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A fuzzy multi attribute decision framework with integration of QFD and grey relational analysis

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A B S T R A C T

Objective: This paper proposes a multi attribute decision support model in a supply chain in order to solve complex decision problems. The paper provides a platform to ease decision process through the integration of quality function deployment (QFD) and grey relational analysis (GRA) in demonstrating main supply chain drivers under fuzzy environment.
Methodology: The proposed method is important because of several points: First of all, in a supply chain system, evaluation factors are not really independent and must be addressed in relation to the external factors such as customer requirements. Hence, we have applied QFD tool. Second, due to the constant uncertainty in the supply chain environment, fuzziness among the factors has to be considered. So, an interval valued fuzzy model was implemented. Third, to examine the proposed decision system in reality, it was applied in **R**isk and **U**ncertain **C**onditions for **A**griculture **P**roduction **S**ystems (RUC-APS) project.
Contribution: An integrated version of QFD and GRA is presented. It is assumed that QFD can act to measure optimal solutions based on the distance to ideal solutions. In an interval-valued fuzzy environment the enormous volume of computation by Euclidean distance doesn't allow decision makers to obtain the results easily. This drawback is addressed using gray relational analysis. The gray relational coefficient is integrated to the fuzzy QFD to measure the distance of potential solutions from ideal solutions. This integration facilitates decision making process in further problems once big data are available.
Results: To obtain the importance degrees of logistic indicators in the supply chain, expert team considered the environmental, social & cultural, and economic factors as external dimension of the QFD. The other dimension of QFD includes supply chain drivers such as quality, environmental management system, supply chain flexibility, corporate social responsibility, transportation service condition, and financial stability. The decision model is solved and the ranking of indicators is achieved. A sensitivity analysis helps to test and check the performance of the decision model.

1. Introduction

A process of supplying raw materials from supplier, transforming them into final products, then delivering and distributing the product to customers through logistics and retail channels is expressed as a supply chain (Genovese, Acquaye, Figueroa, & Koh, 2017). A supply chain is sustainable if the products are designed under environmental regulations; natural resources and energy are consumed efficiently; the final product are guaranteed; customer services are met; and employment ethical issues are considered (Tavana, Yazdani, & Di Caprio, 2017). A sustainable supply chain is governed by prominent customer/stakeholder relations and customer satisfaction plays a key role. Many studies emphasized only on the influence of the traditional criteria on the performance of the supply chain. However, dealing with an intelligent decision making system with inclusion of customer factors not only improve internal processes and practices, but also enhances the company reputation and customer loyalty. Therefore, an effective customer-driven system to translate customer factors into supply chain indicators has significant achievement for the company. The nature of multi attribute decision making (MADM) permits us to explore novel decision approaches.

Establishing knowledge-based techniques has become one of the essential programs for competitive companies (Cantor, Blackhurst, Pan, & Crum, 2014; Patil & Kant, 2014). Significant attention is devoted to the knowledge-based decision models in academia

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and industry. Configuring an intelligent decision system to facilitate managerial decisions is the fundamental issue of many original researches and international projects (Shi, Guo, & Fung, 2017). In decision making environments, an expert system (ES) is recognized as an intelligent and computerized system that supports management decision making operations (Koh et al., 2013; Lolli, Ishizaka, Gamberini, Rimini, & Messori, 2015). It builds a platform to analyze strategic decisions and to support decision makers (DMs) in a complex and weakly structured situation. One of the advantages of such kind of system is to assist top managers and DMs in their tasks in order to improve the quality of decision making (Yazdani, Chatterjee, Zavadskas, & Zolfani, 2017).

Development of the logistics and supply chain management depends on the application and implementation of intelligent and advanced systems. Such system must enable supply chain to incorporate in fundamental decision process, information-sharing, and to create value added to the production system and services. Over the last decades, the direction of companies in managing decision has changed drastically. For instance, to manage the material costs in a manufacturing system, a semi intelligent decision model was developed to choose efficient scenario of total manufacturing costs reduction (Wong & Leung, 2008). Application of the decision making systems provides competitive advantages of knowledge sharing with customers and stakeholders in a supply chain to improve coordination and communication abilities among them (Ngai et al. 2014). Liu et al. (2012) built a sustainable framework in a supply chain with the integration of life cycle assessment and multi-attribute decision tools to support environmental, social and the economic aspects. Seuring (2013) reported that an initial and strategic sustainable supply chain decisions are taken efficiently only if it is defined under a well-structured approach. Bhattacharya et al. (2014) demonstrated a green supply chain performance measurement perspective and delivered a collaborative decision-making model using fuzzy analytical network process. Accorsi, Manzini, and Maranesi (2014) developed a decision making system for the design, management, and control of warehousing systems with solid architecture. Guo, Ngai, Yang, and Liang (2015) proposed radio frequency identification-based intelligent decision system to handle production monitoring and scheduling in a distributed manufacturing environment. A recently developed decision support system for purchasing management realized that the capital-constrained retailer's purchase timing, quantity and financing decisions are necessary for seasonal products (Shi et al., 2017). To be accurate, none of the mentioned models could create a fuzzy group decision system with aggregation of QFD and MADM tools. The present paper proposes GRA as a strategic MADM tool to be logically integrated with QFD. The wide ranges of studies are presented in the literature review section in order to compare them with our proposed model.

The expert's judgments on the assessment of logistic factors in the supply chain such as environmental, economic, and social factors in decision-making processes always involve imprecise and vague information. Expert's linguistic assessments of logistic factors generally involve this kind of uncertainty. Our proposed intelligent framework handles the vagueness and imprecise-ness through the fuzzy set techniques.

Section 2 presents some evidences from the literature, presentation of fuzzy interval and fuzzy QFD and justification of the proposed method. It also discusses the research contribution and application of decision making system in a supply chain project. The mathematical relations, definitions and formulas in order to compose the proposed model are delivered as Section 3. In Section 4, an extended version of fuzzy QFD with interval valued and integration of grey relational analysis is formulated. A case study is offered to test and validate the model along with a sensitivity analysis in Section 5. Conclusion will be highlighted as Section 6.

2. Literature review

The literature review presents several sections to present the existing decision models including QFD, GRA and other extended tools, to compare their performance and finally filling the existing gap by the proposed model in this study.

2.1. QFD integrated technologies

Quality function deployment was developed as a practical problem-solving technique for executing product design and planning to meet clients need and expectations (Onar, Büyüközkan, Öztayşi, & Kahraman, 2016). The model was initiated at Mitsubishi Company and then Toyota and other Japanese companies adopted it to facilitate product development process. It helps to realize customers' needs and meet those needs within their current ability and resources (Liang, 2010). The core of the QFD is the house of quality (HoQ) matrix which demonstrates a bridge between engineering characteristics and customers' requirements (Büyüközkan & Çifçi, 2012; Ignatius, Rahman, Yazdani, Šaparauskas, & Haron, 2016; Tavana et al., 2017). In a decision making system, sometimes designing that bridge contains complex variables and subjective preferences. May other approaches can aid us at this. This is a subject that maters investigation to develop an integrated decision formula.

Fu, Zhu, and Sarkis (2012) depicted that gray system theory can achieve satisfactory outcomes using a small amount of data or with a large amount of variability in the factors. Gray relational analysis originates from gray system theory which mainly is incorporated to ambiguity and uncertainty in particular decision situations (Deng, 1989; Kuo, Yang, & Huang, 2008; Olson & Wu, 2006). GRA was successfully applied in solving a variety of MADM problems, such as the supply chain (Hashemi, Karimi, & Tavana, 2015; Huang, Chiu, & Chen, 2008; Morán, Granada, Míguez, & Porteiro, 2006; Rajesh & Ravi, 2015), material and mechanical engineering for optimization of machining parameters (Lin, Chang, & Chen, 2006; Sarıkaya & Güllü, 2015), etc. Among them, Yang and Chen (2006) addressed the AHP and GRA to evaluate suppliers considering qualitative and quantitative criteria in an outsourcing manufacturing organization. AHP was used to deliver the weights of the decision factors and no integration to the GRA happened. Li, Yamaguchi, and Nagai (2008) proposed a rough set GRA to validate supplier's performance to deal with uncertain information. To introduce a model for evaluating internal barriers of automobile sector, Xia, Govindan, and Zhu (2015) unified DEMATEL tool with GRA to consider factors relationships with each other, and finally generate weights of barriers. Again like above AHP case, there was not any kind of integration.

The dynamism of gray theory is certified through empirical examples. These studies indicated that future customer needs an effective prediction perspective which is possible through logical combination of the quality function deployment and GRA for evaluating and adjusting the importance of customer requirement (Golmohammadi & Mellat-Parast, 2012; Wu, 2006). Song, Ming, and Han (2014) investigated on the development of QFD model by rough set theory and GRA. The approach utilizes GRA in the structuring an analytical framework and discovering required information of the data interactions. In addition, they reported customer relation matrix analysis can be composed using GRA method. In this case, also there was not any evidence to show that GRA acts as a function in QFD. Yeh and Chen (2014) applied the Kano model and gray relational analysis with the quality function deployment to improve service quality in nursing homes in Taiwan. The literature review of MADM intelligent systems suffers from a robust combination of QFD and GRA and we can claim that

Table 1
Fuzzy QFD studies and applications.

Author (s)	Methodology used (Sole/Combined)	Application area
Yang et al. (2003)	Fuzzy QFD	Design of building
Bevilacqua et al. (2006)	Fuzzy QFD	Supplier evaluation
Bottani and Rizzi (2006)	Fuzzy QFD	Logistics and service management in Italian company
Chen, Fung, and Tang (2006)	Fuzzy weighted average in the fuzzy expected value operator	Flexible manufacturing
Chen and Ngai (2008)	Fuzzy QFD	Improvement of the design of a motor car
Su and Lin (2008)	Fuzzy QFD and TRIZ	Creative solutions for service quality improvement
Celik et al. (2009)	F-AHP & fuzzy axiomatic design	Shipping investment decisions in maritime transportation
Liang (2010)	Fuzzy QFD	Service management requirement
Vinodh and Kumar (2011)	Fuzzy QFD	Quality management with lean practices
Lee and Lin (2011)	Fuzzy Delphi, fuzzy interpretive structural modeling & Fuzzy ANP	Thin film transistor liquid crystal display company
Lin, Huang, and Yeh (2012)	Fuzzy group decision making & Fuzzy QFD	Development of service innovation
Yang et al. (2013)	Fuzzy QFD	Design for remanufacturing in automobile industry
Ayağ et al. (2013)	Multi objective Mathematical programming	Supply chain strategy in Turkish dairy industry
Wang (2014)	Fuzzy relative preference relation, fuzzy QFD in fuzzy MCDM	–
Zaim et al. (2014)	ANP and Fuzzy QFD	Developing equipment to squeeze the polyethylene pipes to stop the gas flow
Jamalnia et al. (2014)	fuzzy QFD and fuzzy goal programming	Facility allocation problem
Büyüközkan and Güleryüz (2015)	Group decision making & fuzzy QFD	IT Planning in Collaborative Product Development in Turkish software company
Ma et al. (2016)	Fuzzy FMEA, Fuzzy permanent function	Identification of the to-be-improved components for the operation device of crawler crane
Onar et al. (2016)	New hesitant fuzzy QFD based on AHP & TOPSIS	Computer workstation selection
Lima-Junior and Carpinetti (2016)	MCDM and F-QFD	Supplier selection in automotive company
Arsenyan and Büyüközkan (2016)	Fuzzy-QFD, fuzzy axiomatic design, fuzzy rule-based systems	Collaborative product development in IT sector
Haq and Boddu (2017)	TOPSIS, AHP	Identify the appropriate agile enablers in Indian food processing industry

none of the aforementioned works implemented a gray correlation index to the other tools.

2.2. Fuzzy QFD and MADM theories

Application of fuzzy QFD in MADM based research is vast. Practitioners in various areas have elaborated the employment of fuzzy QFD as seen in Table 1 (Chen & Ngai, 2008; Yang, Ong, & Nee, 2013). One of the first studies was reported by Yang, Wang, Dulaimi, and Low (2003) in buildings design. Bevilacqua, Ciarapica, and Giacchetta (2006) and Bottani and Rizzi (2006) used fuzzy QFD in the supply chain and supplier evaluation. Their effort improved supplier selection process in logistics management. Celik, Cebi, Kahraman, and Er (2009) identified a combined model of fuzzy QFD and fuzzy AHP in shipping investment decisions. This is a classical approach to implement fuzzy AHP and obtain the decision criteria weights to be used in fuzzy QFD. This is a very simple function and is regarded as an initial capability of MADM theories. Although Zhai, Khoo, and Zhong (2010) designed a rough based fuzzy QFD expert system, the extended model deals with a different uncertainty and is distinct to our approach in this paper. Ayağ, Samanlioglu, and Büyüközkan (2013) conducted a model which includes fuzzy QFD to initiate a development program for supply chain requirements in the dairy industry in Turkey. This research did not provide an integrated model of QFD. Ma, Chu, Xue, and Chen (2016) introduced a mixture of fuzzy FMEA and fuzzy QFD to identify the to-be-improved components for the operation device of crawler crane. Jamalnia, Mahdiraji, Sadeghi, Hajiagha, and Feili (2014) overcome the difficulty of a facility location problem with utilization of fuzzy QFD to decide the best international facility location. Then, the outputs are applied for a goal programming allocation problem. Büyüközkan and Güleryüz (2015) focused on IT planning in a product development program in a Turkish Software Company without integration of any concept to the QFD. Zaim et al. (2014) applied a fuzzy QFD and ANP to optimally design a product development plan. The authors indicate the QFD to identify customer needs and ANP to rank technical characteristics of a product. It is figured out that QFD delivers relevant weights for ANP analysis and therefore it does not propose an integrated decision structure. In Indian food processing industry, Haq and Boddu (2017) demonstrated the appropriate agile enablers by using AHP, TOPSIS, and fuzzy QFD. A quick review to all of the studies provided in Table 1, you can easily see the growing importance of fuzzy QFD model. This table announces that there is no study assigned to fuzzy QFD and GRA. Moreover, our proposed model defines a new structure to integrate the QFD and gray relation index that was scarce in the literature. List of the implemented works which are relevant to fuzzy QFD is given in Table 1.

2.3. Research problem and justification

QFD method is integrated with fuzzy sets to increase the preciseness and performance as Table 1 shows. Researchers discussed the advantages of QFD in order to extend and improve its more efficient models which are flexible and adjustable to different applications. In general, extensions of MADM techniques to the QFD enhance the quality of the decision making (Hashemi et al., 2015; Yazdani, Chatterjee et al., 2017; Zaim et al., 2014). It is noticed here that our purpose of integrating is not just to use the outputs of a method as inputs for another method. We extend a method through taking the benefit of a concept or tool reasonably in order to improve the results and decrease computation. The paper introduces a new form of the QFD with the aid of the interval valued fuzzy sets and gray relational index with respect to the following contributions:

1 In QFD tool, HoQ matrix has the main responsibility to convert customer variables to technical factors. It sometimes gets difficult to adjust this matrix and integrate it to other tools. However, in this research we suppose HoQ as an MADM structure with customer requirements (CR) and technical factors (since now it is called supply chain drivers). It is entirely as we have alternatives and criteria in a typical MADM problem. This is the transformation that enhances the dynamism of the QFD and enables DMs to extend and integrate other tools faster, easier and more convenient.
2 The integration of fuzzy QFD and MADM tools is capable of extracting uncertainty and vagueness in customer behavior when such decisions become complex (Hsu, Chang, & Luo, 2017; Yazdani, Zarate, Coulibaly, & Zavadskas 2017). The proposed QFD based GRA with the usage of interval-valued fuzzy values suggests the variety of preference judgment to the decision experts in which they feel less complexity and can count on the reliability of the outcomes. The literature could not bring any similar structure to coherently release an intelligent decision-making model.
3 In an interval-valued fuzzy environment, the huge volume of computation is a deal and Euclidean distance measure makes it difficult for decision makers to obtain the solution. This drawback is addressed using gray relational analysis. The gray relational coefficient is attached to the HoQ matrix to measure the distance of potential solutions from ideal solutions. Utilization of grey correlation coefficient in QFD evaluation process releases flexibility in MADM and enables users to make quicker and more intelligent decisions.

2.4. Application in supply chain research project

Risk and **U**ncertain **C**onditions for **A**griculture **P**roduction **S**ystems (RUC-APS, 2016) is a European Commission project which aims to support advanced knowledge in agricultural production and supply chain process. The project is entitled as “Enhancing and implementing Knowledge based ICT solutions within high Risk and Uncertain Conditions for Agriculture Production Systems” . This project gets benefit from the development of a high impact research project in order to integrate real-life based agriculture requirements, alternative land management scenarios. It supports innovation in the development of agriculture production systems, operations, logistics and supply chain management and the impact of these systems over the end-users and customers. RUC-APS models intelligent decision systems to facilitate a way to achieve a sustainable agriculture supply chain under risk and uncertainty. It contains international academic and non-academic partners coming from seven countries (UK, Spain, France, Poland, Chile, Argentina and Italy). The project domain covers sort of theoretical studies, investigation as well technical achievements. Part of the project is associated to some scientific objectives to model and optimize innovative transport-logistics solutions of horticulture products across the full value chain structure. Under domain of RUC-APS, this paper is assigned to measure supply chain indicators with the aid of the proposed group fuzzy decision support system.

3. Definitions, materials and models

This section provides required materials and methods in order to propose our integrated model. At first, QFD method is introduced. Then grey relational analysis tool is presented along with relevant formulas and mathematical computations. Finally, operations and arithmetic relations assigned to fuzzy interval valued are interpreted.

3.1. QFD structure

QFD (Büyüközkan & Cifci, 2013; Yazdani, Hashemkhani Zolfani, & Zavadskas, 2016) is an engineered technique, to transforms the requirements of customers into specific and measurable characteristics of the product design. QFD transformations are handled by a matrix displaying the relationships between the customers’ preferences and the operational measures. This matrix is usually recognized to express the relationship between the CRs (WHATs) and the technical measures (HOWs) (Ignatius et al., 2016). The general steps for the implementation of the QFD model are as follow:

Step 1 – To identify the WHATs and the HOWs.

Step 2 – To assign priority weights to the CRs.

Step 3 – To link WHATSs to the HOWs in order to build a relationship matrix (using the knowledge of the decision maker using a four-point scale (For more information, see Tavana et al. 2016).

Step 4 – To reveal the priority of technical criteria, suppose that n technical criteria are going to satisfy m customer requirements. In this manner, the significance of technical factors $w_j$while $j = 1$, 2, .., n is attained as follows:

$$w_j = \sum_{i=1}^{m} R_{ij} \times T_i \tag{1}$$

where $j = 1$, 2, .., n and $i = 1$, 2, .., m , R_{ij} denotes the relationship matric between CRs and technical criteria and T_i indicates importance of CRs. The normalized weight of each technical criterion is achieved as this:

$$\dot{w}_j = \frac{w_j}{\sum_{j=1}^{n} w_j} \tag{2}$$

3.2. Grey relational analysis

Grey relation analysis can be announced to capture the correlations between the references (desired) alternative and other compared alternatives in a system. The methodology in GRA aids the MADM problems by combining the entire range of performance attribute values being considered for every alternative into one single value. This function leads to reduction of the original problem to a single attribute decision making problem, so those alternatives with multiple attributes can be compared effectively after the GRA process (Kuo, Liang, & Huang, 2006).

GRA method includes some steps as grey relational generation, reference sequence definition, grey relational coefficient computation and grey relational grade formation (Zhang, Jin, & Liu (2013). The computation process of the GRA method is briefly introduced as follows:

Let $X = \{x_0, x_1, x_2, \ldots, x_i, \ldots x_m\}$ be a sequence (alternative) set. x_0 expresses the referential alternative and x_i refers to the compared alternative. Suppose x_{0j} and x_{ij} are the respective values at criterion j, while $j = 1$, 2, …., n for x_0 and x_i . The grey relation coefficient $\gamma(x_{0j}, x_{ij})$ of the alternatives at criterion j can be obtained by

$$\gamma\left(x_{0j}, x_{ij}\right) = \frac{\min_i \min_j \Delta_{ij} + \zeta \max_i \max_j \Delta_{ij}}{\Delta_{ij} + \zeta \max_i \max_j \Delta_{ij}}, \tag{3}$$

where $\Delta_{ij} = |x_{0j} - x_{ij}|$, and ζ is the resolving coefficient which usually considered 0.5, $\zeta \in [0, 1]$. Now the grey relational grade must be computed:

$$\gamma(x_0, x_i) = \sum_{j=1}^{n} w_j \gamma\left(x_{0j}, x_{ij}\right), \sum_{j=1}^{n} w_j = 1 \tag{4}$$

while w_j denotes the weight assigned to each criterion j.

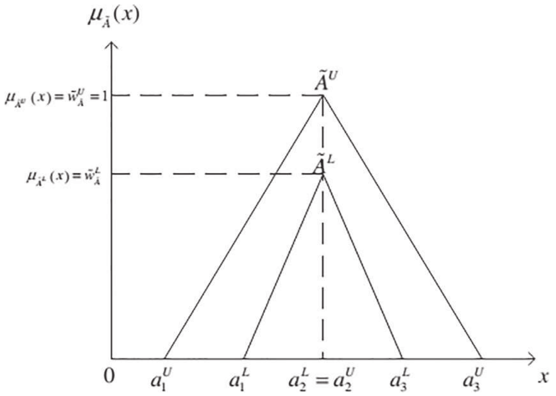

Fig. 1. An interval-valued triangular fuzzy number.

3.3. *Interval valued fuzzy sets and arithmetic operations*

In fuzzy sets theory, it is often tough for a decision expert to precisely quantify his/her opinion as a number in interval [0, 1]. Interval-valued fuzzy numbers efficiently address the ambiguity existing in the available information, as well as the essential fuzziness in human judgment and preference. It is more suitable to represent this degree of certainty by an interval value. The benefit of interval-valued fuzzy sets is to provide more flexibility to represent the imprecise/vague information resulting from a lack of data (Ashtiani, Haghighirad, Makui, & ali Montazer, 2009; Kahraman, Öztayşi, Sarı, & Turanoğlu, 2014; Vahdani, Hadipour, Sadaghiani, & Amiri, 2010). Primarily Gorzalczany (1989) and Turksen (1996) studied on interval extension of fuzzy sets. Wang and Li (1998) introduced interval-valued fuzzy numbers (IVFN) and extended operations.

We consider extension of QFD by using interval-valued fuzzy sets. A typical interval-valued fuzzy set $\tilde{A}$ defined on $(\infty, -\infty)$ is supposed by Gorzalczany (1989) and given by

$$\tilde{A} = \left\{x, \left[\mu_{\tilde{A}^L}(x), \mu_{\tilde{A}^U}(x)\right]\right\}, x \in (\infty, -\infty),$$
$$\mu_{\tilde{A}^L}, \mu_{\tilde{A}^U} : (\infty, -\infty) \to [0, 1]\ ,$$
$$\mu_{\tilde{A}}(x) = \left[\mu_{\tilde{A}^L}(x), \mu_{\tilde{A}^U}(x)\right], \mu_{\tilde{A}^L}(x) \le \mu_{\tilde{A}^U}(x), \forall x \in (\infty, -\infty),$$

where $\mu_{\tilde{A}^L}(x)$ and $\mu_{\tilde{A}^U}(x)$ are the lower and upper limits of the degree of membership.

Definition 1. An interval-valued triangular fuzzy number (Fig. 1) can be depicted by $\tilde{A} = [\tilde{A}^L_x, \tilde{A}^U_x] = [(a^L_1, a^L_2, a^L_3; \hat{w}^L_{\tilde{A}}), (a^U_1, a^U_2, a^U_3; \hat{w}^U_{\tilde{A}})]$, where $\tilde{A}^L$ and $\tilde{A}^U$ states the lower and upper values of an interval-valued triangular fuzzy number and $\mu_{\tilde{A}}(x)$ is the membership function (Yao & Lin, 2002). In this stage, the membership function defines the degree in which an event x may be a member of $\tilde{A}$; $\mu_{\tilde{A}^L}(x) = \hat{w}^L_{\tilde{A}}$ and $\mu_{\tilde{A}^U}(x) = \hat{w}^U_{\tilde{A}}$ are the lower and upper membership functions, respectively. As seen in Fig. 1, the operations among interval-valued fuzzy numbers can be explained as follows:

1.1. If $\tilde{A}^L = \tilde{A}^U$, then we call $\tilde{A}$ a generalized triangular fuzzy number.

1.2. If $a^L_1 = a^U_1 = a^U_2 = a^L_2 = a^L_3 = a^U_3$ and also $\hat{w}^U_{\tilde{A}} = \hat{w}^L_{\tilde{A}}$, then we call $\tilde{A}$ a crisp value.

1.3. If $\hat{w}^U_{\tilde{A}} = \hat{w}^L_{\tilde{A}}$ and $a^U_2 = a^L_2$, an interval-valued triangular fuzzy number $\tilde{A}$ is introduced as $\tilde{A} = [\tilde{A}^L_x, \tilde{A}^U_x] = [(a^U_1, a^L_1), (a^L_2 = a^U_2), (a^L_3, a^U_3;)]$.

It is supposed that two triangular interval-valued fuzzy numbers can be expressed based on definition (1.3.) as $\tilde{A} = [(a^U_1, a^L_1), (a_2), (a^L_3, a^U_3;)]$ and $\tilde{B} = [(b^U_1, b^L_1), (b_2), (b^L_3, b^U_3;)]$, respectively. Then, the arithmetic relation between them can be interpreted as below (Vahdani et al., 2010):

1.4. Addition of IVFNs:

$$\tilde{A} + \tilde{B} = \left[\left(a^U_1 + b^U_1, a^L_1 + b^L_1\right), a_2 + b_2, \left(a^U_3 + b^U_3, a^L_3 + b^L_3\right)\right]. \tag{5}$$

1.5. Subtraction of two IVFNs:

$$\tilde{A} - \tilde{B} = \left[\left(a^U_1 - b^U_3, a^L_1 - b^L_3\right), a_2 - b_2, \left(a^U_3 - b^U_1, a^L_3 - b^L_1\right)\right]. \tag{6}$$

1.6. Multiplication of IVFNs:

$$\tilde{A} \times \tilde{B} = \left[\left(a^U_1 \times b^U_1, a^L_1 \times b^L_1\right), a_2 \times b_2, \left(a^U_3 \times b^U_3, a^L_3 \times b^L_3\right)\right]. \tag{7}$$

1.7. General division of IVFNs:

$$\tilde{A} \div \tilde{B} = \left[\left(a^U_1 \div b^U_3, a^L_1 \div b^L_3\right), a_2 \div b_2, \left(a^U_3 \div b^U_1, a^L_3 \div b^L_1\right)\right]. \tag{8}$$

Definition 2. Linguistic values are used when the structure of decision problem is ill-defined and a complex decision model is running. These values then can be expressed quantitatively as the conventional fuzzy numbers. In this paper, decision variables as well as criteria weights, are represented by linguistic variables. The concept of a linguistic variable is much recommended in dealing with situations that are too complex to be reasonably described in conventional quantitative expressions (Zadeh, 1975). Interval-valued fuzzy sets can generate more flexibility to represent the imprecise/vague information (Ashtiani et al., 2009; Bigand & Colot, 2010).

4. An extension of IVF-QFD and grey relational coefficient

This section provides a new model for quality function deployment based on combining the concepts of GRA and interval-valued fuzzy sets. This model controls technical criteria interaction on final outputs of QFD through a distance based approach that a grey relational coefficient also generates innovative measure particularly assigned to ideal solutions. It is perceived that through interval-valued fuzzy sets, the proposed model is strong enough to deal with vague information/data from customer attitudes. In this paper, we are going to propose QFD as a MADM tool and try to extend it by IVF approach. In fuzzy QFD problems as a fuzzy MADM approach, performance rating values and relative weights are usually characterized by fuzzy numbers (Li, Jin, and Wang 2014). A fuzzy number is a convex fuzzy set, defined by a given interval of real numbers, each with a membership value between 0 and 1 (Ashtiani et al., 2009; Zadeh, 1975).

Let $\tilde{X} = [\tilde{x}_{ij}]_{n \times m}$be a fuzzy QFD matrix for a design or evaluation process in which T_1,T_2,....., T_n are n possible criteria and c_1,c_2,....., c_m are m customer requirements (CRs). Therefore, the rating and interrelation between each T_i with respect to criterion $c_j$is declared as $\tilde{x}_{ij}$. In this case, $\tilde{w}_j$ is counted as weights of each CR. In an interval valued fuzzy environment with triangular numbers, $\tilde{x}$ can be represented as $\tilde{x} = \{(x_1, x_2, x_3),\ \ (\dot{x}_1, x_2, \dot{x}_3)\ .$

Then $\tilde{x}$ can be demonstrated as $\tilde{x} = [(x_1, \dot{x}_1); x_2; (\dot{x}_3, x_3)]$. The development of interval-valued fuzzy numbers pretends an offer to the decision makers (DMs) to define lower and upper bounds values in terms of interval for main QFD elements and also weights of each criterion. In a group QFD process with k experts, the rating for house of quality matrix and importance weights of the criteria are obtained as:

$$\tilde{x}_{ij} = \frac{1}{k}\left[\tilde{x}^1_{ij} + \tilde{x}^2_{ij} + \ldots + \tilde{x}^k_{ij}\right] \tag{9}$$

$$\tilde{w}_j = \frac{1}{k}\left[\tilde{w}^1_j + \tilde{w}^2_j + \ldots + \tilde{w}^k_j\right] \tag{10}$$

These two equations explain how the opinion of each expert in QFD can be incorporated and aggregated. Clearly the output must be an IVFN. The proposed algorithm to develop an IVF-QFD can be released as follows:

Given $\tilde{x}_{ij} = [(a_{ij}, \dot{a}_{ij}); b_{ij}; (\dot{c}_{ij}, c_{ij})]$, then the normalized matric should be calculated as:

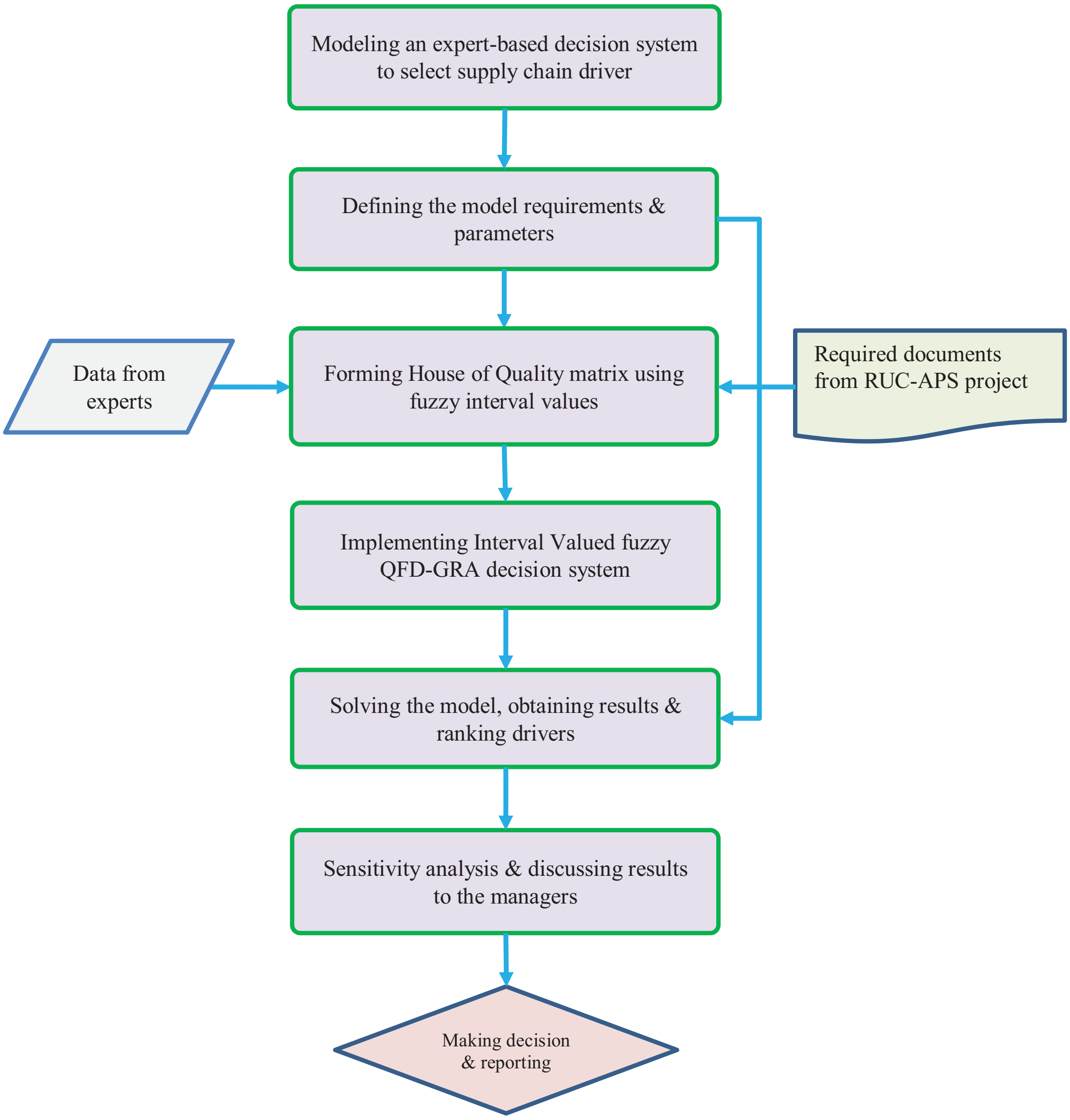

Fig. 2. The proposed algorithm for IVF QFD decision system.

Table 2
Fuzzy linguistic terms for rating.

Linguistic labels	Triangular fuzzy interval values
Very poor (VP)	[(0,0),0,(1,1.5)]
Poor (P)	[(0,0.5),1,(2.5,3.5)]
Moderately poor (MP)	[(0,1.5),3,(4.5,5.5)]
Fair (F)	[(2.5,3.5),5,(6.5,7.5)]
Moderately good (MG)	[(4.5,5.5),7,(8,9.5)]
Good (G)	[(5.5,7.5),9,(9.5,10)]
Very good (VG)	[(8.5,9.5),10,(10,10)]

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{n\times m}$$

$$\tilde{r}_{ij} = \left[\left(\frac{a_{ij}}{c_j^*}, \frac{\dot{a}_{ij}}{c_j^*}\right); \frac{b_{ij}}{c_j^*}; \left(\frac{\dot{c}_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right)\right], i = 1, 2, .., m, \; j \in B \tag{11}$$

$$\tilde{r}_{ij} = \left[\left(\frac{a_j^-}{\dot{a}_{ij}}, \frac{a_j^-}{a_{ij}}\right); \frac{a_j^-}{b_{ij}}; \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{\dot{c}_{ij}}\right)\right], = 1, 2, .., m, \; j \in C \tag{12}$$

$$c_j^* = \max c_{ij}, \; j \in B$$
$$a_j^- = \min \dot{a}_{ij}, \; j \in C$$

Where B is the benefit criteria set, and C is the cost criteria set.

The above formulas assure the property, the elements of normalized triangular IVFN belong to [0,1]. We represent an interval-valued triangular fuzzy number as

$\tilde{r}_{ij} = \left[\left(\ell_{ij}^1, \ell_{ij}^2\right), m_{ij}, \left(r_{ij}^2, r_{ij}^1\right)\right]$

Now, two referential sequences of positive and negative ideas solutions (A^*, A^-) must be clarified by the equations:

$$A^* = \left(\tilde{r}_{01}^*, \tilde{r}_{02}^*, \ldots, \tilde{r}_{0m}^*\right) \tag{13}$$

$$A^- = \left(\tilde{r}_{01}^-, \tilde{r}_{02}^-, \ldots, \tilde{r}_{0m}^-\right) \tag{14}$$

where $\tilde{r}_{0j}^* = [(1, 1), 1, (1, 1)]$ and $\tilde{r}_{0j}^- = [(0, 0), 0, (0, 0)]$, $j = 1, 2, .., n$

As mentioned previously, the paper combines a grey relational coefficient approach into the QFD. At this stage, the weighted grey relational coefficient (WGRC) values between each criterion (in this study it is called supply chain criteria) and other criteria should be determined by the following formulas:

Table 3
Linguistic terms for the importance of each criterion.

Linguistic labels	Triangular fuzzy interval values
Very low (VL)	[(0,0),0,(0.1,0.15)]
Low (L)	[(0,0.05),0.1,(0.25,0.35)]
Medium low (ML)	[(0,0.15),0.3,(0.45,0.55)]
Medium (M)	[(0.25,0.35),0.5,(0.65,0.75)]
Medium high (MH)	[(0.45,0.55),0.7,(0.8,0.95)]
High (H)	[(0.55,0.75),0.9,(0.95,1)]
Very high (VH)	[(0.85,0.95),1,(1,1)]

$$D^* = \gamma\left(\tilde{r}^*_{0j}, \tilde{r}_{ij}\right) = \left(\frac{\min_i \min_j \Delta\left(\tilde{w}_j \tilde{r}^*_{0j}, \tilde{w}_j \tilde{r}_{ij}\right) + \zeta \max_i \max_j \Delta\left(\tilde{w}_j \tilde{r}^*_{0j}, \tilde{w}_j \tilde{r}_{ij}\right)}{\Delta\left(\tilde{r}^*_{0j}, \tilde{r}_{ij}\right) + \zeta \max_i \max_j \Delta\left(\tilde{r}^*_{0j}, \tilde{r}_{ij}\right)}\right) \tag{15}$$

$$D^- = \gamma\left(\tilde{r}^-_{0j}, \tilde{r}_{ij}\right) = \left(\frac{\min_i \min_j \Delta\left(\tilde{w}_j \tilde{r}^-_{0j}, \tilde{w}_j \tilde{r}_{ij}\right) + \zeta \max_i \max_j \Delta\left(\tilde{w}_j \tilde{r}^-_{0j}, \tilde{w}_j \tilde{r}_{ij}\right)}{\Delta\left(\tilde{r}^-_{0j}, \tilde{r}_{ij}\right) + \zeta \max_i \max_j \Delta\left(\tilde{r}^-_{0j}, \tilde{r}_{ij}\right)}\right) \tag{16}$$

where $\tilde{w}_j$ represents the fuzzy weights of supply chain criteria and;

$$\Delta\left(\tilde{r}^*_{0j}, \tilde{r}_{ij}\right) = \left|\tilde{r}^*_{0j} - \tilde{r}_{ij}\right| \tag{17}$$

Once the weighted distances are made, it is required to obtain the expected score of fuzzy interval in order to continue computation and achieve meaningful outcomes. To compute IVFN expected score $E[S]$degree for an interval number like $[(a, b), c, (d, e)]$ (Wu & Chiclana, 2012), the following relation must be regulated:

$$E[S] = \left[\frac{(1-c) \times (d-a) + c \times (e-b) + 1}{2}\right] \tag{18}$$

As before denoted Δ_{ij} realize distance and ζ is the resolving coefficient $\zeta \in [0, 1]$. $\Delta(\tilde{r}^-_{0j}, \tilde{r}_{ij})$ is obtained by the same in (17). Here, $\zeta = 0.5$ is considered. In Eqs. (15) and (16), D^* and D^- produce the positive ideal GRC and negative ideal GRC, respectively. Using Eq. (18), the expected values are achieved. The final ranking of technical factors can be detected based on computation of relative coefficient this:

$$c = \frac{D^-}{D^- + D^*} \tag{19}$$

The highest value in Eq. (19) delivers best criterion for the proposed QFD model. In summary the IVF-QFD based on grey relational analysis can be interpreted by the steps below:

Step 1 – Forming QFD team and determining list of effective criteria and customer/stakeholder requirements.

Step 2 – Rating each criterion with respect to each customer attitude and build a house of quality matrix using triangular fuzzy interval values in Table 2. This step produces a performance matrix.

Step 3 – Determine the weights of criteria through fuzzy linguistic labels in Table 3. These weights must be aggregated using Eq. (10) and they are utilized for the evaluation of criteria in final steps.

Step 4 – Aggregating performance matrix by Eq. (9) and normalizing it using Eqs. (11) and (12).

Step 5 – Calculating WGRC for positive and ideal solutions using Eqs. (15)–(16). The IVFN expected score degree for an interval number is obtained using Eq. (18).

Table 4
Initial decision maker's relationship matrix.

DM_1	T_1	T_2	T_3
C_1	VP	G	MP
C_2	MG	MG	F
C_3	G	MP	G
C_4	G	VG	F
C_5	F	MG	MG
C_6	G	G	F
weight	**M**	**M**	**H**
DM_2			
C_1	P	G	G
C_2	F	G	MG
C_3	G	MG	MP
C_4	G	G	F
C_5	F	MG	MG
C_6	G	G	F
weight	**ML**	**MH**	**M**
DM_3			
C_1	MG	MG	MP
C_2	F	F	G
C_3	MP	F	G
C_4	G	F	F
C_5	MG	F	MP
C_6	G	G	G
weight	**H**	**M**	**L**

Step 6 – Measuring relative closeness score (Eq. (19)) to produce criteria ranking. Then each criterion can be ranked accordingly.

5. Results

5.1. Case study summary and decision problem solution

The role of logistic management in a supply chain is very considerable in order to support a stable production process, satisfy customer and stakeholders and meet demands. Within the domain of RUC-APS, while an agriculture system requires a systematic logistic performance assessment, it is convincingly a favor to establish such kind of intelligent decision making models. In this way, we have proposed a case study assigned to the French association of supply chain and logistics (ASLOG). This is a reference organization for many companies to gather, categorize and organize logistic and transportation systems. It is always encouraged to involve logistics and supply chain directions in the top level of the management decisions. ASLOG is a multi-activity association with over four hundred companies and network which stands as the leading French network of supply chain and logistics professionals. The objective is to provide forward-looking visions, to generate standards and qualifications, to measure and evaluate logistics indicators, and ultimately to produce research dissemination in partnership with the academic sector and benchmark best practices (www.aslog.org). For this research, the essential customer variables and the corresponding technical criteria are interpreted and introduced. The proposed algorithm for this case study is presented in Fig. 2. To evaluate the performance of logistic indicators in the supply chain, two approaches have been chosen by a committee of experts. We consider the environment, social and economic issues in the perspective and guidelines of stakeholders and external customers. The main factors include environmental indicators(T_1), economic downturn(T_2), and social and cultural complains(T_3). Each of those factors can then be subsided to lower levels. For example, one who gives judgment on environmental factors must consider natural disaster and political instability, emission of pollution & hazardous materials, re-cycling process etc. To the social aspects, social responsibility, commitment to health of employee, participating in social and cultural events, of-

Table 5
The aggregated matric and weights from DMs.

	T_1	T_2	T_3
C_1	[(1.5,2),2.7,(3.84,4.8)]	[(5.17,6.84),8.4,(9,9.84)]	[(1.84,3.5),5,(6.17,7)]
C_2	[(3.17,4.17),5.7,(7,8.17)]	[(4.17,5.5),7,(8,9)]	[(4.17,5.5),7,(8,9)]
C_3	[(3.7,5.5),7,(7.8,8.5)]	[(2.4,3.5),5,(6.4,7.5)]	[(3.7,5.5),7,(7.8,8.5)]
C_4	[(5.5,7.5),9,(9.5,10)]	[(5.5,6.84),8,(8.7,9.17)]	[(2.5,3.5),5,(6.5,7.5)]
C_5	[(3.17,4.17),5.7,(7,8.17)]	[(3.8,4.8),6.4,(7.5,8.9)]	[(3,4.17),5.7,(6.84,8.17)]
C_6	[(5.5,7.5),9,(9.5,10)]	[(5.5,7.5),9,(9.5,10)]	[(3.5,4.8),6.4,(7.5,8.4)]
Weights	[(0.27,0.41),0.57,(0.68,0.77)]	[(0.32,0.42),0.57,(0.7,0.82)]	[(0.27,0.38),0.5,(0.62,0.7)]

Table 6
Interval valued fuzzy normalized matrix.

	T_1	T_2	T_3
C_1	[(0.15,0.2),0.27,(0.39,0.49)]	[(0.52,0.7),0.85,(0.9,1)]	[(0.18,0.36),0.5,(0.6,0.7)]
C_2	[(0.35,0.46),0.63,(0.78,0.9)]	[(0.46,0.61),0.78,(0.89,1)]	[(0.46,0.6),0.78,(0.89,1)]
C_3	[(0.43,0.65),0.8,(0.92,1)]	[(0.27,0.41),0.59,(0.74,0.88)]	[(0.43,0.65),0.82,(0.92,1)]
C_4	[(0.55,0.75),0.9,(0.95,1)]	[(0.55,0.68),0.8,(0.87,0.917)]	[(0.25,0.35),0.5,(0.65,0.75)]
C_5	[(0.36,0.47),0.64,(0.8,0.92)]	[(0.43,0.54),0.7,(0.85,1)]	[(0.34,0.47),0.64,(0.77,0.92)]
C_6	[(0.55,0.75),0.9,(0.95,1)]	[(0.55,0.75),0.9,(0.95,1)]	[(0.35,0.48),0.64,(0.75,0.84)]

Table 7
The calculated distances from positive ideal point.

	T_1	T_2	T_3
C_1	[(0.5,0.6),0.72,(0.8,0.85)]	[(0,0.08),0.15,(0.3,0.47)]	[(0.28,0.37),0.5,(0.64,0.81)]
C_2	[(0.09,0.22),0.37,(0.53,0.65)]	[(0,0.11),0.22,(0.39,0.53)]	[(0,0.11),0.22,(0.39,0.53)]
C_3	[(0,0.07),0.17,(0.35,0.57)]	[(0.11,0.25),0.41,(0.59,0.72)]	[(0,0.078),0.17,(0.35,0.56)]
C_4	[(0,0.05),0.1,(0.25,0.45)]	[(0.08,0.14),0.2,(0.31,0.45)]	[(0.25,0.35),0.5,(0.65,0.75)]
C_5	[(0.07,0.2),0.36,(0.52,0.64)]	[(0,0.15),0.28,(0.45,0.57)]	[(0.075,0.22),0.35,(0.52,0.66)]
C_6	[(0,0.05),0.1,(0.25,0.45)]	[(0,0.05),0.1,(0.25,0.45)]	[(0.17,0.25),0.37,(0.51,0.65)]

fering safe and durable product, and sustainable production may be considered. And as economic factors, availability and an affordable price can be minded.

The team of managers is composed of experts from the finance department, engineering department and supply chain executive. They believe that the information and data about performance of the supply chain can be gathered and then reported using fuzzy approach. The decision-making committee assesses the relation between factors from customer/stakeholder viewpoint (call it T_i) and supply chain internal criteria (c_j). The criteria relevant to the supply chain are based on the following items: quality (c_1); environmental management system (c_2); Supply chain and procurement flexibility (c_3); corporate social responsibility (c_4); Transportation service condition (c_5); and Financial stability (c_6).

The QFD committee members are labeled as DM_1, DM_2, and DM_3, respectively. Each member has to present his/her assessments based on the linguistic variables for rating each factor with respect to the criterion by a linguistic variable as depicted in Tables 2 and 3. Table 4 exhibits the relationship between each pair of supply chain factor and customer factors derived by three decision makers (DM). DMs are also asked to assign the weight of each customer.

The linguistic values of decision matrix and weights are converted to fuzzy interval values and then it is needed to accomplish the aggregation rules. The aggregated matrix including main decision matrix and weights for each customer factor can be obtained using fuzzy operations Eq. (5)) and then Eqs. (9) and ((10). Table 5 releases the aggregated QFD matrix based on triangular interval valued fuzzy numbers.

After obtaining the interval-valued fuzzy performance matrix and interval-valued fuzzy weight matrix, the interval valued fuzzy normalized matrix (as shown in Table 6) must be calculated using Eqs. (11) and (12).

Table 8
Weighted distances from positive and negative ideal points.

	$\Delta(\tilde{w}_j\tilde{r}^*_{0j}, \tilde{w}_j\tilde{r}_{ij})$	$\Delta(\tilde{w}_j\tilde{r}^-_{0j}, \tilde{w}_j\tilde{r}_{ij})$
C_1	[(0.21,0.43),0.75,(1.15,1.61)]	[(0.25,0.51),0.88,(1.3,1.7)]
C_2	[(0.02,0.18),0.45,(0.88,1.31)]	[(0.37,0.68),1.18,(1.7,2.21)]]
C_3	[(0.03,0.17),0.42,(0.87,1.43)]]	[(0.31,0.69),1.21,(1.71,2.18)]
C_4	[(0.09,0.21),0.42,(0.79,1.23)]	[(0.38,0.73),1.21,(1.65,2)]
C_5	[(0.04,0.23),0.54,(1,1.41)]	[(0.32,0.6),1.1,(1.61,2.18)]
C_6	[(0.04,0.13),0.3,(0.66,1.16)]	[(0.41,0.81),1.3,(1.77,2.17)]

Table 9
Expected values, grey distance and supply chain criteria ranking.

	Expected values $\Delta(\tilde{w}_j\tilde{r}^*_{0j}, \tilde{w}_j\tilde{r}_{ij})$	Expected values $\Delta(\tilde{w}_j\tilde{r}^-_{0j}, \tilde{w}_j\tilde{r}_{ij})$	D^*	D^-	c	ranking
C_1	1.0576	1.0825	0.8822	1	0.5313	1
C_2	0.9887	1.2832	0.9223	0.8961	0.4928	5
C_3	1.0061	1.2591	0.9119	0.9074	0.4988	3
C_4	0.9187	1.1587	0.9669	0.9578	0.4976	4
C_5	1.0406	1.2962	0.8918	0.8901	0.4995	2
C_6	0.8708	1.1772	1	0.9481	0.4867	6
Min	0.8708	1.0825				
Max	1.0576	1.2962				

Herein, two referential sequences of positive idea point $A^*$and negative ideal point A^- are determined as follows:

$$A^* = \{[(1,1),1,(1,1)],[(1,1),1,(1,1)],[(1,1),1,(1,1)]\}$$

$$A^- = \{[(0,0),0,(0,0)],[(0,0),0,(0,0)],[(0,0),0,(0,0)]\}$$

Currently, the distance between each reference sequence (positive ideal point and negative ideal point) and other compared alternatives can be calculated. The distance from positive ideal point is computed using Eq. (6) and is shown in Table 7. At the same time, weighted distance matrix from positive and negative ideal points

Table 10
Eight scenarios for supply chain drivers.

S(1)	T1	T2	T3	**S(3)**	T1	T2	T3	**S(5)**	T1	T2	T3	**S(7)**	T1	T2	T3
D1	VH	VL	VL	D1	VL	VL	VH	D1	VL	VH	VH	D1	VL	VL	VL
D2	VH	VL	VL	D2	VL	VL	VH	D2	VL	VH	VH	D2	VL	VL	VL
D3	VH	VL	VL	D3	VL	VL	VH	D3	VL	VH	VH	D3	VL	VL	VL
S(2)	T1	T2	T3	**S(4)**	T1	T2	T3	**S(6)**	T1	T2	T3	**S(8)**	T1	T2	T3
D1	VL	VH	VL	D1	VH	VH	VL	D1	VH	VL	VH	D1	VH	VH	VH
D2	VL	VH	VL	D2	VH	VH	VL	D2	VH	VL	VH	D2	VH	VH	VH
D3	VL	VH	VL	D3	VH	VH	VL	D3	VH	VL	VH	D3	VH	VH	VH

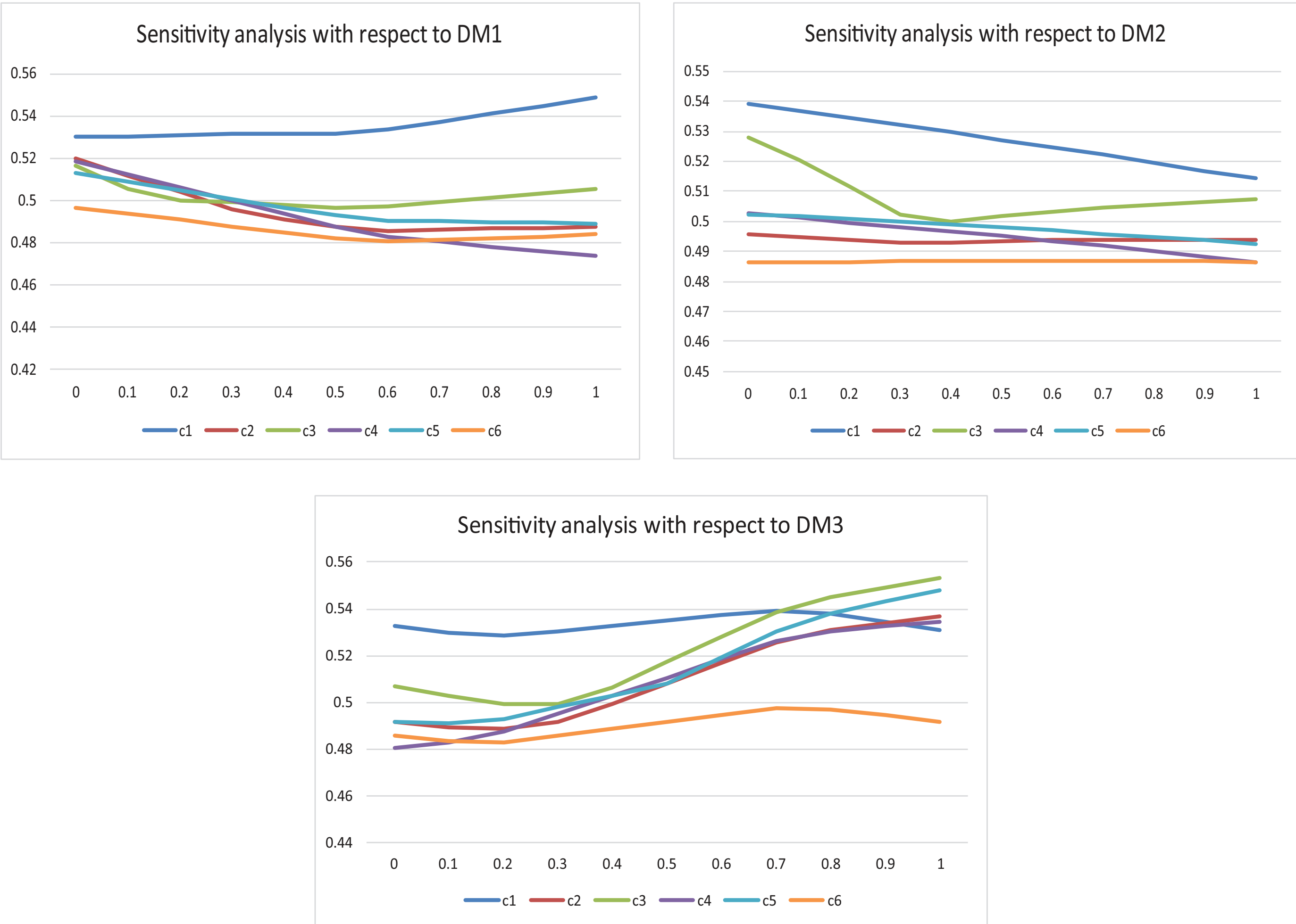

Fig. 3. Sensitivity analysis based on the changes in the weights of decision makers.

is attainable as well which is demonstrated in Table 8.

Table 9 reports the fuzzy expected values and grey distances which are obtained as $D^{*}$and D^{-}. The ranking of the factors indicates that the quality (c_1) is regarded as the most significant in supply chain, while c_6 is considered as the worst option.

5.2. Sensitivity analysis

In this sub-section, we apply a sensitivity analysis to check the robustness of the given decisions with respect to the changes in the weights of customer values with respect to the changes in the weights of decision makers. We design eight scenarios for the sensitivity of customer values as given in Table 10. These scenarios have been conducted by using extreme linguistic terms, e.g. *very low* and *very high* in order to see the limits of possible outcomes. The same linguistic evaluations by the decision makers are used to obtain the extreme linguistic terms as an average.

Using the data in Table 10, the relative coefficients of the criteria are obtained as in Table 11. Quality (c_1) is the most important criterion in Scenarios 1, 2, 3, 5 and 7. Financial stability (c_6) is the most important criterion in Scenarios 4 and 8. Supply and procurement flexibility (c_3) is the most important criterion in Scenario 6. Quality (c_1) is still in the first rank even the extreme evaluations occur in almost all scenarios. These results show that financial stability (c_6) is affected by the main factor economic downturn (T_2) at most. Low level of "economic downturn (T_2)" causes the "supply and procurement (c_3)" to be in the first rank.

In the proposed method, the decisions makers are considered to have equal importance. The weights of decision makers can differ based on their expertise levels. In this sub-section, the weights

Table 11
Relative coefficients of the criteria with respect to scenarios.

Scenarios	Relative coefficients					
	c_1	c_2	c_3	c_4	c_5	c_6
S(1)	**0.512**	0.495	0.493	0.492	0.498	0.487
S(2)	**0.514**	0.501	0.505	0.501	0.505	0.496
S(3)	**0.512**	0.495	0.494	0.499	0.5	0.494
S(4)	0.485	0.473	0.483	0.498	0.47	**0.5**
S(5)	**0.511**	0.492	0.496	0.492	0.483	0.5
S(6)	0.492	0.486	**0.509**	0.498	0.483	0.5
S(7)	**0.511**	0.496	0.495	0.496	0.501	0.49
S(8)	0.45	0.444	0.475	0.476	0.424	**0.5**

of decision makers are changed by using one at a time sensitivity analysis. The relative coefficients of the criteria obtained by the sensitivity analysis are given in Fig. 3. It is observed that the tendency of decision factors is different among decision makers. While DM_1 and DM_2 are experiencing stable and constant growth, DM_3 receives kind of incremental growth. The changes in the first and second decision makers' weights do not change the ranking of *quality* (c_1). It keeps its position as the first rank. However, the ranking of c_1 changes when the weight of DM_3 becomes larger than about 0.7. After this point, "*supply and procurement flexibility* (c_3)" takes the first rank.

6. Conclusion and future investigations

In this paper, we propose a new MADM based fuzzy QFD methodology. The classical QFD is extended by using interval valued fuzzy sets and grey relational analysis in order to increase preciseness and decrease vagueness. The grey relational coefficient is used in the proposed fuzzy QFD to measure the similarity to the ideal solution.

The article adopts fuzzy extension of QFD and GRA decision aid under interval type-2 fuzzy variables. We applied the proposed model to performance measurement of the supply chain. The proposed model provides a framework for sharing knowledge of the supply chain decision making process. It is able to take into account the subjectivity of the supply chain to cope with imprecise conditions in an ever complex decision environment. Conversely, integrating customers' subjective judgment into the supply chain performance is considerably practical. Our findings indicate that aggregation of the gray relational distance measurement with quality function deployment with the benefit of a group decision making system brings sufficient capacity in dealing with fuzziness. The sensitivity analysis is employed to check the robustness of the obtained rankings with respect to the changes in the weights of factors and the weights of decision makers. The quality of service (c_1) is an insensitive criterion to the changes in these weights.

The investigation team and supply chain experts in this study agree that the proposed decision making approach is acceptable and capable of assisting company in further actions. This prepares managers to think of implementing the model practically, to enlarge it. It opens a window in the scientific based decision platforms of the entire organization. The results of the model can be analyzed to understand the weakness and strong points of all the supply indicators. In this study, we made an effort to develop a foundation for company to identify, analyze and monitor supply and logistic dimensions according to customer/stakeholder attitude. This is an initiative for managers to save time, money and workforce and move toward a productive supply chain system. It is assured that our proposed model allows the company policy makers to actively participate to the decision making process and to ultimately achieve company global values based on the detailed customer parameters and needs. Evaluation of the drives reflects the performance of the supply chain strategies and gives the managers the chance to rethink about supply chain practices and operations. Another way to get benefit from this model for instance is to adopt and apply it to other sectors of the company like Marketing strategy, human resource and quality management system to name a few.

The proposed framework is based on multi-expert and intelligent group decision making. Through the gray relational analysis, the integrated version of QFD and GRA under interval-valued fuzzy environment has successfully removed the enormous volume of Euclidean distance computations. The gray relational coefficient has been integrated to the fuzzy QFD to measure the distance of potential solutions from ideal solutions. The proposed intelligent framework could process the experts' linguistic assessments effectively. These contributions make our framework superior to other similar approaches.

It is recommended to seek in these areas to build further research direction. (**1**) QFD is flexible, its application is wide and can be applied/adjusted to other decision making techniques or weighting tools like SWARA, DEMATEL etc. (**2**) Each fuzzy extension has the capacity in making decision convenient, consistent and less complex, Fuzzy extension of QFD and GRA must be considered such as intuitionistic fuzzy sets, type-2 fuzzy sets, hesitant fuzzy sets, neutrosophic sets, fuzzy multi sets and non-stationary fuzzy are some examples. (**3**) One of the significant topics in supply chain is supplier selection problem; the future research can shift to the utilization of any fuzzy QFD extensions with the application of the rank-based methods as TOPSIS, VIKOR, COPRAS and MABAC, EDAS, MOORA etc. The task of QFD is to set the importance degrees of decision factors and the mentioned methods produce the supplier priorities. (**4**) The contribution of rough based multi attribute decision making is increasingly growing and is an interesting topic for many research projects, therefore one can direct a rough based approach combined to some newborn MADM and compare the results with other similar projects to verify the performance. Obviously this model is able to be established in various management decision making areas.

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