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A grey-based green supplier selection model for uncertain environments

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ABSTRACT

The concept of green supply chain management emerged as a response to increasing public awareness of environmental protection in the past few decades. As companies tend to outsource a variety of their activities, green supplier selection as an imperative function of green supply chain management, has a crucial role in helping companies to maintain their strategic competitiveness. Despite the plethora of studies introducing supplier selection models based on economic criteria, studies that take into account the environmental issues are rather limited. In this study, a comprehensive grey-based green supplier selection model is proposed that incorporates both economic and environmental criteria. A novel weight assignment model is proposed by combining best-worst method and fuzzy grey cognitive maps to capture the interdependencies among the criteria. Improved grey relational analysis is advanced to be able to use grey weights of criteria to evaluate green suppliers which are subsequently ranked using an interval analysis approach. This study contributes to the decision-making theory by addressing the shortcomings of the available green supplier selection models. A real-world case study is also presented to show the applicability and effectiveness of the proposed model. The results of this study proved the proposed comprehensive model to be well capable of addressing the green supplier selection problem by taking in to account the interdependencies between criteria as well as the uncertainties associated with experts' judgments.

1. Introduction

Globally increasing awareness of environmental protection has been a driving force for organizations to develop more environmentally responsible solutions. These efforts have gone well far beyond only complying with rigorous environmental regulations and proactive initiatives taken up by certain organizations (Sarkis, 2006). As a part of these efforts, green supply chain management (GSCM) concept emerged which has gained popularity among both scholars and practitioners (Srivastava, 2007; Lin, 2013; Liou et al., 2016). However, there exists a lack of consensus in both definition and practice of GSCM (Zhu and Sarkis, 2004; Ahi and Searcy, 2013). Consequently, several definitions of GSCM can be found in the existing literature (Green et al., 1996; Handfield et al., 1997; Narasimhan and Carter, 1998; Zhu et al., 2005). In this paper the definition of GSCM by Srivastava (2007, p.54–55) is adopted which defines GSCM as "integrating environmental thinking into supply chain management, including product design, material sourcing and selection, manufacturing processes, delivery of the final product to the consumers, as well as end-of life management of the product after its useful life".

Among various functions of GSCM, supplier selection is highly important to managers for the purpose of greening the entire supply chain, as companies are held responsible not only for their own actions, but for the adverse environmental impacts of their partners (Rao and Holt, 2005; Jayaraman et al., 2007; Wu and Barnes, 2016). Additionally, supplier selection plays a pivotal role for organizations to maintain their strategic competitiveness (Chen et al., 2006), as companies usually outsource (mainly) non-competitive activities (and sometimes even) competitive activities.

Supplier selection is a multiple criterion decision-making (MCDM) problem where a limited number of alternative suppliers are evaluated with respect to a limited set of (conflicting) criteria. Accordingly, supplier selection problems are associated with uncertainty as they are highly dependent on subjective judgments of

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decision-makers (DMs) (Li et al., 2007). In real world supplier selection problems, the exact value of all criteria are not always available, hence, the experts evaluate suppliers using linguistic variables such as, "very good" or "medium" or even in terms of interval variables. Deterministic models cannot easily consider this vagueness (Amid et al., 2006). As a result, decision making models that are capable of taking this vagueness in to account are more likely to provide realistic results. Grey systems theory (GST) has been acknowledged to be superior to comparable methods in the mathematical analysis of systems with uncertain information (Li et al., 2007). Therefore, in this study, a grey based model is presented to handle uncertainty in all stages of a supplier selection problem which potentially leads to a more realistic evaluation of suppliers compared to the available deterministic models. Moreover, in order to avoid information loss, all computations are done using grey numbers in all stages of the proposed model, which means no whitenization process is employed.

On the other hand, the interdependencies between evaluation criteria is another important characteristic of supplier selection problems where the significance of these interdependencies is multiplied by incorporating environmental criteria in the decision-making process (Sarkis, 2003; Hashemi et al., 2015). Given that in many real decision making cases, evaluation criteria are not internally independent, determining and considering criteria interdependencies, is of great significance to make more informed decisions. Nevertheless, in spite of great studies been done by various scholars to address criteria interdependencies, there still exist a few limitations. For example, the extremely time consuming nature of their processes along with the inconsistency issue that arises as the number of alternatives and criteria increases, are two important limitations that are needed to be addressed. In this paper, the proposed model is capable of mapping criteria interdependencies in a more time efficient manner because of the combination of best-worst method (BWM) with fuzzy grey cognitive maps (FGCMs), where the number of pairwise comparisons is substantially reduced compared to other available models.

Despite numerous studies addressing supplier selection problem, there still exist limited number of comprehensive models that consider both economic and environmental criteria along with their interdependencies as well as capturing, processing, and integrating uncertainty in all phases of the decision-making process (Kannan et al., 2013, 2015; Büyüközkan and Çifçi, 2012; Handfield et al., 2002; Humphreys et al., 2003). Therefore, the main purpose of this study is to put forward a comprehensive supplier selection model by considering both economic and environmental criteria and their interdependencies under conditions of uncertainty. To this end, BWM and FGCM are integrated to compute the grey (interval) weight of each criterion by considering the interdependencies between criteria. Subsequently, the improved grey relational analysis (IGRA) is advanced to incorporate grey weights, and it is used to evaluate suppliers based on the experts' opinion that is expressed in the form of linguistic variables. At last, an interval analysis approach is used to rank suppliers. A real world case study of automotive industry is presented to show the applicability and effectiveness of the proposed model.

In summary, the contribution of the current study is threefold. First, the proposed comprehensive model addresses the inherent uncertainty in all phases of the decision-making process by using grey values that aids decision-makers to have a more realistic evaluation of their alternatives. Second, a novel weight assignment method is proposed that incorporates BWM and FGCM in a manner so the grey weights of all criteria are computed efficaciously while the interdependencies between them are also considered. Third, the IGRA method is advanced to use grey values of criteria weights and suppliers' evaluations to compute the grey relational degree of each supplier. For the sake of addressing uncertainty in all phases of the decision-making process, an interval analysis approach is used to rank suppliers using their grey relational degrees.

The remainder of the paper is structured as follows. In Section 2, a review of the relevant studies is presented. An overview and a detailed review of the proposed green supplier selection model are presented in Section 3. In Section 4, application of the proposed method is explored in a real-world case study. Managerial and practical implications are explained in Section 5. Subsequently, in Section 6, results are discussed and conclusions along with future research directions are provided in Section 7.

2. Literature review

As mentioned before, green supplier selection is formulated as a MCDM problem, which is why in the next sub-sections an overview of the criteria and methods which have been used for green supplier selection in the existing literature are provided.

2.1. Green supplier selection methods

Despite the large and growing body of literature to supplier evaluation and selection, the existing research addressing green supplier evaluation that considers environmental factors is rather limited (Handfield et al., 2002; Humphreys et al., 2003; Kannan et al., 2013; Govindan et al., 2015). Various supplier selection methods have been proposed in the literature to deal with the complexities associated with this multi-criterion problem. A comprehensive overview of these methods can be found in researches conducted by, De Boer et al. (2001), Ho et al. (2010), Chai et al. (2013) and Govindan et al. (2015). Govindan et al. (2015), propose a classification framework for the existent green supplier evaluation and selection methods based on two main categories including "decision-making methodology base" and "criteria selection base". The former is comprised of individual and integrated methodology approaches, and the latter consists of environmental and traditional criteria bases. Regarding the decision-making methodology base, MCDM techniques such as, analytical hierarchy processes (AHP) (Marufuzzaman et al., 2009; Levary, 2008; Ishizaka et al., 2012; Chan and Chan, 2010; Grisi et al., 2010) and analytical network process (ANP) (Sarkis, 2003; Gencer and Gürpinar, 2007; Hsu and Hu, 2009; Tseng et al., 2009; Büyüközkan and Çifçi, 2011) are methodologies known to be used predominantly in the literature both individually and in integration with other techniques (Govindan et al., 2015). Another more recently developed method is the BWM, that is extensively being used in different contexts including supplier selection (Rezaei et al., 2016; Ahmad et al., 2017; Gupta et al., 2017; Ren et al., 2017; Salimi and Rezaei, 2016; Shojaei et al., 2018), as an efficient pairwise comparison based MCDM method.

Despite the plethora of supplier selection methods present in the literature, a few shortcomings and limitations are associated with the current models such as not considering the interdependencies between criteria, and not addressing the uncertainty in all phases of the decision-making process. In the existing literature two predominant bodies of methods are proposed to capture criteria interactions including, analytical network process (ANP) and the Choquet integral (Baykasoğlu and Gölcük, 2015). Additionally, other methodologies can be found in the literature that strive to consider the interdependencies amongst criteria, namely, fuzzy decision maps (FDMs) (Yu and Tzeng, 2006) and fuzzy cognitive maps (FCMs) (Baykasoğlu and Gölcük, 2015; Xiao et al., 2012).

Within past studies, a major research trend that is aimed at dealing with uncertainties associated with supplier selection, is the

Table 1
Summary of economic criteria for supplier selection.

Criteria	Relevant characteristics in the literature
Quality	Quality systems, process capability, quality assurance, reject rate, compliance with quality, quality philosophy, prompt response, consistent delivery, management commitment to quality, process improvements, warranties and claim policies, capability of handling abnormal quality, continuous improvement programs, documentation and self-audit, quality certifications, shipment quality, product conformance quality, service quality
Price/Cost	Purchasing price, price performance value, compliance with sectoral price behavior, transportation cost, production cost, competitiveness of cost, cost reduction capability, cost reduction effort, cost reduction performance, fluctuation on costs, appropriateness of the materials price to the market price, direct cost, indirect-coordination cost, ordering cost
Delivery	Delivery speed, order fulfillment rate, lead time, order frequency, appropriateness of the delivery date, compliance with due date, delivery delays, delivery efficiency, delivery reliability, number of shipments to arrive on time, waiting time, geographical location
Technology capability	Technology level, capability of R&D, capability of design, suppliers speed in development, current manufacturing facilities/capabilities, technological development of the supplier to meet current and future demand of the firm, technological compatibility, capability of product development
Flexibility	Product volume changes, short set-up time, conflict resolution, service capability number of tasks performable by a worker, using flexible machines, the demand that can be profitably sustained, time or cost required to add new products to the existing production operation
Culture	Feeling of trust, management attitude/outlook for the future, strategic fit, top management compatibility, compatibility among levels and functions, suppliers organizational structure and personnel, future strategy direction, degree of strategic cooperation
Innovativeness	New launch of products, new launch of technologies
Relationship	Long-term relationship, relationship closeness, communication openness, reputation of integrity
Risk	Perceived risk, delivery risk, cost risk, quality risk, flexibility risk, confidence risk

(sources: Kannan et al., 2014; Bai and Sarkis, 2010; Yang and Wu, 2007; Hsu and Hu, 2009; Kuo et al., 2010; Lee et al., 2009; Büyüközkan and Çifçi, 2011; Grisi et al., 2010; Chiou et al., 2008; Choi and Hartley, 1996; Cao, 2011; Ho et al., 2010; Kull and Talluri, 2008; Hashemi et al., 2015)

fuzzy approach (Banaeian et al., 2016; Kannan et al., 2013, 2015), and also the integration of different methodologies with fuzzy set theory (For examples see, Hashim et al. (2017), Zhong and Yao (2017), and Zhou et al. (2018)). Along with fuzzy approach to handle uncertainty, grey systems theory (GST) is also an effective but relatively overlooked approach for uncertain environments, under discrete, small, and uncertain data sets (Deng, 1989). According to Chai et al. (2013) review, GST has been applied to supplier selection from two perspectives including, decision information in the form of grey values and grey relational analysis (GRA). GRA is introduced by Deng (1989) as a part of the GST, which is capable of solving problems with intricate interrelationship between various factors and variables. GRA method has been extensively used for solving problems associated with ambiguity under the discrete data and incomplete information (Wei, 2011a, 2011b; Wu, 2009). Along with the traditional GRA that handles uncertainty by taking into account deterministic numbers (Kuo et al., 2008a; Lee and Lin, 2011; Tseng, 2010), the models proposed by Hashemi et al. (2015) and Manzardo et al. (2012) use grey (interval) values.

2.2. Green supplier selection criteria

Identification and selection of supplier evaluation criteria are of great significance as they lay the foundation of a proper supplier selection (Çelebi and Bayraktar, 2008). Prior to the beginning of the organizations' movement toward adopting environmentally responsible operations, supplier evaluation and selection task was conventionally solely based upon criteria with economic impact on firms. These economic criteria in the literature are thoroughly investigated and ranked by various researchers (Dickson, 1966; Weber et al., 1991). A summary of the most important and frequent economic criteria in the existing literature is presented in Table 1.

Along with organizations greening their supply chains, and selecting their partners from green suppliers, it is essential to incorporate environmental criteria into the decision-making process. However, among the conventional supplier selection models found in the literature, both environmental and social factors are neglected (Bai and Sarkis, 2010). Following early researches that took environmental criteria into consideration (Lamming and

Table 2
Summary of environmental criteria for supplier selection.

Criteria	Relevant characteristics in the literature
Pollution production	The supplier's amount of pollution per time unit including, solid waste, air emissions, waste water and harmful materials released
Pollution control	Reduction of waste, remediation, end-of-pipe controls, use of harmful material, pollution control initiatives, pollution reduction capability
Resource consumption	The supplier's use of different resources such as material and energy
Green/Eco-design	The supplier's investment in new product development in order to reduce environmental effects such as designing the products for reuse and recycle, design of products to avoid or reduce the use of hazardous materials
Environmental management system	Environment protection system certifications, reverse logistics system, environmental policies and planning, environmental implementation and operation, continuous monitoring and regulatory compliance
Green image	The way the stakeholders view the supplier with respect to green programs, green market share, customer's purchasing retention, ratio of green customers to total customers, social responsibility
Green competencies	Clean technology, materials used in the supplied components that reduce the impact on natural resources, ability to alter process and product for reducing the impact on natural resources
Green product	Recycle, environmental friendly product packaging
Green innovativeness	The suppliers' capability in green design, and preventing new products to contain unacceptable levels of restricted substances, green R&D
Management commitment	Commitment of senior managers to support and improve green supply chain management initiatives

(sources: Noci, 1997; Walton et al., 1998; Handfield et al., 2002; Humphreys et al., 2003; Lee et al., 2009; Bai and Sarkis, 2010; Amin and Zhang, 2012; Amindoust et al., 2012; Govindan et al., 2013; Kannan et al., 2014; Rezaei et al., 2016; Hashemi et al., 2015)

Hampson, 1996; Sarkis et al., 1996; Noci, 1997; Walton et al., 1998), increasing number of scholars are addressing supplier selection, taking into account environmental aspects (Lee et al., 2009). Nevertheless, this research intends to propose a comprehensive model for green supplier selection that incorporates both economic and environmental criteria in the decision making process. Thus, a listing of environmental criteria available in the literature is shown in Table 2.

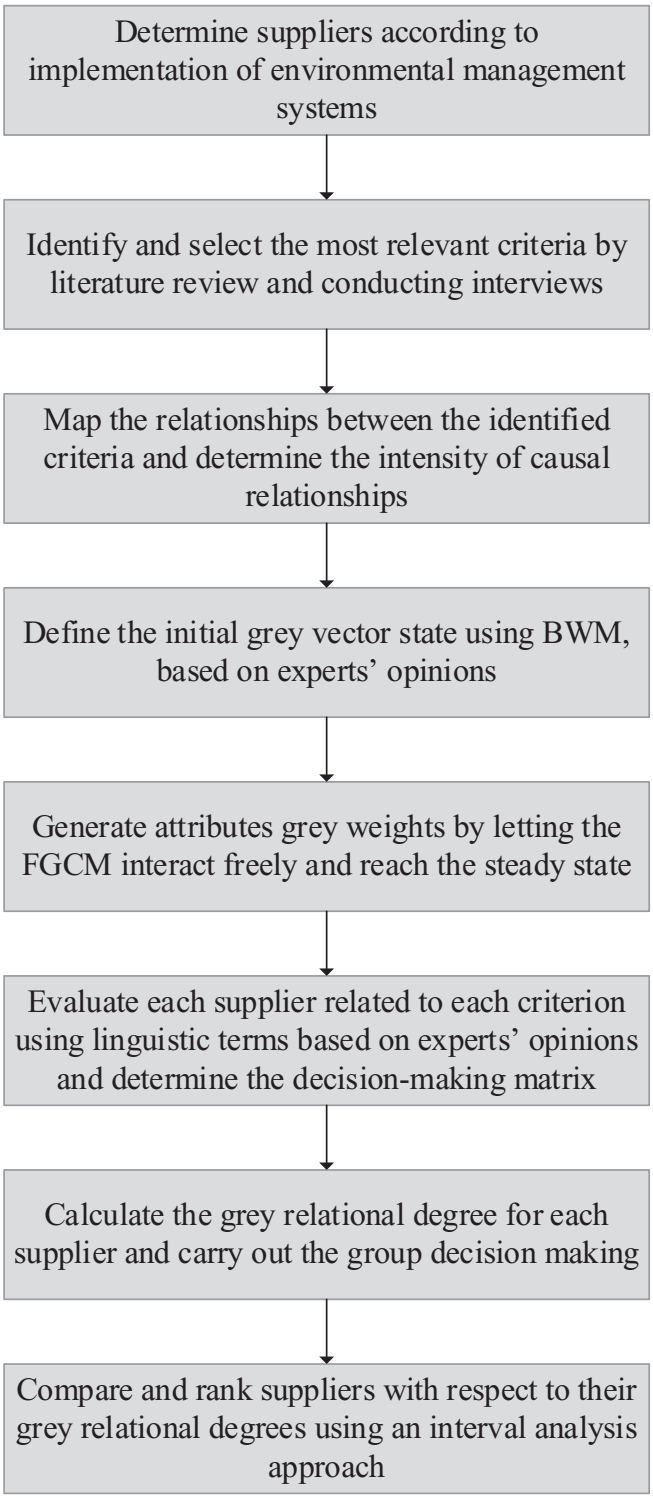

Fig. 1. The flowchart of the proposed green supplier selection method.

3. Methodology

In this study a novel integrated model for green supplier selection is proposed that uses BWM, FGCM and improved GRA. The integration procedure of the proposed method is illustrated in Fig. 1.

As it is illustrated in Fig. 1, first suppliers are screened based on the implementation of environmental management systems such as the ISO 14000 series. This step enables decision makers to ensure that all of the preselected suppliers have met the minimum requirements of environmental criteria. In the next step, the literature on the green supplier selection is reviewed and relevant criteria to evaluate and rank suppliers are collected. Afterwards, interviews with experts are conducted in order to select the most relevant criteria for green supplier selection. For this purpose, a structured questionnaire is employed that consisted of a list of criteria gathered from the literature, in which, experts were asked to mark the relevant criteria for the case company by inserting a check mark and the irrelevant ones by inserting an X mark. Subsequently, relevant criteria were selected for this study based on experts' consensus which means, those criteria are considered for further analysis that received unanimous approval of all experts.

In the next step, the FGCM is constructed based upon the experts' opinions (See Appendix C). Therefore, experts are asked to determine the causal relationship and their intensities between previously selected criteria using linguistic terms. In order to integrate different FGCMs developed by each expert, the augmented approach is used. After creating the augmented adjacency matrix, the developed FGCM requires an initial grey vector state to begin its inference process which its result is the final grey weight of each criterion. BWM is used to generate interval weights of criteria based on experts' opinions that are used as the initial grey vector state for the FGCM (See Appendix A). The grey values produced by the inference process of the FGCM, are used as criteria final weights in the next phase of the proposed model.

In the final step of the proposed model, experts were asked to evaluate each supplier with respect to each criterion using linguistic terms. Moreover, previously calculated criteria grey weights and experts' evaluations are used by IGRA technique to compute the grey relational degree of each supplier (See Appendix D). Subsequently, the grey relational degrees corresponding to each supplier are compared and ranked using an interval analysis approach (See Appendix E).

4. A real world case study

In the recent years, continuous hike of the automobile global market (Kushwaha and Sharma, 2016), along with an increased public awareness of environmental issues, is forcing companies to have a more active role in greening their supply chains and reducing the adverse environmental impacts of their products. In

Table 3
List of supplier selection criteria.

Name	Criteria
C1	Quality
C2	Price
C3	Delivery
C4	Innovativeness
C5	Technology capability
C6	Resource consumption
C7	Green Image
C8	Pollution production
C9	Pollution control
C10	Management commitment

Table 4

Base and vibration values of criteria interrelationships as expressed by each expert.

Edge	E1			E2			E3			E4			E5		
	Base value $\boldsymbol{w_{ij}}(\boldsymbol{b})$	Vibration value $\boldsymbol{\varepsilon_b}$	Grey weight $[\boldsymbol{b}-\boldsymbol{\varepsilon_b},\boldsymbol{b}+\boldsymbol{\varepsilon_b}]$	Base value $\boldsymbol{w_{ij}}(\boldsymbol{b})$	Vibration value $\boldsymbol{\varepsilon_b}$	Grey weight $[\boldsymbol{b}-\boldsymbol{\varepsilon_b},\boldsymbol{b}+\boldsymbol{\varepsilon_b}]$	Base value $\boldsymbol{w_{ij}}(\boldsymbol{b})$	Vibration value $\boldsymbol{\varepsilon_b}$	Grey weight $[\boldsymbol{b}-\boldsymbol{\varepsilon_b},\boldsymbol{b}+\boldsymbol{\varepsilon_b}]$	Base value $\boldsymbol{w_{ij}}(\boldsymbol{b})$	Vibration value $\boldsymbol{\varepsilon_b}$	Grey weight $[\boldsymbol{b}-\boldsymbol{\varepsilon_b},\boldsymbol{b}+\boldsymbol{\varepsilon_b}]$	Base value $\boldsymbol{w_{ij}}(\boldsymbol{b})$	Vibration value $\boldsymbol{\varepsilon_b}$	Grey weight $[\boldsymbol{b}-\boldsymbol{\varepsilon_b},\boldsymbol{b}+\boldsymbol{\varepsilon_b}]$
$\otimes\ w_{12}$	0.75	0.25	[0.5, 1]	0.75	0.083	[0.667, 0.833]	0.91	0.083	[0.827, 0.993]	0.75	0.083	[0.667, 0.833]	0.91	0.25	[0.66, 1]
$\otimes\ w_{32}$	0.5	0.083	[0.417, 0.583]	0	0	0	0.25	0.25	[0, 0.5]	0.25	0.5	[-0.25, 0.75]	0.25	0.083	[0.167, 0.333]
$\otimes\ w_{41}$	0.25	0.5	[-0.25, 0.75]	0.25	0.083	[0.167, 0.333]	0	0	0	0.5	0.25	[0.25, 0.75]	0.5	0.25	[0.25, 0.75]
$\otimes\ w_{43}$	0.25	0.25	[0, 0.5]	0	0	0	0	0	0	0	0	0	0	0	0
$\otimes\ w_{45}$	0.75	0.083	[0.667, 0.833]	0.5	0.25	[0.25, 0.75]	0.25	0.25	[0, 0.5]	0.5	0.25	[0.25, 0.75]	0	0	0
$\otimes\ w_{46}$	0.75	0.25	[0.5, 1]	0.5	0.083	[0.417, 0.583]	0.25	0.25	[0, 0.5]	0.75	0.25	[0.5, 1]	0.5	0.25	[0.25, 0.75]
$\otimes\ w_{47}$	0.75	0.083	[0.667, 0.833]	0.5	0.083	[0.417, 0.583]	0.25	0.083	[0.167, 0.333]	0.25	0.25	[0, 0.5]	0.5	0.25	[0.25, 0.75]
$\otimes\ w_{48}$	0.91	0.083	[0.827, 0.993]	0.75	0.083	[0.667, 0.833]	0.5	0.083	[0.417, 0.583]	0.25	0.083	[0.167, 0.333]	0.5	0.083	[0.417, 0.583]
$\otimes\ w_{49}$	0.91	0.083	[0.827, 0.993]	0.75	0.083	[0.667, 0.833]	0.75	0.083	[0.667, 0.833]	0.25	0.083	[0.167, 0.333]	0.5	0.083	[0.417, 0.583]
$\otimes\ w_{51}$	0.75	0.083	[0.667, 0.833]	0.91	0.083	[0.827, 0.993]	0.75	0.25	[0.5, 1]	0.5	0.25	[0.25, 0.75]	0.75	0.083	[0.667, 0.833]
$\otimes\ w_{52}$	0.25	0.083	[0.167, 0.333]	0.5	0.083	[0.417, 0.583]	0.25	0.083	[0.167, 0.333]	0.5	0.25	[0.25, 0.75]	0.25	0.25	[0, 0.5]
$\otimes\ w_{53}$	0.25	0.083	[0.167, 0.333]	0.25	0.083	[0.167, 0.333]	0	0	0	0.25	0.25	[0, 0.5]	0	0	0
$\otimes\ w_{56}$	0.75	0.083	[0.667, 0.833]	0.5	0.25	[0.25, 0.75]	0.75	0.083	[0.667, 0.833]	0.91	0.25	[0.66, 1]	0.91	0.083	[0.827, 0.993]
$\otimes\ w_{57}$	0.25	0.25	[0, 0.5]	0.25	0.083	[0.167, 0.333]	0.5	0.083	[0.417, 0.583]	0.75	0.25	[0.5, 1]	0.91	0.25	[0.66, 1]
$\otimes\ w_{58}$	−0.75	0.25	[-1, −0.5]	−0.75	0.25	[-1, −0.5]	−0.91	0.083	[-0.993, −0.827]	−0.91	0.083	[-0.993, −0.827]	−0.91	0.25	[-1, −0.66]
$\otimes\ w_{59}$	0.75	0.25	[0.5, 1]	0.75	0.083	[0.667, 0.833]	0.75	0.083	[0.667, 0.833]	0.75	0.083	[0.667, 0.833]	0.75	0.25	[0.5, 0]
$\otimes\ w_{62}$	0.25	0.5	[-0.25, 0.75]	0	0	0	0.25	0.25	[0, 0.5]	0.25	0.083	[0.167, 0.333]	0.5	0.25	[0.25, 0.75]
$\otimes\ w_{67}$	0.91	0.083	[0.827, 0.993]	0.91	0.083	[0.827, 0.993]	0.75	0.083	[0.667, 0.833]	0.91	0.083	[0.827, 0.993]	0.91	0.083	[0.827, 0.993]
$\otimes\ w_{68}$	0.75	0.083	[0.667, 0.833]	0.91	0.083	[0.827, 0.993]	0.91	0.083	[0.827, 0.993]	0.91	0.083	[0.827, 0.993]	0.91	0.083	[0.827, 0.993]
$\otimes\ w_{72}$	0.5	0.25	[0.25, 0.75]	0.25	0.083	[0.167, 0.333]	0	0	0	0	0	0	0.5	0.25	[0.25, 0.75]
$\otimes\ w_{87}$	−0.91	0.083	[-0.993, −0.827]	−0.91	0.083	[-0.993, −0.827]	−0.91	0.083	[-0.993, −0.827]	−0.91	0.083	[-0.993, −0.827]	−0.91	0.083	[-0.993, −0.827]
$\otimes\ w_{97}$	0.91	0.083	[0.827, 0.993]	0.91	0.083	[0.827, 0.993]	0.91	0.083	[0.827, 0.993]	0.91	0.083	[0.827, 0.993]	0.91	0.083	[0.827, 0.993]
$\otimes\ w_{10\ 1}$	0.91	0.083	[0.827, 0.993]	0.75	0.083	[0.667, 0.833]	0.75	0.25	[0.5, 1]	0.91	0.25	[0.66, 1]	0.91	0.083	[0.827, 0.993]
$\otimes\ w_{10\ 4}$	0.5	0.25	[0.25, 0.75]	0.75	0.083	[0.667, 0.833]	0.5	0.083	[0.417, 0.583]	0.25	0.083	[0.167, 0.333]	0.75	0.25	[0.5, 1]
$\otimes\ w_{10\ 7}$	0.75	0.083	[0.667, 0.833]	0.75	0.25	[0.5, 1]	0.91	0.25	[0.66, 1]	0.91	0.25	[0.66, 1]	0.91	0.083	[0.827, 0.993]
$\otimes\ w_{10\ 8}$	−0.5	0.25	[-0.75, −0.25]	−0.75	0.25	[-1, −0.5]	−0.75	0.25	[-1, −0.5]	−0.91	0.25	[-1, −0.66]	−0.91	0.083	[-0.993, −0.827]
$\otimes\ w_{10\ 9}$	0.5	0.25	[0.25, 0.75]	0.75	0.25	[0.5, 1]	0.91	0.25	[0.66, 1]	0.91	0.25	[0.66, 1]	0.91	0.083	[0.827, 0.993]

Table 5
Grey weights of the augmented fuzzy grey cognitive map.

Edge	Grey weight
$\otimes w_{12}$	[0.6642, 0.9318]
$\otimes w_{32}$	[0.0668, 0.4332]
$\otimes w_{41}$	[0.0834, 0.5166]
$\otimes w_{43}$	[0, 0.1]
$\otimes w_{45}$	[0.2334, 0.5666]
$\otimes w_{46}$	[0.3334, 0.7666]
$\otimes w_{47}$	[0.3002, 0.5998]
$\otimes w_{48}$	[0.499, 0.665]
$\otimes w_{49}$	[0.549, 0.715]
$\otimes w_{51}$	[0.5822, 0.8818]
$\otimes w_{52}$	[0.2002, 0.4998]
$\otimes w_{53}$	[0.0668, 0.2332]
$\otimes w_{56}$	[0.6142, 0.8818]
$\otimes w_{57}$	[0.3488, 0.6832]
$\otimes w_{58}$	[-0.9972, −0.6628]
$\otimes w_{59}$	[0.6002, 0.8998]
$\otimes w_{62}$	[0.0334, 0.4666]
$\otimes w_{67}$	[0.795, 0.961]
$\otimes w_{68}$	[0.795, 0.961]
$\otimes w_{72}$	[0.1334, 0.3666]
$\otimes w_{87}$	[-0.993, −0.827]
$\otimes w_{97}$	[0.827, 0.993]
$\otimes w_{10\,1}$	[0.6962, 0.9638]
$\otimes w_{10\,4}$	[0.4002, 0.6998]
$\otimes w_{10\,7}$	[0.6628, 0.9652]
$\otimes w_{10\,8}$	[-0.9486, −0.5474]
$\otimes w_{10\,9}$	[0.5794, 0.9486]

2016, Iran's motor vehicle production ranked 18th globally by producing 1,164,710 vehicles, and had the highest increase rate of 18.6 percent among all countries (OICA, 2016). This increase could be partially attributed to the Iran's nuclear agreement with P5+1 and European Union in 2015, by which some of international economic sanctions are expected to be lifted that will enable Iranian companies to collaborate with prominent foreign corporations to manufacture and export their products. Consequently, many Iranian manufacturing companies are encouraged to prepare themselves for this collaboration by adopting initiatives such as GSCM.

A renowned automobile part manufacturing group was employed in this study to demonstrate the applicability and efficacy of the proposed model, which due to our confidentiality agreement with the company it remains anonymous throughout this research. This manufacturing group provides major motor vehicle manufacturing companies in Iran (e.g. Iran Khodro and Saipa) with a wide range of parts. All members of this manufacturing group have implemented ISO 14000 principles and also cooperate with their suppliers to enhance their environmental performance. This manufacturing group demands various Aluminum materials which are provided by their own suppliers.

For the purpose of this paper, a panel of 5 experts has been formed in order to evaluate and rank 5 suppliers of Aluminum materials. These experts were selected from 5 different departments of the company including, quality assurance, health, safety and environment, research and development (R&D), logistics

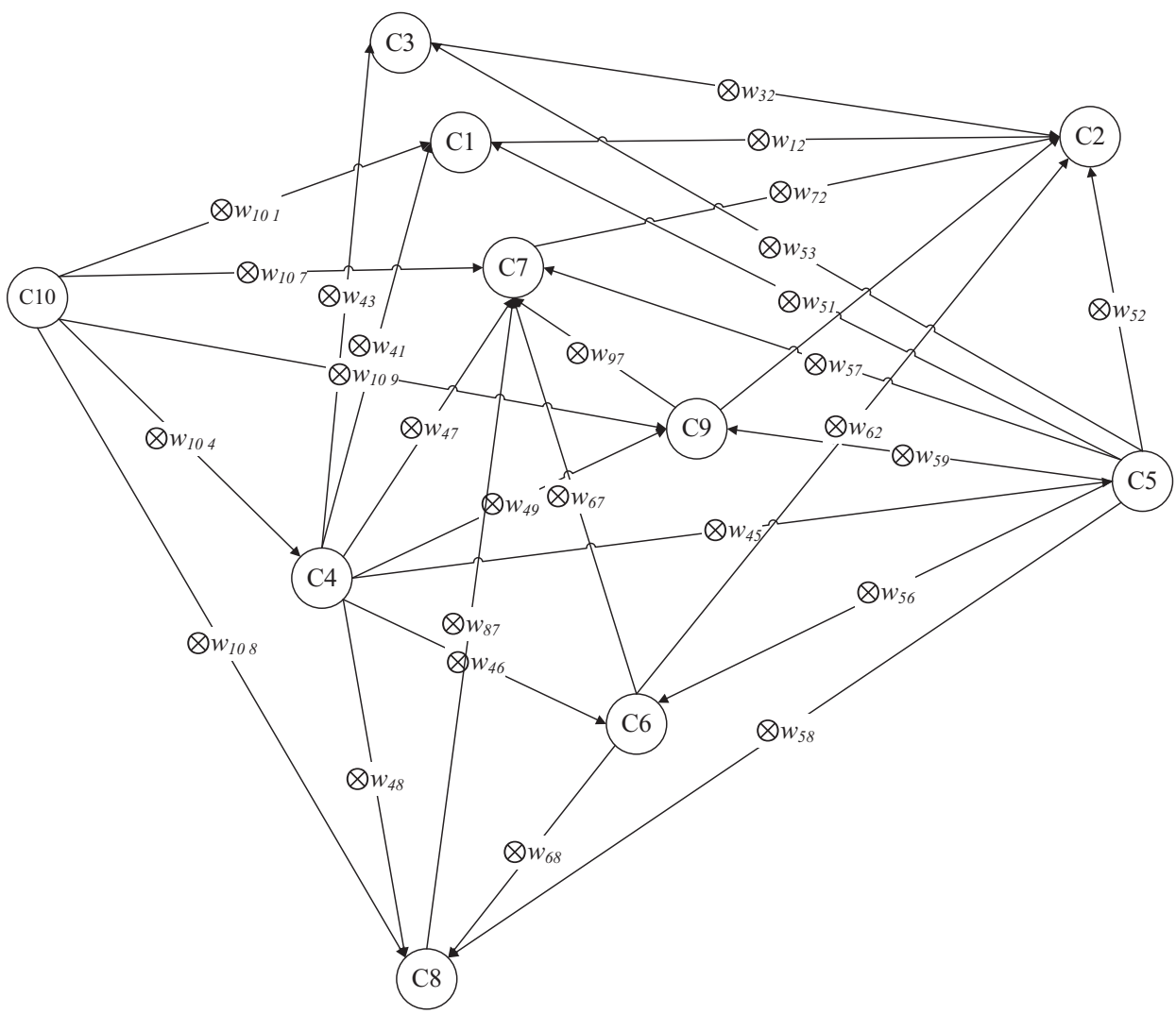

Fig. 2. Graphical representation of the augmented fuzzy grey cognitive map.

Table 6
Best criterion over other criteria preference.

Best criterion	Expert	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	E1	1	4	5	5	4	8	5	4	3	9
	E2	1	3	5	3	3	5	5	4	4	9
	E3	1	4	7	3	3	7	4	3	3	9
	E4	1	5	6	4	4	3	4	4	4	9
	E5	1	3	4	3	3	7	6	4	4	9

Table 7
Other criteria over best criterion preferences.

Worst criterion	C10				
Expert	E1	E2	E3	E4	E5
C1	9	9	9	9	9
C2	3	9	4	4	8
C3	5	5	3	4	6
C4	5	7	7	3	7
C5	6	8	9	4	9
C6	3	4	3	7	3
C7	3	5	4	5	4
C8	6	6	6	5	5
C9	7	6	8	6	4
C10	1	1	1	1	1

Table 9
Consistency ratio of criteria weights calculated based on each expert's opinion.

Expert	ξ^*	Consistency index	Consistency ratio
E1	1.7251	5.23	0.3298
E2	1.7251	5.23	0.3298
E3	1.5756	5.23	0.3012
E4	1.5949	5.23	0.3049
E5	1.5949	5.23	0.3049

Table 10
Steady state values of each node(criterion) after the inference process of the fuzzy grey cognitive map.

Node C_i	Steady state $\left[\underline{C}_i, \overline{C}_i\right]$	Length $l(\otimes C_i)$	Greyness $\phi(\otimes C_i)$
C1	[0.8566, 0.9339]	0.0773	0.038658
C2	[0.8529, 0.9649]	0.111954	0.055977
C3	[0.6725, 0.7281]	0.055602	0.027801
C4	[0.7297, 0.7748]	0.045095	0.022548
C5	[0.7060, 0.7701]	0.064081	0.03204
C6	[0.8166, 0.8975]	0.080973	0.040487
C7	[0.9182, 0.9813]	0.06306	0.03153
C8	[0.5399, 0.7928]	0.252853	0.126426
C9	[0.8906, 0.9435]	0.052919	0.026459
C10	[0.6590, 0.6590]	1.7E-09	8.51E-10

and procurement. These experts are named E1 to E5 respectively. Each of these experts has at least 10 years of work experience in their respective field of expertise and they are selected based on suggestions from the supervisor of each relevant department.

Please recall that in the last step of the IGRA method (See Appendix D), it is required to assign relative weights to each expert opinion. Therefore, experts' opinions considered to be equally important, hence, giving all of them the relative weight of 0.2. However, in Section 6 a sensitivity analysis of the relative weights for each expert is conducted to find how the final results of evaluation would vary with respect to changes in the experts' relative weights.

As it is stated before, experts are interviewed for the purpose of determining the most relevant criteria for green supplier evaluation. A list of these criteria is provided in Table 3.

By following the construction steps of the FGCMs (See Appendix C), the base and vibration values of causal relationships as expressed by each expert are obtained and are represented in Table 4. Afterwards, by using the augmented approach all FGCMs developed by each expert are integrated in to a single FGCM. The final causal grey weights of the augmented FGCM is shown in Table 5, and its graphical representation is presented in Fig. 2.

BWM is used to define the initial grey vector state based on experts' opinions by calculating interval weights of criteria (See Appendix A). To this end, first the best and worst criteria are identified. The panel of experts identified quality and management commitment as the best and worst criteria respectively. Subsequently, the Best-to-Others and Others-to-Worst vectors determined by each expert are shown in Tables 6 and 7 respectively.

In order to obtain the initial grey vector state, all lower and upper bounds of weights calculated for each expert are integrated in to a single vector, by taking their average as shown in Table 8.

In order to verify the consistency of reference pairwise comparisons conducted by experts, a consistency ratio is calculated and shown in Table 9 for each expert, along with the maximum values of ξ as provided in Appendix A. According to Rezaei (2015), the values of consistency ratio close to zero indicates better consistency and conversely values close to 1 indicates lower consistency. Regarding the consistency ratios presented in Table 9 it can be presumed that pairwise comparisons have an acceptable level of consistency.

After developing the FGCM and determining the initial grey vector state using BWM, final grey weights of the criteria are computed using the inference process of the FGCM. The steady states resulted from the inference process of the FGCM along with the length of each node and the greyness associated with each node are detailed at Table 10. The interval weights (i.e. steady state values) generated in this phase will then be used as criteria weights to evaluate suppliers using IGRA.

Table 8
Interval(grey) weights of criteria obtained from best-worst method.

Criterion	Criteria weights for each expert					Mean weight
	E1	E2	E3	E4	E5	
C1	[0.2341, 0.2883]	[0.2171, 0.2238]	[0.1962, 0.2461]	[0.2270, 0.2839]	[0.1919, 0.2363]	[0.2133,0.2557]
C2	[0.0422, 0.1188]	[0.1321, 0.1715]	[0.0467, 0.0971]	[0.0523, 0.0818]	[0.1425, 0.1640]	[0.0832, 0.1266]
C3	[0.0715, 0.0850]	[0.0543, 0.0683]	[0.0267, 0.0448]	[0.0515, 0.0644]	[0.0850, 0.0983]	[0.0578, 0.0722]
C4	[0.0636, 0.0889]	[0.0949, 0.1648]	[0.0892, 0.1651]	[0.0292, 0.0758]	[0.1088, 0.1605]	[0.0771, 0.1310]
C5	[0.0942, 0.1837]	[0.1160, 0.1680]	[0.1331, 0.1701]	[0.0538, 0.1120]	[0.1433, 0.1677]	[0.1081, 0.1603]
C6	[0.0278, 0.0346]	[0.0410, 0.0669]	[0.0261, 0.0332]	[0.1319, 0.1448]	[0.0274, 0.0313]	[0.0508, 0.0622]
C7	[0.0361, 0.0418]	[0.0546, 0.0683]	[0.0467, 0.0971]	[0.0745, 0.1096]	[0.0471, 0.0536]	[0.0518, 0.0741]
C8	[0.0913, 0.1265]	[0.0766, 0.0975]	[0.1005, 0.1615]	[0.0745, 0.1149]	[0.0674, 0.0960]	[0.0821, 0.1193]
C9	[0.1236, 0.2104]	[0.0766, 0.0975]	[0.1215, 0.1689]	[0.1180, 0.1180]	[0.0483, 0.0540]	[0.0976, 0.1298]
C10	[0.0201, 0.0281]	[0.0198, 0.0209]	[0.0186, 0.0233]	[0.0214, 0.0268]	[0.0195, 0.0223]	[0.0199, 0.0243]

Table 11
Linguistic terms and their equivalent grey numbers.

Linguistic variable	Scale of grey number ($\otimes$ $\boldsymbol{G}$)
Very poor (VP)	[1.5,3.0]
Poor (P)	[3.0,4.5]
Medium (M)	[4.5,6.0]
Good (G)	[6.0,7.5]
Very good (VG)	[7.5,9.0]

As it is stated previously, a panel of experts is formed to assess the performance of 5 suppliers. To this end, the experts are asked to evaluate each supplier with respect to each criterion using linguistic terms such as, "very good", "good", "medium", "poor", and "very poor" as shown in Table 11. Consequently, experts formed the decision-making matrix based on their experience which is detailed in Table 12.

After the decision-making matrix is constructed by experts, the value of grey relational degree for each supplier is computed using interval weights of criteria and the group decision-making is carried out and the results are represented in Table 13.

Table 12
Expert's evaluation of suppliers using linguistic terms.

Criterion	Expert	Supplier1	Supplier2	Supplier3	Supplier4	Supplier5
C1	E1	G	VG	M	G	M
	E2	M	G	P	VG	VP
	E3	G	G	M	G	M
	E4	G	M	P	M	P
	E5	P	G	G	VG	M
C2	E1	M	M	M	M	M
	E2	P	P	P	G	M
	E3	G	M	M	M	G
	E4	M	G	G	P	P
	E5	M	P	P	G	G
C3	E1	G	G	M	G	G
	E2	M	G	P	M	M
	E3	M	M	G	G	M
	E4	P	M	M	P	P
	E5	G	G	M	M	P
C4	E1	M	VG	VP	M	M
	E2	M	G	P	G	P
	E3	G	G	M	G	G
	E4	G	M	P	M	M
	E5	P	VG	M	G	P
C5	E1	G	G	P	M	M
	E2	P	VG	M	G	VP
	E3	G	G	M	VG	M
	E4	VG	M	P	M	M
	E5	M	VG	G	G	P
C6	E1	M	P	M	M	M
	E2	P	M	G	P	M
	E3	M	G	G	M	VG
	E4	G	M	M	M	G
	E5	M	M	VG	P	M
C7	E1	M	M	G	M	G
	E2	M	P	VG	M	M
	E3	G	G	M	P	G
	E4	G	P	G	G	VG
	E5	P	P	G	P	M
C8	E1	P	P	G	P	G
	E2	M	M	G	VP	M
	E3	M	M	M	M	G
	E4	G	P	G	G	M
	E5	M	M	VG	M	G
C9	E1	P	P	VG	P	VG
	E2	M	M	G	P	M
	E3	M	M	M	M	G
	E4	G	M	G	G	M
	E5	M	P	G	M	G
C10	E1	M	G	G	M	G
	E2	P	M	M	P	M
	E3	G	G	M	M	VG
	E4	G	P	G	M	M
	E5	P	M	VG	G	M

In order to compare and rank the grey relational degrees of suppliers using an interval analysis approach (See Appendix E), first the matrix of degree of preference is calculated as shown in Table 14. Second, the matrix of preferences is determined and presented in Table 15. Subsequently, the sum of each row is calculated and suppliers are ranked according to the rule that the greater the value of the sum of each row, the better preferred the corresponding supplier.

The final results of the proposed model are presented in Table 15. According to the comparison of the integrated grey relational degrees (γ_i) using an interval analysis approach, the ranking sequence of the suppliers with respect to economic and environmental criteria is as follows:

Supplier 3 $\succ$ Supplier 5 $\succ$ Supplier 2 $\succ$ Supplier 1 $\succ$ Supplier 4

Accordingly, supplier 3 is identified as the best supplier regarding its economic and environmental performance based on the experts' opinions.

5. Managerial and practical implications

Supplier selection is emphasized to be one of the most crucial decisions that supply chain managers must make. Increasing global awareness of environmental protection from one side, and the outsourcing strategy followed by the majority of companies from another side, have been compelling companies to green their supply chains in order to maintain their strategic competitiveness. Consequently, addressing green supplier selection problems efficaciously is highly important. This study proposes a novel grey-based green supplier selection model that incorporates the criteria interdependencies, as well as, uncertainties associated with experts' judgments. Accordingly, this study highlights numerous beneficial managerial and practical implications as follows:

- **Providing a thorough representation of experts' opinions regarding green supplier evaluation criteria interdependencies.** In this study FGCMs are employed to elicit the experts' perception of internal dependencies of evaluation criteria which provides supply chain managers with invaluable insights. By taking a closer look at Fig. 2. It is evident that technology capability (C5) and management commitment (C10) are significantly influencing other criteria, which is supported by the existing literature. Innovativeness (C4) criterion affects almost all other criteria, either directly or indirectly, which is a scarcely investigated phenomenon. To this end, managers are enabled to improve their supply chains' environmental performance by focusing on this criterion. Additionally, each company in the industry can easily elicit the perception of their decision-makers using the proposed model and improve their decision-making processes by eliminating incorrect relationships or adding necessary ones.
- **Providing a framework for a comprehensive evaluation of suppliers.** The proposed model in the current study provides a systematic approach for supply chain managers to evaluate suppliers with regards to both economically and environmentally significant criteria. The proposed model, benefits from BWM which substantially reduces the number of pairwise comparisons relative to similar methods. Further, it provides more consistent weights for the criteria. Therefore, the managers can make more timely and consistent decisions. Another benefit of this study is that the proposed model is applicable for various companies active in Iran's automotive industry without

Table 13
Grey relational degrees of each supplier for each expert and integrated grey relational degrees for each supplier.

Supplier	$\otimes\ \gamma_i^k$					$[\underline{\gamma}_i, \overline{\gamma}_i]$
	E1	E2	E3	E4	E5	
Supplier 1	[1.6604, 4.6900]	[1.4029, 2.7810]	[1.2895, 5.1452]	[1.0986, 4.1797]	[1.2457, 2.8665]	[1.3267, 3.8112]
Supplier 2	[1.7786, 4.9391]	[1.6755, 4.2346]	[1.2677, 4.6088]	[0.8578, 2.6965]	[1.4251, 3.6427]	[1.3580, 3.9378]
Supplier 3	[1.7501, 5.2703]	[1.6643, 4.4339]	[1.1181, 3.1307]	[0.9639, 3.6613]	[1.6631, 5.2251]	[1.3917, 4.2579]
Supplier 4	[1.6137, 4.4057]	[1.6072, 3.7636]	[1.2157, 4.4448]	[0.9002, 2.6080]	[1.4713, 3.8986]	[1.3309, 3.7578]
Supplier 5	[1.8583, 5.7195]	[1.4296, 3.1894]	[1.4092, 6.3439]	[0.8915, 2.4513]	[1.3715, 3.7732]	[1.3556, 4.0356]

Table 14
The matrix of degree of preferences.

	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5
Supplier 1	0.5	0.4844	0.4521	0.5050	0.4754
Supplier 2	0.5155	0.5	0.4675	0.5206	0.4909
Supplier 3	0.5478	0.5324	0.5	0.5529	0.5232
Supplier 4	0.4949	0.4793	0.4470	0.5	0.4703
Supplier 5	0.5245	0.5090	0.4767	0.5296	0.5

major modifications. This is because the case study of this paper provides major automobile manufacturing companies in Iran with a wide range of parts, and the evaluation criteria are gathered by extensive literature review and by experts' consensus.

In the recent years, Iran's industry has been developing rapidly (Industrial Development Report, 2016), which could be attributed to the prioritization of economic growth by the government. On the other hand, as a direct result of the Iran's nuclear deal, more internationalization of domestic industries is highly expected which leads to an inevitable competition between Iranian manufacturing firms with their foreign competitors. Therefore, given the global awareness of environmental protection, Iranian manufacturing companies (and of similar developing countries) must improve their environmental performances in order to remain competitive on an international level. It has been emphasized that the green initiatives must be considered on a supply chain basis rather than on a company basis (Andiç et al., 2012). Accordingly, green initiative such as green supplier selection is considered to be one of the main drivers of green supply chain management performance (Roehrich et al., 2017). Consequently, manufacturing firms in the developing countries need to implement comprehensive green supplier selection models (such as the one proposed in this paper), in order to reduce their negative environmental impacts while enhancing their economic performance.

6. Discussion

The proposed method in this study, improves the model proposed by Hashemi et al. (2015) from three main aspects. First, this study integrates BWM and FGCM to obtain each criterion weight by considering the interdependencies between them, while Hashemi et al. (2015) used ANP for the same purpose. ANP method requires significantly more pairwise comparisons by its nature, which in cases with numerous criteria and suppliers, the decision making process becomes extremely less time efficient, and inconsistent results becomes more probable. However, BWM significantly reduces the number of pairwise comparisons by eliminating secondary comparisons that makes BWM-FGCM integration more efficacious compared to ANP. Second, by advancing the IGRA method to incorporate grey weights of criteria, decision makers are enabled to make more realistic decisions, since real world cases are always associated with incomplete information and vague judgements of the experts. Moreover, despite the abundance of studies proposing new supplier selection models, there is a limited number of comprehensive models that are capable of capturing, processing and integrating uncertainty in all phases of a MCDM problem—from criteria weight identification to ranking the alternatives (Kannan et al., 2013, 2015; Büyüközkan and Çifçi, 2012). Third, in the last step of the proposed model an interval analysis approach is used to rank suppliers rather than going through the whitenization process. It is emphasized that if the distribution of a grey number is not known, whiteniztion can lead to the loss of partial known information (Liu and Zeng, 2011; Lin et al., 2004), which in turn can potentially create unreasonable rankings. Therefore, the proposed model in this study addresses uncertainty in all stages of the

Table 16
Supplier ranking results for different scenarios.

Scenario	Expert(s)	Supplier ranking
Initial condition	E1(0.2), E2(0.2), E3(0.2), E4(0.2), E5(0.2)	3 > 5>2 > 1>4
Scenario 1	E1	5 > 3>2 > 1>4
Scenario 2	E2	3 > 2>4 > 5>1
Scenario 3	E3	5 > 1>2 > 4>3
Scenario 4	E4	1 > 3>2 > 4>5
Scenario 5	E5	3 > 4>5 > 2>1
Scenario 6	E1(0.5), E2(0.125), E3(0.125), E4(0.125), E5(0.125)	3 > 5>2 > 1>4
Scenario 7	E1(0.125), E2(0.5), E3(0.125), E4(0.125), E5(0.125)	3 > 2>4 > 5>1
Scenario 8	E1(0.125), E2(0.125), E3(0.125), E4(0.125), E5(0.5)	3 > 5>2 > 4>1
Scenario 9	E1(0.125), E2(0.125), E3(0.125), E4(0.5), E5(0.125)	3 > 1>2 > 5>4
Scenario 10	E1(0.125), E2(0.125), E3(0.5), E4(0.125), E5(0.125)	5 > 1>2 > 4>3

Table 15
The matrix of preferences and suppliers ranking.

	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5	Sum	Rank
Supplier 1	0	0	0	1	0	1	4
Supplier 2	1	0	0	1	0	2	3
Supplier 3	1	1	0	1	1	4	1
Supplier 4	0	0	0	0	0	0	5
Supplier 5	1	1	0	1	0	3	2

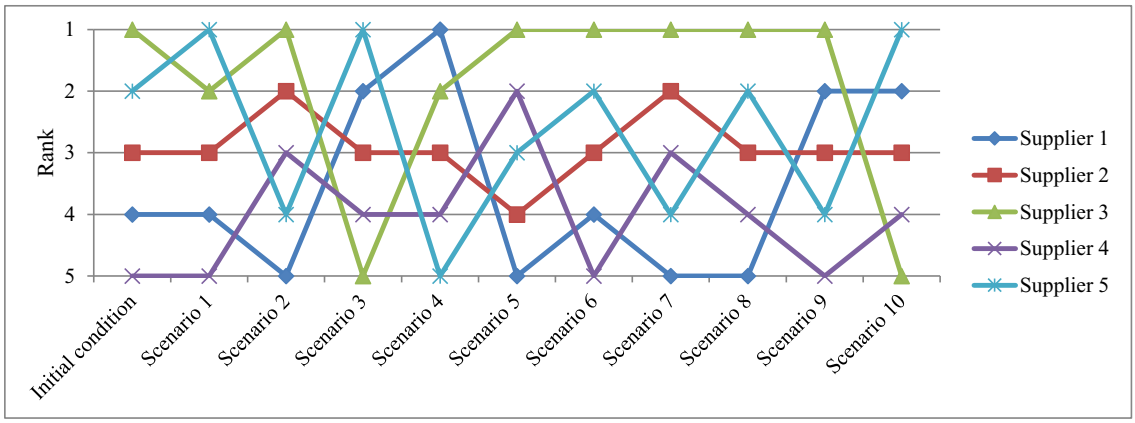

Fig. 3. Sensitivity analysis of the suppliers ranking.

decision making process.

As elaborated in Section 2, other similar methodologies tried to address the interdependencies amongst criteria. However, these methods also have a few shortcomings. Both of the methods proposed by Yu and Tzeng (2006) and Xiao et al. (2012) are based on the eigenvalue approach to calculate the local weight vector of the criteria from pairwise comparison matrices. Consequently, as the number of criteria and alternatives increase, the inconsistency of pairwise comparisons increases and conducting pairwise comparisons becomes more onerous. Moreover, the MCDM model developed by Baykasoğlu and Gölcük (2015) combines hierarchical TOPSIS and FCM, that only handles MCDM problems with hierarchical interdependencies and neglects problems with network structures. Accordingly, the proposed model addresses the previously mentioned limitations by integrating BWM and FGCM, where decision makers are enabled to solve problems with many criteria and alternatives more conveniently, as they have to conduct a limited number of pairwise comparisons required by BWM. Also they are able to handle problems with network structure using the proposed method in this study.

In order to evaluate the robustness of the model with respect to changes in relative weights of experts' opinions, a sensitivity analysis of relative weights of experts' opinions is carried out. For that reason, various scenarios are developed (see Table 16). Firstly, the final results of each expert are calculated individually in Scenario 1 through Scenario 5. Secondly, in Scenario 6 through Scenario 10 one of the experts' opinions is given superiority to others by assigning the relative weight of 0.5 to it. Table 16 represents the results of the sensitivity analysis and Fig. 3 is a graphical representation of these results.

As it is evident from the ranking results for different scenarios it can be concluded that the sequence of suppliers is to some extent dependent on the experts' opinions and their relative weights. However, in 7 scenarios out of 11, supplier 3 was ranked the best supplier among all. Therefore, it is reasonable to assume that the proposed method is robust to changes in the experts' opinions relative weights, and the company must select supplier 3, as its economic and environmental performance is superior to others in most of the possible decision-making scenarios.

7. Conclusion

Globally increased environmental awareness of both public and private sectors in recent decades compelled organizations (specifically manufacturing organizations) to incorporate environmentally friendly processes and products to maintain their strategic competitiveness. Among these green initiatives GSCM has gained prominence among both scholars and practitioners to improve environmental performance of manufacturing organizations. Green supplier selection is known to be a critical function of GSCM. It comprises of selecting the best supplier with reference to environmental and economic criteria. For that purpose, an integrated grey based green supplier selection model was proposed in this paper that incorporates both economic and environmental criteria. The proposed model is particularly developed to address inherent uncertainties of this multiple criterion decision-making problem along with the interdependencies between the evaluation criteria in a more efficient and effective manner compared to the models available in the literature.

While the proposed model provides valuable contributions, this study contains some limitations. One limitation is that the final results of the case study rely heavily on the experts' opinions. In order to decrease the variations in final results the number of experts can be increased. Moreover, since proposing a comprehensive model was the main objective of this study, an augmented approach is employed to integrate various mental models (FGCMs) generated by the experts. However, this can potentially lead to conflicts in the decision-making process, as there may exist some causal relations amongst criteria that are considered to be significant by one expert and insignificant by the rest of the experts. The Delphi methodology can be used in order to build consensus among the decision-makers and develop a single FGCM when the disparities of their mental models are consequential.

As it was claimed before, the integrated model solves the problem of criteria interdependencies consideration. Therefore, the proposed model is well capable of solving other evaluation and ranking problems that involve criteria internal dependencies in any given context. Moreover, the core decision-making method in this paper is IGRA that in future studies could be substituted by other methods such as VIKOR and TOPSIS. Additionally, the proposed method can be used to employ social criteria along with economic and environmental criteria in order to evaluate and rank sustainable suppliers.

Appendix

A) Best-worst method

The five steps proposed by Rezaei (2015) to apply best-worst method are as follows:

Step 1. A set of decision criteria is determined as $\{C_1, C_2, C_3 \ldots, C_n\}$.
Step 2. The best and the worst criteria are determined by an expert or decision-maker or a panel of experts.
Step 3. The preference of the best criterion over all the other criteria is determined using a number from 1 to 9 which will result in the Best-to-Others vector as:

$$A_B = (a_{B1}, a_{B2}, a_{B3}, \ldots, a_{Bn}),$$

Where a_{Bj} indicates the preference of the best criterion B over criterion j.

Step 4. The preferences of all the other criteria over the worst criterion are determined by a number from 1 to 9 which will result in the Others-to-Worst vector as:

$$A_W = (a_{1W}, a_{2W}, a_{3W}, \ldots, a_{nW})^T,$$

where a_{jW} indicates the preference of the criterion j over the worst criterion W and it is clear that.

Step 5. Find the optimal weights $(\omega_1^*, \omega_2^*, \ldots, \omega_n^*)$.

If $a_{ik} \times a_{kj} = a_{ij}, \forall i, j$, the pairwise comparison vectors will be perfectly consistent. According to the consistency condition mentioned, the optimal weights for each criterion is the one where for each pair of ω_B/ω_j and ω_j/ω_W, the value of $\omega_B/\omega_j = a_{Bj}$ and $\omega_j/\omega_W = a_{jW}$. This implies that it is required to find a solution so that the maximum absolute differences $\left|\frac{\omega_B}{\omega_j} - a_{Bj}\right|$ and $\left|\frac{\omega_j}{\omega_W} - a_{jW}\right|$ for all j are minimized. Having the non-negativity and sum condition of the weights, by solving the following problem the optimal weights are obtained:

$$min\ max_j \left\{ \left|\frac{\omega_B}{\omega_j} - a_{Bj}\right|, \left|\frac{\omega_j}{\omega_W} - a_{jW}\right| \right\}$$

$$s.t.$$

$$\sum_j \omega_j = 1$$

$$\omega_j \geq 0, \text{for all j} \tag{1}$$

This problem can be transformed as follows and used to obtain optimal weights and ξ^*:

$$\min \xi$$

$$s.t.$$

$$\left|\frac{\omega_B}{\omega_j} - a_{Bj}\right| \leq \xi, for\ all\ j$$

$$\left|\frac{\omega_j}{\omega_W} - a_{jW}\right| \leq \xi, \text{for all j}$$

$$\sum_j \omega_j = 1$$

$$\omega_j \geq 0, \text{For all j} \tag{2}$$

Rezaei (2016) mentions that for not fully-consistent comparison systems ($\xi^* \neq 0$) with more than three criteria it is likely to have multiple optimal solutions. This feature of BWM enables us to obtain optimal weights of criteria as intervals which provide more information about the optimal solution. In order to calculate upper and lower bounds of criterion j, Rezaei (2016) proposes the following two models which should be solved after solving model (2) and finding ξ^*.

$$\min \omega_j$$

$$s.t.$$

$$\left|\frac{\omega_B}{\omega_j} - a_{Bj}\right| \leq \xi^*, \text{for all j}$$

$$\left|\frac{\omega_j}{\omega_W} - a_{jW}\right| \leq \xi^*, \text{for all j}$$

$$\sum_j \omega_j = 1$$

$$\omega_j \geq 0, \text{for all j} \tag{3}$$

$$\max \omega_j$$

$$s.t.$$

$$\left|\frac{\omega_B}{\omega_j} - a_{Bj}\right| \leq \xi^*, \text{for all j}$$

$$\left|\frac{\omega_j}{\omega_W} - a_{jW}\right| \leq \xi^*, \text{for all j}$$

$$\sum_j \omega_j = 1$$

$$\omega_j \geq 0, for\ all\ j \tag{4}$$

By solving models (3) and (4), the lower and upper bounds of criteria interval weights are determined respectively. The center of intervals can be used as final weights to rank criteria or alternatives (Rezaei, 2016), nevertheless, for the purpose of this paper it is decided to use the interval values. By using interval weights instead of their crisp values, this study aims to address uncertainty in all phases of the decision-making process.

According to Rezaei (2015) a consistency ratio should be computed for pairwise comparisons. This ratio is computed using the following formulation:

$$Consistency\ Ratio = \frac{\xi^*}{Consistency\ Index} \tag{5}$$

where ξ^* is obtained by solving model (2) and for the "consistency index" he proposes a set of fixed values indicating the corresponding index for each possible value of a_{BW} which is the preference of best criterion over worst criterion (i.e. a number between 1 and 9). This index is considered to be the maximum value of ξ for each a_{BW} (see Table 1).

Table 1
Consistency index.

a_{BW}	1	2	3	4	5	6	7	8	9
Consistency index (max ξ)	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

(source: Rezaei, 2015)

B) Grey numbers operations

Grey systems theory identifies three types of numbers including: black, white and grey numbers. A number such as $\otimes G$ where $\otimes G \in (-\infty, +\infty)$, is known as a black number that has neither upper nor lower bound. When $\otimes G \in [\underline{a}, \overline{a}]$ and $\underline{a} = \overline{a}$, $\otimes G$ is a white number that its exact value is known. However, a grey number is represented as an interval whose precise value is unknown but the range within which it resides is known (Liu and Lin, 2006). A grey number is denoted as $\otimes G \in \left[\underline{G}, \overline{G}\right]$, where $\underline{G}$ is the lower limit and $\overline{G}$ is the upper limit and both of them are fixed numbers. Additionally, the length of a grey number is defined as $l(\otimes G) = |\underline{G} - \overline{G}|$. In that sense if the length of a grey number equals zero ($l(\otimes G) = 0$), it is a white number. However, if $l(\otimes G) = \infty$ the grey number is not necessarily a black one, since the length of a grey number with only one limit (lower or upper limit) is also infinite, $\otimes G \in [-\infty, \overline{G}]$ or $\otimes G \in [\underline{G}, +\infty]$, but it is not a black number.

If there are two grey numbers $\otimes G_1 \in \left[\underline{G}_1, \overline{G}_1\right]$ and $\otimes G_2 \in \left[\underline{G}_2, \overline{G}_2\right]$ and the white number b, then the following basic operations are defined (all parameters including $\underline{G}_1, \overline{G}_1, \underline{G}_2, \overline{G}_2$ and b are greater than zero):

$$\otimes G_1 + \otimes G_2 \in \left[\underline{G}_1 + \underline{G}_2, \overline{G}_1 + \overline{G}_2\right] \tag{6}$$

$$\otimes G_1 - \otimes G_2 \in \left[\underline{G}_1 - \overline{G}_2, \overline{G}_1 - \underline{G}_2\right] \tag{7}$$

$$\otimes G_1 \times \otimes G_2 \in \left[\min\left(\underline{G}_1 \cdot \underline{G}_2, \underline{G}_1 \cdot \overline{G}_2, \overline{G}_1 \cdot \underline{G}_2, \overline{G}_1 \cdot \overline{G}_2\right), \max\left(\underline{G}_1 \cdot \underline{G}_2, \underline{G}_1 \cdot \overline{G}_2, \overline{G}_1 \cdot \underline{G}_2, \overline{G}_1 \cdot \overline{G}_2\right)\right] \tag{8}$$

$$\otimes G_1 \div \otimes G_2 \in \left[\min\left(\underline{G}_1 \cdot \frac{1}{\overline{G}_2}, \underline{G}_1 \cdot \frac{1}{\underline{G}_2}, \overline{G}_1 \cdot \frac{1}{\overline{G}_2}, \overline{G}_1 \cdot \frac{1}{\underline{G}_2}\right), \max\left(\underline{G}_1 \cdot \frac{1}{\overline{G}_2}, \underline{G}_1 \cdot \frac{1}{\underline{G}_2}, \overline{G}_1 \cdot \frac{1}{\overline{G}_2}, \overline{G}_1 \cdot \frac{1}{\underline{G}_2}\right)\right] \tag{9}$$

$$\frac{\otimes G_1}{b} \in \left[\frac{\underline{G}_1}{b}, \frac{\overline{G}_1}{b}\right] \tag{10}$$

$$b \times \otimes G_1 \in \left[b\underline{G}_1, b\overline{G}_1\right] \tag{11}$$

A detailed description of grey numbers operations and FGCMs can be found in (Salmeron, 2010).

C) FGCMs fundamentals and construction method

FGCMs are dynamic systems involving feedbacks that allow an effect of change in one node, propagate through the whole system and affect the initiating node. In FGCMs, directed edges linking nodes model the influence of causal grey concept on the effect grey concept, and the intensity of each edge is measured by its grey intensity as follows:

$$w_{ij} \in \left[\underline{w}_{ij}, \overline{w}_{ij}\right] \left| \underline{w}_{ij} \le \overline{w}_{ij}, \left\{\underline{w}_{ij}, \overline{w}_{ij}\right\} \in [-1, 1]\right. \tag{12}$$

where i is the cause node and j is the effect one. Fig. 1 illustrates an example of FGCMs and $A(\otimes)$ is its adjacency matrix (Eq. (13)).

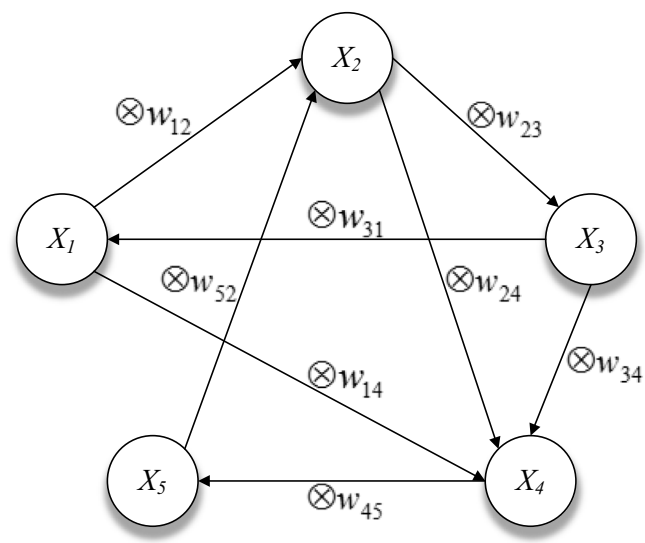

Fig. 1. An example of fuzzy grey cognitive maps (FGCMs).

$$A(\otimes) = \begin{pmatrix} 0 & \otimes w_{12} & 0 & \otimes w_{14} & 0 \\ 0 & 0 & \otimes w_{23} & \otimes w_{24} & 0 \\ \otimes w_{31} & 0 & 0 & \otimes w_{34} & 0 \\ 0 & 0 & 0 & 0 & \otimes w_{45} \\ 0 & \otimes w_{52} & 0 & 0 & 0 \end{pmatrix} \tag{13}$$

According to Salmeron (2010), dynamics of FGCMs starts with the determination of the initial grey vector state $\otimes \vec{C}^0$, that denotes a proposed initial grey stimuli. The initial grey vector state with n nodes is defined as:

$$\begin{aligned} \otimes \vec{C}^0 &= \left(\otimes C_1^0 \otimes C_2^0 \ldots \otimes C_n^0\right) \\ &= \left(\left[\otimes \underline{C}_1^0, \otimes \overline{C}_1^0\right]\left[\otimes \underline{C}_2^0, \otimes \overline{C}_2^0\right] \ldots \left[\otimes \underline{C}_n^0, \otimes \overline{C}_n^0\right]\right) \end{aligned} \tag{14}$$

The updated value of each node is computed by an iterative inference process using an activation function (Salmeron, 2010), that monotonically maps the grey node values into a normalized range $[0, +1]$ or $[-1, +1]$. Moreover, Eq. (15) is used to calculate the updated value of each node.

$$\otimes C_j^{t+1} = f\left(\otimes C_j^t + \sum_{\substack{i=1 \\ j \ne i}}^{N} \otimes w_{ij} \otimes \otimes C_i^t\right)$$

$$= f\left(\otimes C^{t*}\right)$$

$$= f\left(\left[\underline{C}^{t*}, \overline{C}^{t*}\right]\right)$$

$$= \left[f\left(\underline{C}^{t*}\right), f\left(\overline{C}^{t*}\right)\right]$$
$$= \left[\underline{C}^{t+1}, \overline{C}^{t+1}\right]. \quad (15)$$

Numerous activation functions have been proposed in the literature including, bivalent function, trivalent function, unipolar sigmoid (logistic) function and hyperbolic tangent function (Yesil et al., 2014). The most frequently used activation function when concepts' values map in the range [0, + 1], is the unipolar sigmoid activation function (Bueno and Salmeron, 2009), that is also used in this paper. Thus, if the unipolar sigmoid activation function is used, the component i of the vector state $\otimes \overrightarrow{C}^{t+1}$ after the inference process is denoted as follows:

$$\otimes C_i^{t+1} \in \left[\left(1 + e^{-\lambda \underline{C}_i^{t*}}\right)^{-1}, \left(1 + e^{-\lambda \overline{C}_i^{t*}}\right)^{-1}\right]. \quad (16)$$

As the system evolves through the inference process, there will be three possible final conditions for the steady grey vector state, which demonstrates the impact of the initial grey vector state on the state of each FGCM node (Salmeron and Papageorgiou, 2012). These conditions are as follows:

- Values of the vector state could settle down to a fixed pattern of nodes' states, the so-called grey hidden pattern or grey fixed-point attractor.
- The vector state's values could enter a limit grey cycle in which they keep moving between several fixed states.
- The FGCM continues to produce different grey vector state for each iteration that is known as the grey chaotic attractor state.

In order to estimate the level of uncertainty associated with each node within a FGCM, Salmeron (2010) introduces greyness as an uncertainty measure. Accordingly, the greater the value of greyness, the higher the uncertainty associated with results. This measure is computed as follows:

$$\phi(\otimes C_i) = \frac{|l(\otimes C_i)|}{l(\otimes \psi)} \quad (17)$$

where $|l(\otimes C_i)|$ is the absolute value of the length of grey node $\otimes C_i$ state value, and $l(\otimes \psi)$ is the absolute value of the range of information space denoted by $\otimes \psi$. Therefore, if FGCM maps the nodes' states within interval [0, + 1], the value of $l(\otimes \psi)$ is defined as:

$$l(\otimes \psi) = 1 \; if \{\otimes C_i, \otimes w_{ij}\} \subseteq [0, +1] \quad (18)$$

Generally, there are two main approaches to develop and construct FCMs (in the same sense FGCMs) including, expert-based approaches (deductive modeling) and the computational methods (inductive modeling) (Stach et al., 2010). The expert-based approach relies solely on human expertise and domain knowledge. However, the computational method employs available data and a learning algorithm to construct or support development of a FCM (or FGCM) model for a given system. The approach used in this research is the expert-based one.

The expert-based approach uses the following three steps to construct FCMs (Khan and Quaddus, 2004):

1. Identification of important concepts (nodes)
2. Identification of causal relationship between these concepts
3. Estimation of the strength of the causal relationship.

A panel of experts is used to accomplish the abovementioned three steps. Each expert determines the degree of influence (causal relationship) between nodes using linguistic variables, such as strong influence, medium influence, weak influence, etc. (Papageorgiou et al., 2006).

In the process of developing FGCMs, grey causal weights must be determined. To this end, Salmeron (2010) proposes to use grey numbers that vibrate around a base value namely $\otimes G(b)$. Thus, $\otimes w_{ij}(b) \in [b - \varepsilon_b, b + \varepsilon_b]$. Furthermore, the value of ε_b represents the extent of uncertainty associated with the base value. For example, if the base value is a white number, then $\varepsilon_b = 0$. If the base value is a black number, then $\varepsilon_b = \infty$, and $b \pm \varepsilon_b = \pm 1$ in FGCM models. Accordingly, the grey weights are assigned using a two stage process. First, the base value is determined the same as in FCMs by using a linguistic variable (e.g. negatively very strong, negatively strong, negatively medium, negatively weak, etc.), that is a value within the FGCM grey weights' range $b \in \{[0, + 1]\}$.

In the second stage, the vibration value ε_b is also determined by linguistic variables (e.g. very high uncertainty, high uncertainty, medium uncertainty, weak uncertainty, etc.). The value of ε_b depends on the level of trust experts have on their own judgments about the base value. When an expert has the whole trust on the base value, then $\varepsilon_b = 0$. On the contrary, if an expert is indecisive about the base value, then $w_{ij}(b) \pm \varepsilon_b = \pm 1$. Eq. (19) depicts the computation process of the $\otimes w(b)$ upper and lower limits:

$$\otimes w(b) \in \begin{cases} [b - \varepsilon_b, b + \varepsilon_b] if (b + \varepsilon_b \le +1) \wedge (b - \varepsilon_b \ge -1), \\ [b - \varepsilon_b, +1] if (-1 \le b - \varepsilon_b \le +1) \wedge (b + \varepsilon_b > +1), \\ [-1, b + \varepsilon_b] if (-1 \le b + \varepsilon_b \le +1) \wedge (b - \varepsilon_b < -1), \\ [-1, +1] if (b + \varepsilon_b > +1) \wedge (b - \varepsilon_b < -1). \end{cases} \quad (19)$$

Note that in the process of constructing expert-based FCMs (in the same sense FGCMs), each expert will possibly develop a distinct FCM, therefore it is crucial to integrate various maps into a single one. Multiple approaches have been proposed to address this issue such as, Delphi method (Dickerson and Kosko, 1994) which strives to reach a consensus among experts by constantly returning to experts so they can modify their judgments. However, the augmented approach (Salmeron, 2009) does not require that experts change their judgments. Accordingly, the augmented adjacency matrix is built by adding the adjacency matrix of each expert.

Consider two distinct FGCMs as, $FGCM_x$ and $FGCM_y$ with no common nodes and, $\otimes C^{[x_i]}$ and $\otimes C^{[y_i]}$ as their nodes respectively. The adjacency matrix of $FGCM_x$ is denoted by $(\otimes w_{i \to j}^x)$ and the adjacency matrix of $FGCM_y$ is considered as $(\otimes w_{i \to j}^y)$. The augmented adjacency matrix is:

$$Adj_{Aug} = \begin{pmatrix} \otimes w_{i \to j}^x & 0 \\ 0 & \otimes w_{i \to j}^y \end{pmatrix} \quad (20)$$

If there are common nodes, then the element $\otimes w_{i \to j}^{Aug}$ in the augmented matrix is calculated as:

$$\otimes w_{i \to j}^{Aug} = \frac{\sum_{i=1}^n \otimes w_{i \to j}^k}{n} = \frac{\sum_{i=1}^n \left[\underline{w}_{i \to j}^k, \overline{w}_{i \to j}^k\right]}{n} = \left[\frac{\sum_{i=1}^n \underline{w}_{i \to j}^k}{n}, \frac{\sum_{i=1}^n \overline{w}_{i \to j}^k}{n}\right] \quad (21)$$

where n is the number of FGCMs added, k is the identifier of each FGCM, and i and j are the identifier of the relationships.

D) Improved Grey relational analysis (IGRA)

The proposed improved GRA method comprises of the following steps:

Step 1: Determining the grey decision-making matrix according to experts' opinions which is assumed to have m alternatives characterized with n criteria as follows:

$$\otimes G^k = \begin{bmatrix} \otimes G^k_{11} & \otimes G^k_{12} & \cdots & \otimes G^k_{1n} \\ \otimes G^k_{21} & \otimes G^k_{22} & \cdots & \otimes G^k_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \otimes G^k_{m1} & \otimes G^k_{m2} & \cdots & \otimes G^k_{mn} \end{bmatrix} \tag{22}$$

where $\otimes G^k_{ij}$ represents the grey performance of alternative i with regard to criterion j, based on kth expert's evaluation.

Step 2: Normalizing the grey decision-making matrix using Eqs. (23) and (24) respectively for the benefit and the cost criteria:

$$\otimes y^k_{ij} = \frac{\otimes G^k_{ij}}{\max^m_{i=1}\left\{\overline{G}^k_{ij}\right\}}, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; j \in \text{benefit criteria} \tag{23}$$

$$\otimes y^k_{ij} = \frac{\min^m_{i=1}\left\{\underline{G}^k_{ij}\right\}}{\otimes G^k_{ij}}, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; j \in \text{cost criteria} \tag{24}$$

where $\otimes y^k_{ij}$ is the element of the normalized grey matrix. Subsequent to the normalization of the grey decision-making matrix all performance values are scaled into $[0, 1]$. The normalization procedure used is the 'Linear Scale Transformation (Max)' procedure that is proved to produce consistent results within the decision process with various decision making techniques (Chakraborty and Yeh, 2007, 2009).

Step 3: Defining the reference sequence (reference alternative) by Eqs. (25) and (26) as follows:

$$y^{k,0} = \left\{y^{k,0}_1, y^{k,0}_2, \ldots, y^{k,0}_n\right\} \tag{25}$$

$$\otimes y^{k,0}_j = \left(\max^m_{i=1}\underline{y}^k_{ij}, \max^m_{i=1}\overline{y}^k_{ij}\right), j = 1, 2, \ldots, n \tag{26}$$

where $y^{k,0}$ is the reference value related to the criterion j, and $y^{k,0}_{ij}$ are the values obtained from the grey normalized matrix using Eqs. (25) and (26).

Step 4: Calculating the difference between the reference alternative and other alternatives in order to generate the difference matrix as shown in Eqs. (27) and (28):

$$\otimes \Delta^k = \begin{bmatrix} \otimes \Delta^k_{11} & \otimes \Delta^k_{12} & \cdots & \otimes \Delta^k_{1n} \\ \otimes \Delta^k_{21} & \otimes \Delta^k_{22} & \cdots & \otimes \Delta^k_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \otimes \Delta^k_{m1} & \otimes \Delta^k_{m2} & \cdots & \otimes \Delta^k_{mn} \end{bmatrix} \tag{27}$$

$$\otimes \Delta^k_{ij} = \left[y^{k,0}_j - \overline{y}^k_{ij}, y^{k,0}_j - \underline{y}^k_{ij}\right], i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \tag{28}$$

Step 5: Computing the grey relational coefficient for all alternatives as follows:

$$\otimes \nu^k_{ij} = \left[\underline{\nu}^k_{ij}, \overline{\nu}^k_{ij}\right] \tag{29}$$

$$\underline{\nu}^k_{ij} = \frac{\min^m_{i=1}\min^n_{j=1}\underline{\Delta}^k_{ij} + \max^m_{i=1}\max^n_{j=1}\overline{\Delta}^k_{ij}}{\overline{\Delta}^k_{ij} + \max^m_{i=1}\max^n_{j=1}\overline{\Delta}^k_{ij}} \tag{30}$$

$$\overline{\nu}^k_{ij} = \frac{\min^m_{i=1}\min^n_{j=1}\underline{\Delta}^k_{ij} + \max^m_{i=1}\max^n_{j=1}\overline{\Delta}^k_{ij}}{\underline{\Delta}^k_{ij} + \max^m_{i=1}\max^n_{j=1}\overline{\Delta}^k_{ij}} \tag{31}$$

where $\otimes \nu^k_{ij}$ is the grey relational coefficient, and ρ represents the distinguishing coefficient with a value from range $[0, 1]$. The value of ρ reflects the degree to which the minimum scores are emphasized relative to the maximum scores (Zhang et al., 2005). According to Kuo et al. (2008b), the distinguishing coefficient can be determined by decision-makers which in this study decision-makers set it as 0.5.

Step 6: Calculating the grey relational degree for each alternative by the kth expert, using interval weights of criteria as:

$$\otimes \gamma^k_i = \sum_{j=1}^{n} \otimes \nu^k_{ij} \times \otimes \omega_j \tag{32}$$

where $\otimes \omega_j$ represents the grey value of criteria weights. By using grey numbers multiplication operation presented in Appendix B, Eq. (32) can be rewritten as Eq. (33):

$$\otimes \gamma^k_i = \left[\left(\otimes \nu^k_{11} \times \otimes \omega_1\right) + \left(\otimes \nu^k_{12} \times \otimes \omega_2\right) + \ldots + \left(\otimes \nu^k_{1n} \times \otimes \omega_n\right)\right]$$

$$= \begin{pmatrix} \left[\min\left(\underline{\nu}^k_{11}\cdot\underline{\omega}_1, \underline{\nu}^k_{11}\cdot\overline{\omega}_1, \overline{\nu}^k_{11}\cdot\underline{\omega}_1, \overline{\nu}^k_{11}\cdot\overline{\omega}_1\right), \max\left(\underline{\nu}^k_{11}\cdot\underline{\omega}_1, \underline{\nu}^k_{11}\cdot\overline{\omega}_1, \overline{\nu}^k_{11}\cdot\underline{\omega}_1, \overline{\nu}^k_{11}\cdot\overline{\omega}_1\right)\right] \\ +\left[\min\left(\underline{\nu}^k_{12}\cdot\underline{\omega}_2, \underline{\nu}^k_{12}\cdot\overline{\omega}_2, \overline{\nu}^k_{12}\cdot\underline{\omega}_2, \overline{\nu}^k_{12}\cdot\overline{\omega}_2\right), \max\left(\underline{\nu}^k_{12}\cdot\underline{\omega}_2, \underline{\nu}^k_{12}\cdot\overline{\omega}_2, \overline{\nu}^k_{12}\cdot\underline{\omega}_2, \overline{\nu}^k_{12}\cdot\overline{\omega}_2\right)\right] + \ldots + \\ \left[\min\left(\underline{\nu}^k_{1n}\cdot\underline{\omega}_n, \underline{\nu}^k_{1n}\cdot\overline{\omega}_n, \overline{\nu}^k_{1n}\cdot\underline{\omega}_n, \overline{\nu}^k_{1n}\cdot\overline{\omega}_n\right), \max\left(\underline{\nu}^k_{1n}\cdot\underline{\omega}_n, \underline{\nu}^k_{1n}\cdot\overline{\omega}_n, \overline{\nu}^k_{1n}\cdot\underline{\omega}_n, \overline{\nu}^k_{1n}\cdot\overline{\omega}_n\right)\right] \end{pmatrix}$$

$$= \left[\begin{array}{l} \left(\min\left(\underline{\nu}^k_{11}\cdot\underline{\omega}_1, \underline{\nu}^k_{11}\cdot\overline{\omega}_1, \overline{\nu}^k_{11}\cdot\underline{\omega}_1, \overline{\nu}^k_{11}\cdot\overline{\omega}_1\right) + \min\left(\underline{\nu}^k_{12}\cdot\underline{\omega}_2, \underline{\nu}^k_{12}\cdot\overline{\omega}_2, \overline{\nu}^k_{12}\cdot\underline{\omega}_2, \overline{\nu}^k_{12}\cdot\overline{\omega}_2\right) + \ldots + \min\left(\underline{\nu}^k_{1n}\cdot\underline{\omega}_n, \underline{\nu}^k_{1n}\cdot\overline{\omega}_n, \overline{\nu}^k_{1n}\cdot\underline{\omega}_n, \overline{\nu}^k_{1n}\cdot\overline{\omega}_n\right)\right), \\ \left(\max\left(\underline{\nu}^k_{11}\cdot\underline{\omega}_1, \underline{\nu}^k_{11}\cdot\overline{\omega}_1, \overline{\nu}^k_{11}\cdot\underline{\omega}_1, \overline{\nu}^k_{11}\cdot\overline{\omega}_1\right) + \max\left(\underline{\nu}^k_{12}\cdot\underline{\omega}_2, \underline{\nu}^k_{12}\cdot\overline{\omega}_2, \overline{\nu}^k_{12}\cdot\underline{\omega}_2, \overline{\nu}^k_{12}\cdot\overline{\omega}_2\right) + \ldots + \max\left(\underline{\nu}^k_{1n}\cdot\underline{\omega}_n, \underline{\nu}^k_{1n}\cdot\overline{\omega}_n, \overline{\nu}^k_{1n}\cdot\underline{\omega}_n, \overline{\nu}^k_{1n}\cdot\overline{\omega}_n\right)\right) \end{array}\right] \tag{33}$$

Step 7: Carrying out group decision-making by integrating lower and upper limits of relational degrees of the alternatives based on Eqs. (34) and (35):

$$\underline{\gamma}_i = \prod_{k=1}^{L} \left(\underline{\gamma}_i^k\right)^{w_k} \tag{34}$$

$$\overline{\gamma}_i = \prod_{k=1}^{L} \left(\overline{\gamma}_i^k\right)^{w_k} \tag{35}$$

where L is the number of experts employed to evaluate alternatives, and w_k is the relative weight of experts' opinions.

E) Interval analysis

Wang et al. (2005) proposed an interval analysis approach to compare and rank grey (interval) numbers. Considering the grey numbers operations mentioned in Appendix B, this new approach is described as follows:

Let $A = [\underline{a}, \overline{a}]$ and $B = \left[\underline{b}, \overline{b}\right]$ be two interval numbers. The degree of preference of A over B (or $A > B$) is defined as:

$$P(A > B) = \frac{\max(0, \overline{a} - \underline{b}) - \max\left(0, \underline{a} - \overline{b}\right)}{(\overline{a} - \underline{a}) + \left(\overline{b} - \underline{b}\right)} \tag{36}$$

The degree of preference of B over A is also computed as:

$$P(B > A) = \frac{\max\left(0, \overline{b} - \underline{a}\right) - \max(0, \underline{b} - \overline{a})}{(\overline{a} - \underline{a}) + \left(\overline{b} - \underline{b}\right)} \tag{37}$$

Accordingly, $P(A > B) + P(B > A) = 1$ and $P(A > B) = P(B > A) = 0.5$ when $A = B$, which means when $\underline{a} = \underline{b}$ and $\overline{a} = \overline{b}$.

Wang et al. (2005) mention that if $P(A > B) > 0.5$ (or similarly $P(A > B) > P(B > A)$) then A is considered to be superior to B the degree of $P(A > B)$, which is denoted by $A \overset{P(A>B)}{>} B$; if $P(A > B) = P(B > A) = 0.5$, then A is said to be indifferent to B, that is shown by $A \sim B$; if $P(B > A) > 0.5$ (or similarly $P(B > A) > P(A > B)$), then A is said to be inferior to B to the degree of $P(B > A)$, that is denoted by $A \overset{P(B>A)}{<} B$.

In order to compare grey numbers, two matrices including the 'matrix of degree of preference' DP_{ij} and the 'matrix of preferences' P_{ij}, are calculated respectively as follows:

$$\begin{array}{cccc} A & B & \dots & N \end{array} DP_{ij} = \begin{array}{c} A \\ B \\ \vdots \\ N \end{array} \begin{pmatrix} P(A>A) & P(A>B) & \cdots & P(A>N) \\ P(B>A) & P(B>B) & \cdots & P(B>N) \\ \vdots & \vdots & \ddots & \vdots \\ P(N>A) & P(N>B) & \cdots & P(N>N) \end{pmatrix} \tag{38}$$

$$\begin{array}{cccc} A & B & \dots & N \end{array} P_{ij} = \begin{array}{c} A \\ B \\ \vdots \\ N \end{array} \begin{pmatrix} P_{AA} & P_{AB} & \cdots & P_{AN} \\ P_{BA} & P_{BB} & \cdots & P_{BN} \\ \vdots & \vdots & \ddots & \vdots \\ P_{NA} & P_{NB} & \cdots & P_{NN} \end{pmatrix} \tag{39}$$

Where:

$$P_{ij} = \begin{cases} 1, \ if \ P(i > j) > 0.5, \\ 0, \ if \ P(i > j) \le 0.5, \end{cases} i, j = A, B, \dots, N \tag{40}$$

Subsequently, the grey numbers are compared by calculating the sum of each row in the matrix P_{ij}, and their ranking is obtained according to the rule that the higher the sum of the row, the better preferred the corresponding number.

References

Ahi, P., Searcy, C., 2013. A comparative literature analysis of definitions for green and sustainable supply chain management. J. Clean. Prod. 52, 329–341.
Ahmad, W.N.K.W., Rezaei, J., Sadaghiani, S., Tavasszy, L.A., 2017. Evaluation of the external forces affecting the sustainability of oil and gas supply chain using Best Worst Method. J. Clean. Prod. 153, 242–252.
Amid, A., Ghodsypour, S.H., O'Brien, C., 2006. Fuzzy multiobjective linear model for supplier selection in a supply chain. Int. J. Prod. Econ. 104 (2), 394–407.
Amin, S.H., Zhang, G., 2012. An integrated model for closed-loop supply chain configuration and supplier selection: multi-objective approach. Expert Syst. Appl. 39 (8), 6782–6791.
Amindoust, A., Ahmed, S., Saghafinia, A., Bahreininejad, A., 2012. Sustainable supplier selection: a ranking model based on fuzzy inference system. Appl. Soft Comput. 12 (6), 1668–1677.
Andiç, E., Yurt, Ö., Baltacıoğlu, T., 2012. Green supply chains: efforts and potential applications for the Turkish market. Resour. Conserv. Recycl. 58, 50–68.
Bai, C., Sarkis, J., 2010. Integrating sustainability into supplier selection with grey system and rough set methodologies. Int. J. Prod. Econ. 124 (1), 252–264.
Banaeian, N., Mobli, H., Fahimnia, B., Nielsen, I.E., Omid, M., 2018. Green supplier selection using fuzzy group decision making methods: A case study from the agri-food industry. Comp. Oper. Res. 89, 337–347.
Baykasoğlu, A., Gölcük, İ., 2015. Development of a novel multiple-attribute decision making model via fuzzy cognitive maps and hierarchical fuzzy TOPSIS. Inf. Sci. 301, 75–98.
Bueno, S., Salmeron, J.L., 2009. Benchmarking main activation functions in fuzzy cognitive maps. Expert Syst. Appl. 36 (3), 5221–5229.
Büyüközkan, G., Çifçi, G., 2011. A novel fuzzy multi-criteria decision framework for sustainable supplier selection with incomplete information. Comput. Ind. 62 (2), 164–174.
Büyüközkan, G., Çifçi, G., 2012. A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers. Expert Syst. Appl. 39 (3), 3000–3011.
Cao, H., 2011. May. The study of the suppliers evaluating and choosing strategies based on the green supply chain management. In: Business Management and Electronic Information (BMEI), 2011 International Conference on, vol. 3. IEEE, pp. 788–791.
Çelebi, D., Bayraktar, D., 2008. An integrated neural network and data envelopment analysis for supplier evaluation under incomplete information. Expert Syst. Appl. 35 (4), 1698–1710.
Chai, J., Liu, J.N., Ngai, E.W., 2013. Application of decision-making techniques in supplier selection: a systematic review of literature. Expert Syst. Appl. 40 (10), 3872–3885.
Chakraborty, S., Yeh, C.H., 2007. February. A simulation based comparative study of normalization procedures in multi attribute decision making. In: Proceedings of the 6th Conference on 6th WSEAS Int. Conf. On Artificial Intelligence, Knowledge Engineering and Data Bases, vol. 6, pp. 102–109.
Chakraborty, S., Yeh, C.H., 2009. July. A simulation comparison of normalization procedures for TOPSIS. In: Computers & Industrial Engineering, 2009. CIE 2009. International Conference on. IEEE, pp. 1815–1820.
Chan, F.T., Chan, H.K., 2010. An AHP model for selection of suppliers in the fast changing fashion market. Int. J. Adv. Manuf. Technol. 51 (9), 1195–1207.
Chen, C.T., Lin, C.T., Huang, S.F., 2006. A fuzzy approach for supplier evaluation and selection in supply chain management. Int. J. Prod. Econ. 102 (2), 289–301.
Chiou, C.Y., Hsu, C.W., Hwang, & W.Y., 2008. Comparative investigation on green supplier selection of the American, Japanese and Taiwanese Electronics Industry in China. In: International Conference on IE&EM, IEEE 8-11 Dec, pp. 1909–1914.
Choi, T.Y., Hartley, J.L., 1996. An exploration of supplier selection practices across the supply chain. J. Oper. Manag. 14 (4), 333–343.
De Boer, L., Labro, E., Morlacchi, P., 2001. A review of methods supporting supplier selection. Eur. J. Purch. Supply Manag. 7 (2), 75–89.
Deng, J.L., 1989. The introduction of Grey system. J. Grey Syst. 1, 1–24.
Dickson, G.W., 1966. An analysis of vendor selection systems and decisions. J. Purch. 2 (1), 5–17.
Dickerson, J.A., Kosko, B., 1994. Virtual worlds as fuzzy cognitive maps. Pres.: Tel. Virt. Environ. 3 (2), 173–189.
Gencer, C., Gürpinar, D., 2007. Analytic network process in supplier selection: a case study in an electronic firm. Appl. Math. Model. 31 (11), 2475–2486.
Govindan, K., Khodaverdi, R., Jafarian, A., 2013. A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach. J. Clean. Prod. 47, 345–354.
Govindan, K., Rajendran, S., Sarkis, J., Murugesan, P., 2015. Multi criteria decision making approaches for green supplier evaluation and selection: a literature review. J. Clean. Prod. 98, 66–83.
Green, K., Morton, B., New, S., 1996. Purchasing and environmental management: interactions, policies and opportunities. Bus. Strateg. Environ. 5 (3), 188–197.
Grisi, R.M., Guerra, L., Naviglio, G., 2010. Supplier performance evaluation for green supply chain management. In: Business Performance Measurement and Management. Springer Berlin Heidelberg, pp. 149–163.
Gupta, P., Anand, S., Gupta, H., 2017. Developing a roadmap to overcome barriers to energy efficiency in buildings using best worst method. Sustain. Cities Soc. 31, 244–259.
Handfield, R., Walton, S.V., Sroufe, R., Melnyk, S.A., 2002. Applying environmental

criteria to supplier assessment: a study in the application of the Analytical Hierarchy Process. Eur. J. Oper. Res. 141 (1), 70–87.
Handfield, R.B., Walton, S.V., Seegers, L.K., Melnyk, S.A., 1997. 'Green'value chain practices in the furniture industry. J. Oper. Manag. 15 (4), 293–315.
Hashemi, S.H., Karimi, A., Tavana, M., 2015. An integrated green supplier selection approach with analytic network process and improved Grey relational analysis. Int. J. Prod. Econ. 159, 178–191.
Hashim, M., Nazam, M., Yao, L., Baig, S.A., Abrar, M., Zia-ur-Rehman, M., 2017. Application of multi-objective optimization based on genetic algorithm for sustainable strategic supplier selection under fuzzy environment. J. Ind. Eng. Manag. 10 (2), 188–212.
Hsu, C.W., Hu, A.H., 2009. Applying hazardous substance management to supplier selection using analytic network process. J. Clean. Prod. 17 (2), 255–264.
Ho, W., Xu, X., Dey, P.K., 2010. Multi-criteria decision making approaches for supplier evaluation and selection: a literature review. Eur. J. Oper. Res. 202 (1), 16–24.
Humphreys, P.K., Wong, Y.K., Chan, F.T.S., 2003. Integrating environmental criteria into the supplier selection process. J. Mater. Process. Technol. 138 (1), 349–356.
United Nations Industrial Development Organization, Industrial Development Report, 2016. The Role of Technology and Innovation in Inclusive and Sustainable Industrial Development. Vienna, 2015.
Ishizaka, A., Pearman, C., Nemery, P., 2012. AHPSort: an AHP-based method for sorting problems. Int. J. Prod. Res. 50 (17), 4767–4784.
Jayaraman, V., Klassen, R., Linton, J.D., 2007. Supply chain management in a sustainable environment. J. Oper. Manag. 25 (6), 1071–1074.
Kannan, D., de Sousa Jabbour, A.B.L., Jabbour, C.J.C., 2014. Selecting green suppliers based on GSCM practices: using fuzzy TOPSIS applied to a Brazilian electronics company. Eur. J. Oper. Res. 233 (2), 432–447.
Kannan, D., Govindan, K., Rajendran, S., 2015. Fuzzy Axiomatic Design approach based green supplier selection: a case study from Singapore. J. Clean. Prod. 96, 194–208.
Kannan, D., Khodaverdi, R., Olfat, L., Jafarian, A., Diabat, A., 2013. Integrated fuzzy multi criteria decision making method and multi-objective programming approach for supplier selection and order allocation in a green supply chain. J. Clean. Prod. 47, 355–367.
Khan, M.S., Quaddus, M., 2004. Group decision support using fuzzy cognitive maps for causal reasoning. Group Decis. Negot. 13 (5), 463–480.
Kull, T.J., Talluri, S., 2008. A supply risk reduction model using integrated multicriteria decision making. IEEE Trans. Eng. Manag. 55 (3), 409–419.
Kuo, R.J., Wang, Y.C., Tien, F.C., 2010. Integration of artificial neural network and MADA methods for green supplier selection. J. Clean. Prod. 18 (12), 1161–1170.
Kuo, Y., Yang, T., Huang, G.W., 2008a. The use of grey relational analysis in solving multiple attribute decision-making problems. Comput. Ind. Eng. 55 (1), 80–93.
Kuo, Y., Yang, T., Huang, G.W., 2008b. The use of a grey-based Taguchi method for optimizing multi-response simulation problems. Eng. Optim. 40 (6), 517–528.
Kushwaha, G.S., Sharma, N.K., 2016. Green initiatives: a step towards sustainable development and firm's performance in the automobile industry. J. Clean. Prod. 121, 116–129.
Lamming, R., Hampson, J., 1996. The environment as a supply chain management issue. Br. J. Manag. 7 (s1).
Lee, A.H., Kang, H.Y., Hsu, C.F., Hung, H.C., 2009. A green supplier selection model for high-tech industry. Expert Syst. Appl. 36 (4), 7917–7927.
Lee, W.S., Lin, Y.C., 2011. Evaluating and ranking energy performance of office buildings using Grey relational analysis. Energy 36 (5), 2551–2556.
Levary, R.R., 2008. Using the analytic hierarchy process to rank foreign suppliers based on supply risks. Comput. Ind. Eng. 55 (2), 535–542.
Li, G.D., Yamaguchi, D., Nagai, M., 2007. A grey-based decision-making approach to the supplier selection problem. Math. Comput. Model. 46 (3), 573–581.
Liu, X.Y., Zeng, B., 2011. Whitenization of interval grey number sequence and its properties. In: Grey Systems and Intelligent Services (GSIS), 2011 IEEE International Conference. IEEE, pp. 460–463.
Liu, S., Lin, Y., 2006. Grey information: theory and practical applications. Springer Science & Business Media.
Lin, R.J., 2013. Using fuzzy DEMATEL to evaluate the green supply chain management practices. J. Clean. Prod. 40, 32–39.
Lin, Y., Chen, M.Y., Liu, S., 2004. Theory of grey systems: capturing uncertainties of grey information. Kybernetes 33 (2), 196–218.
Liou, J.J., Tamošaitienė, J., Zavadskas, E.K., Tzeng, G.H., 2016. New hybrid COPRAS-G MADM Model for improving and selecting suppliers in green supply chain management. Int. J. Prod. Res. 54 (1), 114–134.
Manzardo, A., Ren, J., Mazzi, A., Scipioni, A., 2012. A grey-based group decision-making methodology for the selection of hydrogen technologies in life cycle sustainability perspective. International journal of hydrogen energy 37 (23), 17663–17670.
Marufuzzaman, M., Ahsan, K.B., Xing, K., 2009. Supplier selection and evaluation method using Analytical Hierarchy Process (AHP): a case study on an apparel manufacturing organisation. Int. J. Value Chain Manag. 3 (2), 224–240.
Narasimhan, R., Carter, J.R., 1998. Environmental Supply Chain Management. The Center for Advanced Purchasing Studies, Arizona State University, Tempe, AZ, USA.
Noci, G., 1997. Designing 'green'vendor rating systems for the assessment of a supplier's environmental performance. Eur. J. Purch. Supply Manag. 3 (2), 103–114.
Papageorgiou, E.I., Stylios, C., Groumpos, P.P., 2006. Unsupervised learning techniques for fine-tuning fuzzy cognitive map causal links. Int. J. Hum. Comput. Stud. 64 (8), 727–743.
Rao, P., Holt, D., 2005. Do green supply chains lead to competitiveness and economic performance? Int. J. Oper. Prod. Manag. 25 (9), 898–916.
Ren, J., Liang, H., Chan, F.T., 2017. Urban sewage sludge, sustainability, and transition for Eco-City: multi-criteria sustainability assessment of technologies based on best-worst method. Technol. Forecast. Soc. Change 116, 29–39.
Rezaei, J., 2015. Best-worst multi-criteria decision-making method. Omega 53, 49–57.
Rezaei, J., 2016. Best-worst multi-criteria decision-making method: some properties and a linear model. Omega 64, 126–130.
Rezaei, J., Nispeling, T., Sarkis, J., Tavasszy, L., 2016. A supplier selection life cycle approach integrating traditional and environmental criteria using the best worst method. J. Clean. Prod. 135, 577–588.
Roehrich, J.K., Hoejmose, S.U., Overland, V., 2017. Driving green supply chain management performance through supplier selection and value internalisation: a self-determination theory perspective. Int. J. Oper. Prod. Manag. 37 (4), 489–509.
Salimi, N., Rezaei, J., 2016. Measuring efficiency of university-industry Ph. D. projects using best worst method. Scientometrics 109 (3), 1911–1938.
Salmeron, J.L., Papageorgiou, E.I., 2012. A fuzzy grey cognitive maps-based decision support system for radiotherapy treatment planning. Knowl. Base Syst. 30, 151–160.
Salmeron, J.L., 2009. Augmented fuzzy cognitive maps for modelling LMS critical success factors. Knowledge-based Syst. 22 (4), 275–278.
Salmeron, J.L., 2010. Modelling grey uncertainty with fuzzy grey cognitive maps. Expert Syst. Appl. 37 (12), 7581–7588.
Sarkis, J. (Ed.), 2006. Greening the Supply Chain. Springer Science & Business Media.
Sarkis, J., 2003. A strategic decision framework for green supply chain management. J. Clean. Prod. 11 (4), 397–409.
Sarkis, J., Nehman, G., Priest, J., 1996. May. A systemic evaluation model for environmentally conscious business practices and strategy. In: Electronics and the Environment, 1996. ISEE-1996., Proceedings of the 1996 IEEE International Symposium on. IEEE, pp. 281–286.
Shojaei, P., Haeri, S.A.S., Mohammadi, S., 2018. Airports evaluation and ranking model using Taguchi loss function, best-worst method and VIKOR technique. J. Air Trans. Manag. 68, 4–13.
Srivastava, S.K., 2007. Green supply-chain management: a state-of-the-art literature review. Int. J. Manag. Rev. 9 (1), 53–80.
Stach, W., Kurgan, L., Pedrycz, W., 2010. Expert-based and computational methods for developing fuzzy cognitive maps. Fuzzy Cognit. Maps 23–41.
Tseng, M.L., 2010. Using linguistic preferences and grey relational analysis to evaluate the environmental knowledge management capacity. Expert Syst. Appl. 37 (1), 70–81.
Tseng, M.L., Chiang, J.H., Lan, L.W., 2009. Selection of optimal supplier in supply chain management strategy with analytic network process and choquet integral. Comput. Ind. Eng. 57 (1), 330–340.
Walton, S.V., Handfield, R.B., Melnyk, S.A., 1998. The green supply chain: integrating suppliers into environmental management processes. J. Supply Chain Manag. 34 (1), 2–11.
Wang, Y.M., Yang, J.B., Xu, D.L., 2005. A preference aggregation method through the estimation of utility intervals. Comput. Oper. Res. 32 (8), 2027–2049.
Weber, C.A., Current, J.R., Benton, W.C., 1991. Vendor selection criteria and methods. Eur. J. Oper. Res. 50 (1), 2–18.
Wei, G.W., 2011a. Grey relational analysis method for 2-tuple linguistic multiple attribute group decision making with incomplete weight information. Expert Syst. Appl. 38 (5), 4824–4828.
Wei, G.W., 2011b. Gray relational analysis method for intuitionistic fuzzy multiple attribute decision making. Expert Syst. Appl. 38 (9), 11671–11677.
World motor vehicle production statistics, 2016. OrganisationInternationale des Constructeursd'Automobiles (OICA). http://www.oica.net/category/production-statistics/. Accessed 4 September 2017.
Wu, C., Barnes, D., 2016. An integrated model for green partner selection and supply chain construction. J. Clean. Prod. 112, 2114–2132.
Wu, D.D., 2009. Supplier selection in a fuzzy group setting: a method using grey related analysis and Dempster–Shafer theory. Expert Syst. Appl. 36 (5), 8892–8899.
Xiao, Z., Chen, W., Li, L., 2012. An integrated FCM and fuzzy soft set for supplier selection problem based on risk evaluation. Appl. Math. Model. 36 (4), 1444–1454.
Yang, Y., Wu, L., 2007. September. Grey entropy method for green supplier selection. In: Wireless Communications, Networking and Mobile Computing, 2007. WiCom 2007. International Conference on. IEEE, pp. 4682–4685.
Yesil, E., Urbas, L., Demirsoy, A., 2014. FCM-gui: a graphical user interface for big bang-big crunch learning of FCM. In: Fuzzy Cognitive Maps for Applied Sciences and Engineering. Springer Berlin Heidelberg, pp. 177–198.
Yu, R., Tzeng, G.H., 2006. A soft computing method for multi-criteria decision making with dependence and feedback. Appl. Math. Comput. 180 (1), 63–75.
Zhang, J., Wu, D., Olson, D.L., 2005. The method of grey related analysis to multiple attribute decision making problems with interval numbers. Math. Comput. Model. 42 (9–10), 991–998.
Zhong, L., Yao, L., 2017. An ELECTRE I-based multi-criteria group decision making method with interval type-2 fuzzy numbers and its application to supplier selection. Appl. Soft Comput. 57, 556–576.
Zhou, X., Xu, Z., Yao, L., Tu, Y., Lev, B., Pedrycz, W., 2018. A novel data envelopment analysis model for evaluating industrial production and environmental

management system. J. Clean. Prod. 170, 773–788.
Zhu, Q., Sarkis, J., 2004. Relationships between operational practices and performance among early adopters of green supply chain management practices in Chinese manufacturing enterprises. J. Oper. Manag. 22 (3), 265–289.
Zhu, Q., Sarkis, J., Geng, Y., 2005. Green supply chain management in China: pressures, practices and performance. Int. J. Oper. Prod. Manag. 25 (5), 449–468.