'TOPSIS is A_3, whereas the closest to the ideal is A_2. According to R'TOPSIS method Q_j the best solution is A_2 since $Q_2 = 0.7862$. The alternative A_2 is the best according to $D^* = 0.1020$ (the separation of each alternative from the ideal solution). However, A_2 is not the closest to the ideal since $D_2^- = 0.3581$ and $D_3^- = 0.3600$ (the separation of each alternative from the negative ideal solution).

From these values we can see that A2 is ranked best by R'TOPSIS, although it is not the closest to the ideal, because $D_3^- = 0.3600$ and $D_2^- < D_3^-$. According to the formulation of ranking index (Q_j) in R'TOPSIS model, alternative a_j is better then a_k if $Q_j > Q_k$ or $D_j^-/(D_j^* +$

Table 15
Unweighted supermatrix $W = (T_c^{\alpha})'$.

Criteria	C_1		C_2		C_3		C_4		C_5		C_6		C_7		C_8		C_9		…	C_{15}	
C_1	0.114	0.192	0.155	0.262	0.146	0.221	0.179	0.287	0.087	0.148	0.173	0.291	0.135	0.202	0.170	0.272	0.122	0.192		0.102	0.168
C_2	0.205	0.271	0.120	0.221	0.191	0.257	0.206	0.315	0.102	0.159	0.198	0.315	0.195	0.255	0.200	0.292	0.169	0.230		0.145	0.199
C_3	0.206	0.279	0.151	0.275	0.133	0.202	0.212	0.319	0.133	0.186	0.197	0.317	0.157	0.222	0.200	0.292	0.165	0.228		0.143	0.198
C_4	0.200	0.268	0.164	0.269	0.213	0.271	0.158	0.250	0.120	0.171	0.204	0.316	0.178	0.228	0.199	0.284	0.194	0.242		0.130	0.178
C_5	0.231	0.311	0.195	0.310	0.231	0.298	0.246	0.350	0.094	0.152	0.220	0.347	0.216	0.278	0.225	0.332	0.193	0.257		0.150	0.209
C_6	0.193	0.260	0.157	0.269	0.180	0.241	0.205	0.302	0.098	0.150	0.130	0.235	0.151	0.206	0.194	0.280	0.184	0.239		0.123	0.177
C_7	0.207	0.282	0.161	0.279	0.185	0.257	0.222	0.326	0.083	0.168	0.196	0.319	0.121	0.188	0.209	0.311	0.196	0.260		0.113	0.177
C_8	0.181	0.252	0.150	0.252	0.189	0.250	0.189	0.294	0.094	0.142	0.170	0.290	0.138	0.199	0.128	0.216	0.162	0.220		0.120	0.173
C_9	0.174	0.250	0.142	0.260	0.192	0.258	0.187	0.303	0.099	0.158	0.172	0.301	0.165	0.228	0.186	0.287	0.114	0.178		0.124	0.183
C_{10}	0.219	0.292	0.184	0.293	0.212	0.278	0.232	0.329	0.154	0.205	0.190	0.320	0.190	0.250	0.190	0.301	0.156	0.221		0.133	0.190
C_{11}	0.105	0.185	0.096	0.198	0.099	0.170	0.136	0.246	0.067	0.122	0.115	0.243	0.110	0.177	0.122	0.220	0.093	0.158		0.075	0.135
C_{12}	0.123	0.201	0.110	0.210	0.114	0.182	0.144	0.241	0.078	0.131	0.122	0.245	0.120	0.179	0.150	0.238	0.112	0.172		0.099	0.150
C_{13}	0.098	0.177	0.093	0.208	0.094	0.164	0.136	0.227	0.064	0.112	0.109	0.223	0.090	0.163	0.103	0.213	0.089	0.156		0.070	0.126
C_{14}	0.239	0.317	0.204	0.320	0.203	0.273	0.255	0.357	0.169	0.224	0.221	0.340	0.221	0.282	0.234	0.339	0.232	0.284		0.155	0.219
C_{15}	0.251	0.325	0.213	0.332	0.248	0.313	0.267	0.369	0.165	0.220	0.246	0.366	0.225	0.280	0.251	0.352	0.228	0.292		0.119	0.177

Table 16
Weighted supermatrix $W^{\alpha} = (T_D^{\alpha}) \times W$.

Criteria	C_1		C_2		C_3		C_4		C_5		C_6		C_7		C_8		C_9		…	C_{15}	
C_1	0.060	0.080	0.069	0.114	0.060	0.084	0.070	0.097	0.076	0.092	0.079	0.109	0.040	0.084	0.070	0.099	0.067	0.080		0.088	0.093
C_2	0.063	0.099	0.060	0.096	0.073	0.098	0.076	0.106	0.062	0.099	0.044	0.118	0.058	0.106	0.077	0.106	0.061	0.095		0.075	0.110
C_3	0.053	0.102	0.068	0.120	0.067	0.077	0.077	0.107	0.054	0.116	0.044	0.119	0.047	0.092	0.077	0.106	0.060	0.095		0.084	0.110
C_4	0.062	0.098	0.051	0.117	0.059	0.103	0.065	0.084	0.049	0.106	0.046	0.119	0.053	0.095	0.077	0.103	0.078	0.100		0.077	0.099
C_5	0.070	0.113	0.059	0.135	0.064	0.113	0.064	0.118	0.068	0.095	0.049	0.130	0.065	0.115	0.073	0.120	0.078	0.107		0.066	0.116
C_6	0.070	0.095	0.060	0.117	0.060	0.092	0.075	0.102	0.060	0.093	0.069	0.088	0.045	0.085	0.076	0.101	0.065	0.099		0.066	0.098
C_7	0.054	0.103	0.051	0.122	0.071	0.098	0.079	0.110	0.064	0.105	0.094	0.120	0.066	0.078	0.089	0.113	0.079	0.108		0.072	0.098
C_8	0.047	0.092	0.038	0.110	0.052	0.095	0.072	0.099	0.058	0.088	0.038	0.109	0.041	0.083	0.060	0.078	0.069	0.091		0.065	0.096
C_9	0.065	0.091	0.076	0.113	0.053	0.098	0.091	0.102	0.040	0.098	0.038	0.113	0.079	0.095	0.064	0.104	0.064	0.074		0.077	0.102
C_{10}	0.057	0.106	0.076	0.128	0.058	0.106	0.071	0.111	0.063	0.128	0.043	0.120	0.057	0.104	0.085	0.109	0.077	0.092		0.070	0.105
C_{11}	0.057	0.067	0.074	0.086	0.057	0.065	0.060	0.083	0.067	0.076	0.066	0.091	0.063	0.073	0.079	0.080	0.058	0.066		0.068	0.075
C_{12}	0.052	0.073	0.068	0.092	0.059	0.069	0.072	0.081	0.062	0.082	0.067	0.092	0.066	0.074	0.065	0.086	0.064	0.071		0.077	0.083
C_{13}	0.055	0.064	0.063	0.091	0.056	0.062	0.060	0.076	0.066	0.070	0.064	0.084	0.057	0.068	0.064	0.077	0.057	0.065		0.066	0.070
C_{14}	0.062	0.115	0.052	0.139	0.076	0.104	0.096	0.120	0.079	0.139	0.059	0.128	0.066	0.117	0.055	0.123	0.070	0.118		0.068	0.122
C_{15}	0.065	0.118	0.054	0.145	0.088	0.119	0.089	0.124	0.067	0.137	0.055	0.137	0.067	0.116	0.059	0.127	0.068	0.121		0.075	0.098

Table 17
Influential weights of stable matrix of rough DANP when $\lim_{g\to\infty}(W^{\alpha})^{g}$.

Criteria	C_1		C_2		C_3		C_4		C_5		C_6		C_7		C_8		C_9		…	C_{15}	
C_1	0.084	0.098	0.084	0.098	0.084	0.098	0.084	0.098	0.084	0.098	0.084	0.098	0.084	0.098	0.084	0.098	0.084	0.098		0.084	0.098
C_2	0.067	0.094	0.067	0.094	0.067	0.094	0.067	0.094	0.067	0.094	0.067	0.094	0.067	0.094	0.067	0.094	0.067	0.094		0.067	0.094
C_3	0.065	0.075	0.065	0.075	0.065	0.075	0.065	0.075	0.065	0.075	0.065	0.075	0.065	0.075	0.065	0.075	0.065	0.075		0.065	0.075
C_4	0.063	0.080	0.063	0.080	0.063	0.080	0.063	0.080	0.063	0.080	0.063	0.080	0.063	0.080	0.063	0.080	0.063	0.080		0.063	0.080
C_5	0.055	0.082	0.055	0.082	0.055	0.082	0.055	0.082	0.055	0.082	0.055	0.082	0.055	0.082	0.055	0.082	0.055	0.082		0.055	0.082
C_6	0.058	0.081	0.058	0.081	0.058	0.081	0.058	0.081	0.058	0.081	0.058	0.081	0.058	0.081	0.058	0.081	0.058	0.081		0.058	0.081
C_7	0.065	0.071	0.065	0.071	0.065	0.071	0.065	0.071	0.065	0.071	0.065	0.071	0.065	0.071	0.065	0.071	0.065	0.071		0.065	0.071
C_8	0.061	0.070	0.061	0.070	0.061	0.070	0.061	0.070	0.061	0.070	0.061	0.070	0.061	0.070	0.061	0.070	0.061	0.070		0.061	0.070
C_9	0.056	0.068	0.056	0.068	0.056	0.068	0.056	0.068	0.056	0.068	0.056	0.068	0.056	0.068	0.056	0.068	0.056	0.068		0.056	0.068
C_{10}	0.066	0.069	0.066	0.069	0.066	0.069	0.066	0.069	0.066	0.069	0.066	0.069	0.066	0.069	0.066	0.069	0.066	0.069		0.066	0.069
C_{11}	0.050	0.075	0.050	0.075	0.050	0.075	0.050	0.075	0.050	0.075	0.050	0.075	0.050	0.075	0.050	0.075	0.050	0.075		0.050	0.075
C_{12}	0.052	0.064	0.052	0.064	0.052	0.064	0.052	0.064	0.052	0.064	0.052	0.064	0.052	0.064	0.052	0.064	0.052	0.064		0.052	0.064
C_{13}	0.058	0.062	0.058	0.062	0.058	0.062	0.058	0.062	0.058	0.062	0.058	0.062	0.058	0.062	0.058	0.062	0.058	0.062		0.058	0.062
C_{14}	0.056	0.060	0.056	0.060	0.056	0.060	0.056	0.060	0.056	0.060	0.056	0.060	0.056	0.060	0.056	0.060	0.056	0.060		0.056	0.060
C_{15}	0.036	0.062	0.036	0.062	0.036	0.062	0.036	0.062	0.036	0.062	0.036	0.062	0.036	0.062	0.036	0.062	0.036	0.062		0.036	0.062

$D_j^-) > D_k^-/(D_k^* + D_k^-)$ which is satisfied if: (1) $D_j^* < D_k^*$ and $D_j^- > D_k^-$; or (2) $D_j^* > D_k^*$ and $D_j^- > D_k^-$, but $D_j^* < D_k^*\; D_j^-/D_k^-$. We can conclude that the R'TOPSIS method determines a solution according to distance from the ideal/negative-ideal solution but the main issue in TOPSIS negligence the relative importance of these distances.

The alternatives ranked highest by R'VIKOR are A_3 and A_2, of which alternative A_3 is closer to the ideal according to the “Green purchasing”, “Green production” and “Green Warehousing” dimensions (C_6-C_{12}). Alternative A_3 has the additional defect in Saving Energy (C_3) and Green management abilities (C_5). As an alternative for a final solution, alternative A_3 could be considered the best compromise.

Ranking by R'MAIRCA and R'COPRAS are the same and gives similar results as ranking in R'VIKOR. The initially best-ranked alternative is A_3 with the smallest total gap value $Q_j = 0.0716$. Since the dominance index of the alternative A_3 in relation to alternative A_2 (initially the second-ranked alternative) is smaller than $I_D = 0.160$ we conclude that A_3 does not have enough advantage in relation to A_2, and thus alternative A_2 has the same rank as A_3. The other values of the dominance index are higher than 0.160 so the initial rank is retained for the other alternatives. It may be concluded that two alternatives $\{A_3, A_2\}$ are indicated as good solutions.

The R'VIKOR, R'COPRAS and R'MAIRCA result stands only for the given set of alternatives. Inclusion (or exclusion) of an alternative could affect the R'VIKOR, R'COPRAS and R'MAIRCA ranking of new set of alternatives. By fixing the best and the worst values, this effect could be avoided, but that would mean that the decision maker could define a fixed ideal solution.

Finally, the stability of the R'MAIRCA ranking results was checked by comparing them with the results obtained by using other MCDM methods. In this paper, the Spearman's rank-correlation coefficient (R) was used to find the relations between the rankings obtained by using the proposed approach and other methods. The results are presented in Table 26.

The analysis shows that the average correlation between the methods is very high ($R = 0.825$) which clearly suggests that the set $\{A_3, A_2\}$ are dominant and the ranking given in Table 24 is credible.

4.7. The sensitivity analysis based on changing the weights of criteria

Roy (1998) suggests applying the concept of robustness not only to solutions but, more generally to conclusions. A conclusion is an information deduced from the model and given to the decision maker during the decision process. A conclusion is called robust if it is true for all (or almost all) of the scenarios (where a scenario is a plausible set of values for the parameters of the model used to solve the problem). Hites et al. (2002) introduces another notion where a robust solution is one that is simultaneously good and not too risky. In other words, a robust solution is one that is satisfactory to the decision maker in as many scenarios as possible without being too unsatisfactory to the decision maker in any single scenario. This notion introduces an idea of quality into the problem, that is also discussed in Sorensen (2001). Different decision makers (DMs) will have different levels of aversion to risk, and therefore will want solutions that are more or less conservative in function of this aversion. In our opinion, the concept of robustness is naturally very subjective and should allow the decision maker to give input regarding his preferences to find a solution that is satisfactory for him.

In our model a sensitivity analysis was performed to determine the influence of the preferences given by the DMs based on changing the weights of the criteria for selecting green suppliers. The sensitivity analysis was performed based on 15 scenarios (S_1 to

Table 18
Ranking weight coefficients of the dimensions and criteria.

Dimensions/Criteria	Weight coefficient		Rank	
Green design (D_1)	**0.216**	**0.267**	**1**	
Increasing innovation capabilities(C_1)	0.084	0.098		1
Abstaining from toxic substances(C_2)	0.067	0.094		2
Saving Energy(C_3)	0.065	0.075		4
Green purchasing (D_2)	**0.176**	**0.243**	**2**	
Green Image (C_4)	0.063	0.080		3
Green management abilities (C_5)	0.055	0.082		6
Green competencies (C_6)	0.058	0.081		5
Green production (D_3)	**0.182**	**0.209**	**3**	
Green recycling and lean production (C_7)	0.065	0.071		7
Cleaner production technologies (C_8)	0.061	0.070		9
Decrease Scrap rate (C_9)	0.056	0.068		11
Green Warehousing (D_4)	**0.168**	**0.208**	**4**	
Eco-packaging (C_{10})	0.066	0.069		8
Decrease Inventory Levels (C_{11})	0.050	0.075		10
Sale of excess capital equipment (C_{12})	0.052	0.064		13
Green Transportation (D_5)	**0.150**	**0.184**	**5**	
Use Green fuels (Low sulfur content) (C_{13})	0.058	0.062		12
Reverse logistics(C_{14})	0.056	0.060		13
Environmental friendly distribution(C_{15})	0.036	0.062		15

Table 19
Expert evaluation of the alternatives.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
	Expert 1														
A_1	5	4	3	3	3	2	2	2	2	1	4	1	3	5	3
A_2	3	1	5	5	3	2	5	2	4	4	5	3	5	4	4
A_3	2	3	1	2	2	4	4	5	5	5	5	5	2	2	5
A_4	2	3	3	4	3	2	1	4	2	1	3	5	1	4	4
A_5	4	4	2	1	3	4	1	4	1	2	2	4	1	2	5
	Expert 2														
A_1	5	5	3	3	5	2	2	2	2	3	5	1	3	5	5
A_2	3	2	5	5	4	4	5	2	5	4	5	3	5	5	5
A_3	3	3	1	2	2	5	5	5	5	5	5	5	4	4	5
A_4	4	5	4	5	3	2	1	4	2	2	4	5	1	5	4
A_5	5	4	2	3	4	5	2	5	3	2	3	5	3	3	4
	Expert 3														
A_1	4	4	3	5	3	3	2	3	3	3	4	3	5	4	4
A_2	4	1	4	5	4	4	4	4	5	4	4	4	5	4	5
A_3	3	3	1	2	2	4	5	5	5	5	5	5	3	3	4
A_4	3	3	5	5	3	2	3	5	2	2	4	4	3	5	4
A_5	5	5	4	3	4	4	2	4	1	3	4	4	2	2	5
	Expert 4														
A_1	5	5	3	5	4	2	3	3	4	3	5	1	3	5	5
A_2	4	1	5	5	4	2	5	2	5	4	4	4	5	4	4
A_3	3	4	1	4	2	5	5	4	5	5	5	4	2	4	5
A_4	4	5	4	5	5	3	3	4	3	1	4	4	2	4	5
A_5	5	4	2	3	4	5	2	4	1	4	3	4	1	2	4

S_{15}). In the *first scenario* (S_1), the weight of the criterion C_1 was increased by 35%, and all other criteria weights were decreased by 35%. In *second scenario* (S_2), the weight of the criterion C_2 was increased by 35%, while the weights of all other criteria were

Table 20
Initial decision matrix.

Crit./Alt.	C_1		C_2		C_3		C_4		C_5		C_6		C_7		C_8		C_9		C_{10}		C_{11}		C_{12}		C_{13}		C_{14}		C_{15}	
A_1	4.26	4.76	4.26	4.76	3.00	3.00	3.44	4.45	3.27	4.25	2.05	2.39	2.06	2.43	2.23	2.73	2.25	3.20	1.98	2.86	4.26	4.76	1.09	1.74	3.10	3.78	4.58	4.95	3.73	4.73
A_2	1.06	1.42	1.06	1.42	4.58	4.95	5.00	5.00	3.54	3.93	2.43	3.44	4.58	4.95	2.10	2.77	4.55	4.93	4.00	4.00	4.25	4.75	3.23	3.73	5.00	5.00	4.06	4.44	4.23	4.73
A_3	3.06	3.43	3.06	3.43	1.00	1.00	2.12	2.83	2.00	2.00	4.26	4.76	4.55	4.93	4.54	4.93	5.00	5.00	5.00	5.00	5.00	5.00	4.54	4.93	2.25	3.20	2.71	3.72	4.58	4.95
A_4	3.49	4.50	3.49	4.50	3.55	4.38	4.55	4.93	3.12	3.85	2.06	2.43	1.39	2.43	4.05	4.40	2.06	2.43	1.21	1.72	3.54	3.93	4.25	4.75	1.22	2.16	4.23	4.73	4.06	4.44
A_5	4.05	4.40	4.05	4.40	2.10	2.77	1.98	2.86	3.54	3.93	4.26	4.76	1.52	1.93	4.06	4.44	1.11	1.80	2.25	3.20	2.54	3.37	4.06	4.44	1.23	2.18	2.06	2.43	4.23	4.73

Table 21
Theoretical estimates (T_p).

Crit./Alt.	C_1		C_2		C_3		C_4		C_5		C_6		C_7		C_8		C_9		C_{10}		C_{11}		C_{12}		C_{13}		C_{14}		C_{15}	
A_1	0.017	0.020	0.013	0.019	0.013	0.015	0.013	0.016	0.011	0.016	0.012	0.016	0.013	0.014	0.012	0.014	0.011	0.014	0.013	0.014	0.010	0.015	0.010	0.013	0.012	0.012	0.011	0.012	0.007	0.012
A_2	0.017	0.020	0.013	0.019	0.013	0.015	0.013	0.016	0.011	0.016	0.012	0.016	0.013	0.014	0.012	0.014	0.011	0.014	0.013	0.014	0.010	0.015	0.010	0.013	0.012	0.012	0.011	0.012	0.007	0.012
A_3	0.017	0.020	0.013	0.019	0.013	0.015	0.013	0.016	0.011	0.016	0.012	0.016	0.013	0.014	0.012	0.014	0.011	0.014	0.013	0.014	0.010	0.015	0.010	0.013	0.012	0.012	0.011	0.012	0.007	0.012
A_4	0.017	0.020	0.013	0.019	0.013	0.015	0.013	0.016	0.011	0.016	0.012	0.016	0.013	0.014	0.012	0.014	0.011	0.014	0.013	0.014	0.010	0.015	0.010	0.013	0.012	0.012	0.011	0.012	0.007	0.012
A_5	0.017	0.020	0.013	0.019	0.013	0.015	0.013	0.016	0.011	0.016	0.012	0.016	0.013	0.014	0.012	0.014	0.011	0.014	0.013	0.014	0.010	0.015	0.010	0.013	0.012	0.012	0.011	0.012	0.007	0.012

Table 22
Real assessments (T_r).

Crit./Alt.	C_1		C_2		C_3		C_4		C_5		C_6		C_7		C_8		C_9		C_{10}		C_{11}		C_{12}		C_{13}		C_{14}		C_{15}	
A_1	0.015	0.020	0.012	0.019	0.007	0.008	0.006	0.013	0.006	0.016	0.000	0.002	0.002	0.004	0.001	0.003	0.003	0.007	0.003	0.006	0.007	0.014	0.000	0.002	0.006	0.008	0.010	0.012	0.000	0.010
A_2	0.000	0.002	0.000	0.002	0.012	0.015	0.013	0.016	0.008	0.014	0.002	0.008	0.012	0.014	0.000	0.003	0.010	0.013	0.010	0.010	0.007	0.013	0.006	0.009	0.012	0.012	0.008	0.010	0.003	0.010
A_3	0.009	0.013	0.007	0.012	0.000	0.000	0.001	0.005	0.000	0.000	0.009	0.016	0.012	0.014	0.011	0.014	0.011	0.014	0.013	0.014	0.010	0.015	0.009	0.013	0.003	0.006	0.003	0.007	0.005	0.012
A_4	0.011	0.018	0.009	0.017	0.008	0.013	0.011	0.016	0.006	0.013	0.000	0.002	0.000	0.004	0.008	0.011	0.003	0.005	0.000	0.002	0.004	0.008	0.009	0.012	0.000	0.003	0.008	0.011	0.002	0.007
A_5	0.014	0.018	0.011	0.017	0.004	0.007	0.000	0.005	0.008	0.014	0.009	0.016	0.000	0.002	0.008	0.012	0.000	0.002	0.004	0.007	0.000	0.005	0.008	0.011	0.000	0.003	0.000	0.002	0.003	0.010

Table 23
The total gap matrix.

Crit. /Alt.	C_1		C_2		C_3		C_4		C_5		C_6		C_7		C_8		C_9		C_{10}		C_{11}		C_{12}		C_{13}		C_{14}		C_{15}	
A_1	−0.003	0.005	−0.005	0.007	0.005	0.008	0.000	0.010	−0.005	0.010	0.010	0.016	0.009	0.012	0.009	0.013	0.004	0.010	0.007	0.011	−0.004	0.008	0.008	0.013	0.003	0.007	−0.001	0.002	−0.003	0.012
A_2	0.015	0.020	0.012	0.019	−0.002	0.003	−0.003	0.003	−0.003	0.009	0.003	0.015	−0.001	0.003	0.009	0.014	−0.002	0.004	0.003	0.004	−0.003	0.008	0.002	0.007	−0.001	0.001	0.001	0.004	−0.003	0.009
A_3	0.004	0.010	0.001	0.012	0.013	0.015	0.008	0.015	0.011	0.016	−0.005	0.007	−0.001	0.003	−0.002	0.003	−0.002	0.002	−0.001	0.001	−0.005	0.005	−0.002	0.003	0.005	0.009	0.004	0.009	−0.005	0.007
A_4	−0.001	0.009	−0.004	0.010	0.000	0.007	−0.003	0.005	−0.002	0.011	0.009	0.016	0.009	0.014	0.001	0.006	0.007	0.011	0.011	0.014	0.002	0.011	−0.002	0.004	0.009	0.012	0.000	0.004	0.000	0.010
A_5	−0.001	0.006	−0.004	0.008	0.006	0.011	0.008	0.016	−0.003	0.009	−0.005	0.007	0.011	0.014	0.001	0.006	0.009	0.014	0.006	0.010	0.005	0.015	−0.001	0.005	0.008	0.012	0.010	0.012	−0.003	0.009

Table 24
Alternative ranking according to rough MAIRCA (R′ MAIRCA).

Alternative	$RN(Q_i)$		Initial rank	$A_{D,1-j}$	Final rank
A_1	0.034	0.146	4	0.182	4
A_2	0.025	0.122	2	0.022	1*
A_3	0.024	0.119	1	0.000	1
A_4	0.034	0.143	3	0.172	3
A_5	0.048	0.154	5	0.288	5

Table 26
Spearman correlation co-efficient among various MCDM methods in rough domain.

	Rough MAIRCA	Rough VIKOR	Rough TOPSIS	Rough COPRAS
Rough MAIRCA	1	0.9	0.6	1
Rough VIKOR		1	0.8	0.8
Rough TOPSIS			1	0.6
Rough COPRAS				1

decreased by 35%, etc. The details of 15 scenarios are given in Table 27.

The initially best-ranked alternative is the one with the smallest total gap value, i.e. A_3, as shown in Table 24. The ranking results in Table 27 indicate that alternative A_3 and A_2 are the best ranked, with good advantage, for the weight sets S_1, S_2, S_6-S_{12} and S_{15}. With the weights in S_3-S_5 the sets are obtained {A_2, A_3, A_4} and {A_2, A_3, A_1}, respectively.

- In S_3 the first ranked alternatives (A_2 and A_3) has no advantage to be a single solution since the dominance index $A_{D,2\text{-}j}$ of the best-ranked alternative (A_2) in relation to A_3 and A_4 ($A_{D,2\text{-}3} = 0.060$ and $A_{D,2\text{-}4} = 0.041$) is smaller than $I_D = 0.160$ we cannot say that the alternative A_2 has enough advantage and therefore to A_3 and A_4 will be assigned a rank "1*". Similar results occur in S_4.
- In S_5 the first ranked alternatives (A_2 and A_3) again has no advantage since the dominance index ($A_{D,2\text{-}3} = 0.081$ and $A_{D,2\text{-}1} = 0.111$) is smaller than $I_D = 0.160$ and therefore to A_3 and A_1 will be assigned a rank "1*". If the weights of Green management abilities (C_5) is increased (S_5), the index of domination of the alternative A_2 in relation to alternative A_3 increases by 25.92% (from $A_{D,2\text{-}3} = 0.060$ to $A_{D,2\text{-}3} = 0.081$). Although the alternative A_2 still has no advantage, we can conclude that A_2 has better Green management abilities then A_3 and A_1 for 25.92%. Similar conclusions can be drawn in S_3 and S_4 when we observe the criteria Saving Energy (C_3) and Green Image (C_4).
- Only in S_6 and S_{10}, the alternative A_2 has enough advantage under all other alternatives since the dominance index is $A_D(S_6)_{,2\text{-}3} = 0.197$ and $A_D(S_{10})_{,2\text{-}3} = 0.161$). From this values of the $A_D(S_6)_{,2\text{-}3}$ and $A_D(S_{10})_{,2\text{-}3}$ we can conclude that the alternative A_2 has better Green competencies (C_6) and Eco-packaging (C_{10}) abilities then other alternatives.

The Spearman's correlation coefficient of 15 scenarios used for checking the stability of the ranking result is presented in Table 28, while its graphical representation is given in Fig. 3.

Changing the criteria weights through scenarios resulted in changing the ranks of the remaining alternatives. However, it can be said that these changes were not so drastic, which is confirmed by correlation of the ranks through scenarios (Table 28). Spearman's correlation coefficients (SCC) were obtained by comparing the initial ranks of the R-D'AMATEL-MAIRCA model (Table 24) with the ranks obtained through the scenarios. Based on Table 28 it can be noticed that there is significant correlation of the ranks since in 80% of the scenarios, the SCC is higher than 0.80, while in the remaining scenarios it exceeded the value of 0.6. The mean SCC value in all scenarios is 0.836, which is a considerably high correlation. Since mean SCC values is higher than 0.80 it can be concluded that there is a considerably high correlation between the ranks and that the proposed rank is both confirmed and credible.

After changing criteria weights where certain criteria were favored, while the preference for all the alternatives was the same ($P_{A_i} = 0.2$). In the next scenarios S_{16}-S_{17}, the criteria weights remained unchanged, but the preferences for alternatives were changed. As shown in section 3.3 (Step 2). The experts are neutral with respect to the alternatives during alternative selection and all the alternatives are considered and selected with equal probability. In the S_{16} and S_{17} the second and third ranked alternatives were favored. In S_{16} the second-ranked alternative (A_2) has a 15% advantage over the first-ranked alternative (A_3). In S_{17} shows that the second-ranked alternative (A_2) has a 15% advantage over the third-ranked alternative (A_4). (S_{16}) shows that the first-ranked alternative (A_3) and the next one (A_2) are very close, that is, A_3 ranking is a mere 2.9% better than A_2. Scenario 17 shows that the second-ranked alternative (A_2) has enough advantage over A_4 since in this scenario the ranks are stayed unchanged. The analysis can serve to confirm the ranks obtained in Table 24, and for the selection of the optimal set of alternatives {A_2, A_3}.

4.8. *The sensitivity analysis based on different weights assigned by decision makers*

The sensitivity analysis was performed to assess the influence of the decision makers on ranking of the alternatives and the criteria along with dimensions. The details of the analysis are given in Tables 29 and 30.

Table 25
Ranking patterns of alternatives under different rough based MCDM methodology.

Methods		Alternatives					Ranking
		A1	A2	A3	A4	A5	
R'MAIRCA	Q_j	0.0899	0.0738	0.0716	0.0889	0.1006	A3 > A2 > A1 ≈ A4 > A5
	I_D	0.160					–
	$A_{D,1\text{-}j}$	0.1819	0.0225	0.0000	0.1723	0.2881	–
	$R_{j\,(final)}$	0.0899	0.0738	0.0716	0.0889	0.1006	A3 ≈ A2 > A1 ≈ A4 > A5
R'VIKOR	S_j	0.6323	0.5521	0.4987	0.5570	0.6436	A3 > A2 > A4 > A1 > A5
	R_j	0.0783	0.0732	0.0715	0.0735	0.0853	A3 > A2 > A4 > A1 > A5
	Q_j	0.5852	0.4746	0.4150	0.5516	0.6177	A3 > A2 > A4 > A1 > A5
R'TOPSIS	D_j^*	0.3160	0.1020	0.1360	0.2280	0.2660	A2 > A3 > A4 > A5 > A1
	D_j^-	0.1140	0.3581	0.3600	0.2832	0.1826	A3 > A2 > A4 > A1 > A5
	Q_j	0.2337	0.7862	0.7223	0.5261	0.4389	A2 > A3 > A4 > A5 > A1
R'COPRAS	Q_j	0.2007	0.2189	0.2197	0.2004	0.1891	A3 > A2 > A1 > A4 > A5
	P_j	91.34	99.62	100.00	91.19	86.04	

Table 27
Sensitivity analysis in alternative ranking based on variation in weights of criteria.

Alternatives	Scenario														
	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}
	Ranking of alternatives														
A_1	2	3	4	4	3	5	3	4	3	3	3	4	3	3	4
A_2	3	2	1	1	1	2	2	2	2	2	2	2	1	1	2
A_3	1	1	2	2	2	1	1	1	1	1	1	1	2	2	1
A_4	4	4	3	3	4	4	4	3	4	4	4	3	4	4	3
A_5	5	5	5	5	5	3	5	5	5	5	5	5	5	5	5

Table 28
Spearman correlation co-efficient on 15 scenarios taken.

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}
S_1	1	0.9	0.5	0.5	0.7	0.3	0.9	0.7	0.9	0.9	0.9	0.7	0.7	0.7	0.7
S_2		1	0.8	0.8	0.9	0.6	1	0.9	1	1	1	0.9	0.9	0.9	0.9
S_3			1	1	0.9	0.6	0.8	0.9	0.8	0.8	0.8	0.9	0.9	0.9	0.9
S_4				1	0.9	0.6	0.8	0.9	0.8	0.8	0.8	0.9	0.9	0.9	0.9
S_5					1	0.5	0.9	0.8	0.9	0.9	0.9	0.8	1	1	0.8
S_6						1	0.6	0.7	0.6	0.6	0.6	0.7	0.5	0.5	0.7
S_7							1	0.9	1	1	1	0.9	0.9	0.9	0.9
S_8								1	0.9	0.9	0.9	1	0.8	0.8	1
S_9									1	1	1	0.9	0.9	0.9	0.9
S_{10}										1	1	0.9	0.9	0.9	0.9
S_{11}											1	0.9	0.9	0.9	0.9
S_{12}												1	0.8	0.8	1
S_{13}													1	1	0.8
S_{14}														1	0.8
S_{15}															1

The DMs having different knowledge of the investigated object and the existing methods related to the GSC do not show the required flexibility in reflecting the actual preferences in a segmented market. Thus, in using decision making methods, the experts make judgements depending on their level of participation in the survey, experience and the product-related knowledge. In this research, three types of ranking (*related to the alternatives, criteria and dimensions, respectively*) were assessed, prioritizing the weights assigned by the DMs. The results are given in Figs. (4)–(6).

The aim was to determine the variation between the ranking results when *one* DM obtained a larger weight compared to other DMs (*depending on their knowledge of criteria*) and the ranking result when equal weights were assigned to all DMs. Since a unified result had not been obtained in the case study, another

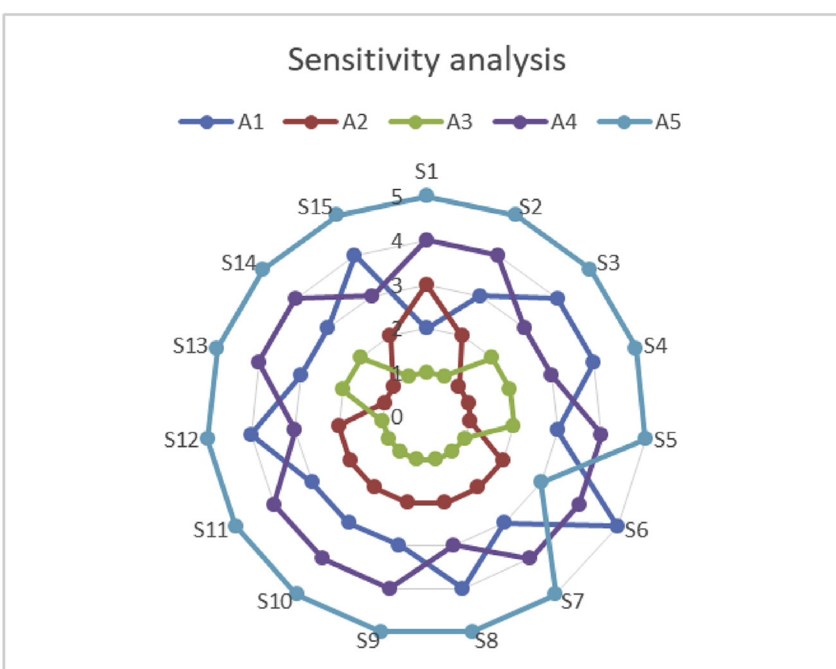

Fig. 3. Sensitivity analysis of the *alternative ranking* on different scenarios of criteria weight.

Table 29
Sensitivity analysis for alternative ranking taking varying weights of DMs.

Alternatives	DM_1 (0.6)	DM_2 (0.6)	DM_3 (0.6)	DM_4 (0.6)
A_1	4	4	4	4
A_2	1	2	2	3
A_3	2	1	1	1
A_4	3	3	3	2
A_5	5	5	5	5

combination of DMs' weights was taken to check for any difference in ranking result. Based on variation in ranking results in Tables 29 and 30, the proposed methodology shows the flexibility and its capability of accepting various assumptions and conditions.

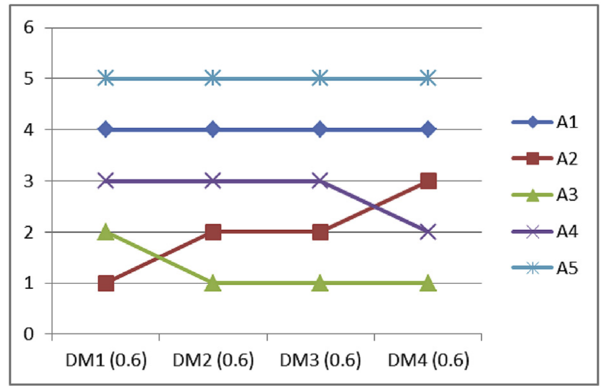

Fig. 4. Sensitivity analysis of *alternatives ranking* prioritizing DMs weights.

5. Managerial implications

The utility of proposed decision-making tool is evident but acceptance by management could be a concern. Most of managers and decision makers will find acceptance in tools and models that can be easily understood. R'AMATEL-MAIRCA model used in this paper may not readily fall into the easily understood category. This situation is true for most mathematically complex approaches. The utilization of this tool as part of the toolset of a decision support system will make it more acceptable to management. This tool will be more acceptable to managers who have to deal with greater magnitudes of uncertainties and imprecision in supplier environment and also to those who have prior knowledge of supplier performance. At this time, tables for ranking scheme are provided, but graphical representation of the criteria relations may enhance managerial acceptance.

The objective of this case study is to select the best green supplier for the development of new products which abides the environmental criteria and traditional criteria. By examining the five main criteria and 15 sub criteria, this study helps the firm managers in understanding the green supplier evaluation and selection process and offers the following benefits.

- The first benefit of this study is developing main and sub-criteria selection using cause and effect relationship diagram and R-

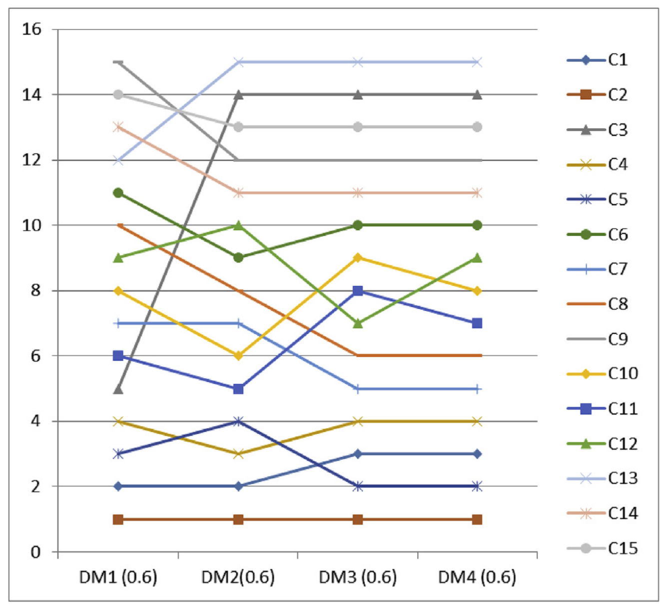

Fig. 5. Sensitivity analysis for criteria ranking prioritizing DMs weights.

Table 30
Details of sensitivity analysis for criteria and dimensions.

	DM_1 (0.6)			DM_2 (0.6)			DM_3 (0.6)			DM_4 (0.6)		
	w		Rank	w		Rank	w		Rank	w		Rank
D_1	**0.2393**	**0.2903**	**1**	**0.2157**	**0.2667**	**3**	**0.1924**	**0.2434**	**4**	**0.2107**	**0.2617**	**3**
C_1	0.0811	0.0951	2	0.0880	0.1020	2	0.0909	0.1049	3	0.0909	0.1049	3
C_2	0.0803	0.1073	1	0.0889	0.1159	1	0.0907	0.1177	1	0.0859	0.1129	1
C_3	0.0779	0.0879	5	0.0388	0.0488	14	0.0108	0.0208	14	0.0339	0.0439	14
D_2	**0.2071**	**0.2741**	**2**	**0.2257**	**0.2927**	**1**	**0.2427**	**0.3097**	**1**	**0.234**	**0.301**	**1**
C_4	0.0771	0.0941	4	0.0855	0.1025	3	0.0893	0.1063	4	0.0887	0.1057	4
C_5	0.0734	0.1004	3	0.0782	0.1052	4	0.0850	0.1120	2	0.0846	0.1116	2
C_6	0.0566	0.0796	11	0.0620	0.0850	9	0.0684	0.0914	10	0.0607	0.0837	10
D_3	**0.1852**	**0.2122**	**4**	**0.2014**	**0.2284**	**4**	**0.23**	**0.257**	**3**	**0.211**	**0.238**	**4**
C_7	0.0749	0.0809	7	0.0798	0.0858	7	0.0915	0.0975	5	0.0848	0.0908	5
C_8	0.0673	0.0763	10	0.0711	0.0801	8	0.0872	0.0962	6	0.0810	0.0900	6
C_9	0.043	0.055	15	0.0505	0.0625	12	0.0513	0.0633	12	0.0452	0.0572	12
D_4	**0.2106**	**0.2506**	**3**	**0.2263**	**0.2663**	**2**	**0.2483**	**0.2883**	**2**	**0.2265**	**0.2665**	**2**
C_{10}	0.0763	0.0793	8	0.0838	0.0868	6	0.0859	0.0889	9	0.0806	0.0836	8
C_{11}	0.0674	0.0924	6	0.0755	0.1005	5	0.0777	0.1027	8	0.0714	0.0964	7
C_{12}	0.0669	0.0789	9	0.0670	0.0790	10	0.0847	0.0967	7	0.0745	0.0865	9
D_5	**0.1578**	**0.1918**	**5**	**0.1308**	**0.1648**	**5**	**0.0865**	**0.1205**	**5**	**0.1177**	**0.1517**	**5**
C_{13}	0.0620	0.0660	12	0.0354	0.0394	15	0.0098	0.0138	15	0.0296	0.0336	15
C_{14}	0.0564	0.0604	13	0.0623	0.0663	11	0.0677	0.0717	11	0.0601	0.0641	11
C_{15}	0.0394	0.0654	14	0.0331	0.0591	13	0.0090	0.0350	13	0.0280	0.0540	13

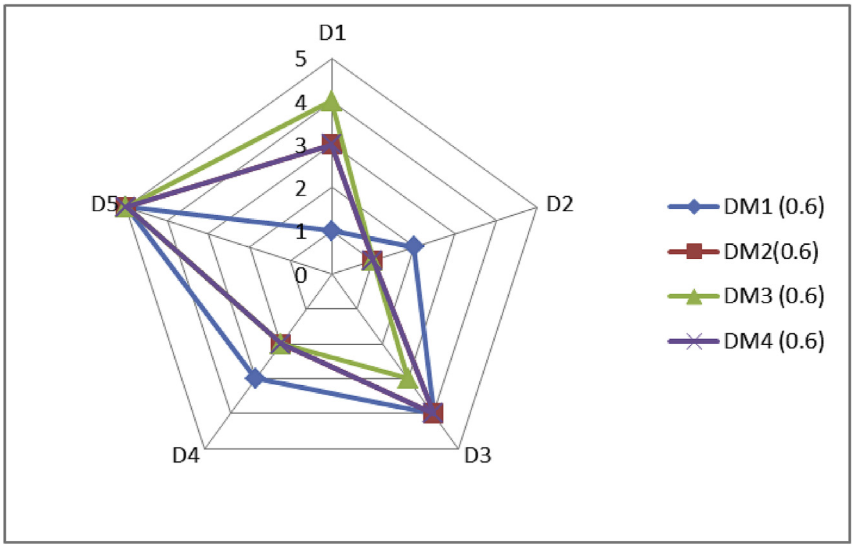

Fig. 6. Sensitivity analysis for ranking of Dimensions prioritizing DMs weights.

D'AMATEL model based on comprehensive literature review and case company requirement.

- The second benefit is not only in selecting the best green supplier, but also were used to analyse the supplier who did not satisfy the firm requirement and intimate the area where they can improve their performance.
- The result of this study helps firm to establish the systematic approach to select the best green supplier within the set of criteria and helps to analyse the most appropriate alternate supplier which shows the great difference when compared to the other approaches.

The methodology's flexibility in selection and weighting of performance measures to be used is also valuable. This flexibility will allow management to perform sensitivity analyses at many levels and thus obtain more robust and relevant solutions. This technique can also provide strategic guidance for the organization. For example, if the organization and management feel that stock holders, consumers, governmental or supply chain partners are putting more pressure on various sustainability practices (more financial or environmental emphasis, for example) the technique can be used to select suppliers to develop more effective partnership opportunities. The methodology helps managers to select the most appropriate set of suppliers by choosing suitable sets of measures for their current operating environment.

6. Conclusion and future direction of research

The dimensions and criteria outlined in the paper serve as a linking mechanism allowing for effective evaluation of green activities of companies under the conditions of lack of information. This aim was achieved using the hybrid rough R'AMATEL-MAIRCA multi-criteria decision making approach, introducing the rough DEMATEL and the rough MAIRCA methods with the previously defined rough ANP. The authors hope that a description of this complex method and its application could enrich the literature on the use of the MCDM methods. The contribution of this study is twofold. *First*, the DEMATEL and ANP methods were combined in a rough domain to develop the R'AMATEL method for prioritizing the weights of the relative influence of the criteria and handling complex interactions and interdependencies between the GSCM dimensions and the criteria. *Second*, the alternative suppliers were described in terms of their GSCM activities and the proposed rough MAIRCA method was used for evaluating the suppliers.

Besides, the proposed modification of the DEMATEL using RN makes it possible to take into account doubts that occur during the expert evaluation of criteria thus bridging the existing gap in the methodology in the treatment of uncertainty based on RN. In such a way, the quality of the existing data in the collective decision making process can be retained, as well as the experts' perception, which is expressed through the aggregation matrix. In the surveyed literature, no works on the problem of performance evaluation of green suppliers, taking into account the interdependencies between the criteria in the framework of the rough number-based MCDM approach, have been found. The suggested method was validated through a case study of the Taiwanese electronics company by describing five alternative companies in terms of the predefined green supply chain management dimensions and the respective criteria.

The results obtained by the proposed method can be considered promising when the reliability and stability of the ranking results are checked. Therefore, it may be concluded that the application of a rough number-based model to support decisions has shifted from the evaluation of the most desirable methodologies to the improvement of the existing methods' performance. The proposed model can identify the mutual influence of the criteria, thereby aiding purchasing managers to better understand the performance-related issues and to devise the appropriate improvement strategies. The paper does not consider the trade-offs involved by normalization in obtaining the aggregating function in MAIRCA method and this topic remains for further research. Besides that, future research should include extension of the MAIRCA method with a stability analysis determining the weight stability intervals. That research should include determination of the weight stability interval for each criterion, separately, with the initial values of weights. Furthermore, it allows for applying the developed framework for case studies from the perspective of particular countries and comparing the results by examining possible differences and their causes. The suggested methodology provides the DMs with the required flexibility for making any possible changes by adding or omitting the identified GSC criteria or the supplier alternatives if required.

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