Expert Systems With Applications 88 (2017) 376–392

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

A group decision making support system in logistics and supply chain management

Morteza Yazdani[a,*], Pascale Zarate[a], Adama Coulibaly[a], Edmundas Kazimieras Zavadskas[b]

[a] University of Toulouse, Institut de Recherche en Informatique de Toulouse (IRIT), Toulouse, France
[b] Research Institute of Smart Building Technologies, Vilnius Gediminas Technical University, Lithuania

ARTICLE INFO

Article history:
Received 11 May 2017
Revised 10 July 2017
Accepted 11 July 2017
Available online 13 July 2017

Keywords:
Group decision support system
Fuzzy linguistic variables
Logistic provider
Quality function deployment
Supply chain
Technique for order preference by similarity to ideal solution

ABSTRACT

Purpose: The paper proposes a decision support system for selecting logistics providers based on the quality function deployment (QFD) and the technique for order preference by the similarity to ideal solution (TOPSIS) for agricultural supply chain in France. The research provides a platform for group decision making to facilitate decision process and check the consistency of the outcomes.
Methodology: The proposed model looks at the decision problem from two points of view considering both technical and customer perspectives. The main customer criteria are confidence in a safe and durable product, emission of pollutants and hazardous materials, social responsibility, etc. The main technical factors are financial stability, quality, delivery condition, services, etc. based on the literature review. The second stage in the adopted methodology is the combination of quality function deployment and the technique for order preference by similarity to ideal solution to effectively analyze the decision problem. In final section we structure a group decision system called GRoUp System (GRUS) which has been developed by *Institut de Recherche en Informatique de Toulouse* (IRIT) in the Toulouse University.
Results: This paper designs a group decision making system to interface decision makers and customer values in order to aid agricultural partners and investors in the selection of third party logistic providers. Moreover, we have figured out a decision support system under fuzzy linguistic variables is able to assist agricultural parties in uncertain situations. This integrated and efficient decision support system enhances quality and reliability of the decision making.
Novelty/Originality: The novelty of this paper is reflected by several items. The integration of group multi-criteria decision tools enables decision makers to obtain a comprehensive understanding of customer needs and technical requirements of the logistic process. In addition, this investigation is carried out under a European commission project called *Risk and Uncertain Conditions for Agriculture Production Systems* (RUC-APS) which models risk reduction and elimination from the agricultural supply chain. Ultimately, we have implemented the decision support tool to select the best logistic provider among France logistics and transportation companies.

1. Introduction

Knowledge-based decision models are getting significant attention in academia and industry. A vast amount of original research and thesis projects have been carried out in order to make robust decision support systems (DSS) to facilitate managerial decisions. Decision Support Systems are categorized as a specific class of computerized information system that supports management decision making activities. By the early 1970 s, the concept of decision support systems had been conceived through the work of Scott Morton. The approach tries to analyze strategic decisions to offer support to decision makers (DMs) in a complex and poorly structured situation. DSSs have some advantages in decision making process through assisting decision makers in their tasks and improving quality of decision process (Zarate, 2013). The concept of DSS comes from a balance between human judgment and information process by a computer. There are three fundamental components of DSSs. Firstly; there is database management system (DBMS) which serves as a data bank for the DSS. The second component is Model-based management system (MBMS). The role of MBMS is analogous to that of a DBMS and, finally the method of dialog generation and management system (DGMS) (Erfani,

* Corresponding author.
E-mail addresses: morteza.yazdani@irit.fr, morteza_yazdani21@yahoo.com (M. Yazdani), pascale.zarate@irit.fr (P. Zarate), adama.coulibaly@irit.fr (A. Coulibaly), edmundas.zavadskas@vgtu.lt (E.K. Zavadskas).

http://dx.doi.org/10.1016/j.eswa.2017.07.014
0957-4174/

Afrougheh, Ardakani, & Sadeghi, 2015; Power, Sharda & Burstein, 2015; Khademolqorani & Hamadani, 2013; Marakas, 2003).

The selection of logistics providers (LPs) is an emergence of today's competitive market. With the development and advancement of the supply chain theories, the selection of logistic providers for the function of logistics support becomes considerable. Over the last decades, the direction of decision support systems has changed drastically. Computer and industrial professionals made efforts to systematize decision making process in manufacturing and production sectors (Guo, Ngai, Yang, & Liang, 2015). For example, Zha, Sriram, Fernandez, and Mistree (2008) modeled a compromise decision support problem technique and the fuzzy synthetic decision model (FSD) to quantitatively incorporate qualitative design knowledge and preferences of designers for multiple, conflicting attributes. They argue that the model is generic and flexible enough to be used in a variety of decision problems. Application of a decision support system in supply chains by employing multi-criteria decision-making is a constant challenge (Kristianto, Gunasekaran, Helo, & Sandhu, 2012; Scott, Ho, Dey & Talluri, 2015; Shi, Yan, Shi, & Ke, 2015). Integrated models are highly appreciated because each method has a unique function. However, choosing the most accurate approach is often a dilemma and intriguing practical question faced by supply chain managers. An unsuitable integrated model can cause terrible results and failure of the system.

To adopt a reliable and practical decision making model, we propose the integration of quality function deployment (QFD) and technique for order preference by similarity to ideal solution (TOPSIS) with aid of fuzzy linguistic variables made by group of decision makers. From the technical and practical viewpoint, the proposed model has some advantages when it approaches a group decision system with such combination. In MCDM modeling, it is recommended to weight decision factors (attributes) using combined structures (Tavana, Yazdani, & Di Caprio, 2017). In many decision making problems, the reliability of the decision criteria is strictly dependent on the stakeholders and customers' preferences as external weights. It is tough for customers to deliver judgments via solid and numerical values. Fuzzy linguistic variables allow us to assure the quality of judgment and then fuzzy MCDM conducts optimal procedure to final objectives. An efficient and flexible decision tool which is able to find optimal weights of customer attitudes is the QFD model. It assures a convenient and compatible decision making process.

The paper is arranged as follows: after this introduction, the literature review on supply chain is presented. Then application of decision models in agriculture projects is reported in Section 3. The proposed multiple criteria decision methods will be described as Section 4. Then decision frames and a case study for logistic provider selection are addressed in Section 5. Section 6 represents the results and sensitivity analysis tests. Section 7 will interpret the GRUS system implementation and conclusion is reported in Section 8.

2. Literature review and related works

2.1. Supply chain and logistics management via DSSs

A supply chain is defined as a process with a complete set of activities wherein raw materials are transformed into final products, then delivered to customers by distribution, logistics, and retail. All inter-organizational practices as planning, purchasing, distribution, delivery process, and reverse logistics are taken into account as a supply chain management system (Brandenburg, Govindan, Sarkis, & Seuring, 2014; Fahimnia, Sarkis, & Davarzani, 2015; Yazdani, Hashemkhani Zolfani, & Zavadskas, 2016). In addition, outsourcing phenomena emerged in the supply chain to optimally manage all those practices and in this way, the physical and information flow exchanged among all players in a supply chain (Konig & Spinler, 2016).

Development of the new theories and methodologies in logistics and supply chain management can lead to the higher level intelligent and advanced systems. Such kind of systems enable supply chain experts to facilitate information-sharing, high qualified decisions and to increase the value to products and services by internal coordination (Chandra & Kumar, 2000). Supply chain management has tied up with the application of information technology (IT) which brings competitive advantages of knowledge sharing with customers and stakeholders to improve coordination and communication among suppliers and partners for companies (Ngai, Peng, Alexander, & Moon, 2014). The selection of logistic providers for the function of logistics support becomes considerable. Over the last decades, the direction of decision support systems has changed drastically. To monitor the materials cost in a garment manufacturer, a decision support model has assisted decision-makers in selecting efficient ways to reduce total manufacturing costs (Wong & Leung, 2008). Couple of review projects has been conducted in terms of intelligent models, decision support tools and system in supply chain field (Seuring, 2013; Taticchi, Tonelli & Pasqualino 2013). Seuring (2013) argued that the performance of sustainability and supply-chain management must be researched practically by a strategic decision-making support model. Liu, Wang and Liu (2012) structured a sustainability analysis framework with the integration of life cycle assessment and a multi-criteria decision-making process to support environmental, social and the economic aspects of the supply chain management. Bhattacharya, Mohapatra, Kumar, Dey, Brady and Tiwari (2014) demonstrated a green supply chain performance measurement perspective and made an effort to deliver a collaborative decision-making model using fuzzy analytical network process. Accorsi, Manzini, and Maranesi (2014) developed an original decision-support system for the design, management, and control of warehousing systems with solid DBMS architecture. Guo et al. (2015) proposed radio frequency identification -based intelligent decision support system to handle production monitoring and scheduling in a distributed manufacturing environment. A decision model for supplier selection and in stochastic, multi-stakeholder and multi-criteria environments has been build, but the research did not offer any real DSS (Scott et al., 2015). A recent decision support tool for purchasing management investigated that the capital-constrained retailer's purchase timing, quantity and financing decisions are necessary for seasonal products (Shi, Guo, & Fung, 2017).

3rd party logistic providers (3PLP) are recognized as companies or enterprises that perform the various logistics activities of a customer either completely or only in part by transportation, such as ocean or shipping freight, air cargo, truck freight or storing in warehouse facilities. The logistic provider has been widely promoted by the concept of outsourcing. Logistics outsourcing is mainly concerned with cost reduction and improvement (Rajesh, Pugazhendhi, Ganesh, Ducq, & Koh, 2012). Aguezzoul (2014) classified logistic process to transportation, distribution, warehousing, inventory management, packaging, and reverse logistics. All of those categories can be outsourced by a logistic provider.

Supply chain success highly depends on the commitment of sub-systems performances. A complete supply chain happens when the sub system functions work accurately and try to eliminate diagnoses from design, production and distribution to the logistics and transportation (Govindan, Palaniappan, Zhu, & Kannan, 2012). In assessing the performance of an Agri-food supply chain, a performance measurement system can be established to enable a firm to monitor the relevant performance indicators of logistics processes in an appropriate time horizon (Bosona & Gebresenbet, 2013). Partners in the supply chain are confronted with conflicting goals making the performance evaluation more complex. Therefore, when the supply chain is faced with outsourcing parts of logistic functions, evaluating, selecting and contracting a third party logistics provider would be a crucial problem (Aguezzoul, 2014; Diabat, Khreishah, Kannan, Panikar, & Gunasekaran, 2013).

In the 60 s, academics began to work on quantitative models to computerize decision making and assist policy makers and investors (Holt & Huber, 1969; Turban, E., & Watkins, 1986). Particular projects were directed on logistic provider evaluation using decision making models and tools. Multi-criteria decision making has aided academics and industrial practitioners in their decisions in such fields from economy and management to engineering and manufacturing (Carvalho, Varela, Putnik, Hernández, & Ribeiro, 2014). Zavadskas, Turskis, Vilutienė, and Lepkova (2017) verified the role of analytical MCDM tools including ARAS, TOPSIS to the problem of facility management strategy selection. Gupta and Walton (2016) explored the applicability of interpretive structural modeling (ISM) in the selection of third party logistic providers by twelve main criteria (cost, reputation, quality, locations, collaboration and range of services etc.). Dweiri, Kumar, Khan, and Jain (2016) designed an AHP model to assist the automotive industry in the supplier selection problem. The authors used expert choice software and solved the decision problem. It must be stated that even expert choice is a formerly developed software package relying on AHP and has some shortages that other methods (TOPSIS, VIKOR, etc) cannot be implemented on it. Several studies have accomplished integrated decision structures for logistic providers as well. Hashemian, Behzadian, Samizadeh, and Ignatius (2014) introduced a fuzzy AHP and PROMETHEE decision system to increase the quality of the supplier evaluation system. They did not propose an applied decision support tool and the model will failure when large amount to data must be analyzed. Akman and Baynal (2014) worked on an integrated model of AHP and TOPSIS in fuzzy environments. Yayla, Oztekin, Gumus, and Gunasekaran (2015) combined fuzzy AHP and TOPSIS to achieve an optimal list of third party transportation providers. AHP can be an appropriate choice, but despite its capability, it is unable to connect customer values to the decision making process. In other side, while the study needs to satisfy customers and stakeholders demand to reach a sustainable supply chain, utilization of AHP seems useless. Therefore, we use QFD due to its ability to conduct interrelationship among decision factors and customer factors. In another way, to refuse AHP pairwise comparison, computations and complexity, QFD brings the more reliable approach that can be combined to MCDM methods quicker and with less difficulty (Ignatius, Rahman, Yazdani, Šaparauskas, & Haron, 2016). Piltan and Sowlati (2016) developed a model to support decision with aim of evaluating partnership performance in British Colombia, Canada. Their study correlates to a model to support decision and surprisingly is too far from a decision support system structure and definition. In total, it has been observed that several papers have focused on just an individual or an integrated decision making model and not even an efficient decision support system.

2.2. Collaborative decision making

By 1967, Morton built, implemented, and realized a model-driven DSS which was a great achievement in DSS literature. Gorry and Morton (1971) defined the term “decision support system” as systems that assist decision makers in semi-structured and unstructured decision problems. Later, Alter and Alter (1980) suggested a thinking framework for both management and business DSSs. They suggest six categories: (a) file drawer systems, (b) data analysis systems, (c) accounting and financial systems, (d) representational systems, (e) optimization systems, and (f) suggestion systems. In 1982, Sprague and Carlson (1982) defined DSSs as a class of information system that draws on transaction processing systems and interacts with the other parts of the overall information system to support the decision making activities of managers and other knowledge workers in organizations. Ic and Yurdakul (2009) distinguished these items; robustness, ease of control, simplicity, and completeness of relevant detail for evaluation of DSSs. Bonczek, Holsapple, and Whinston (2014) introduced a framework to understand four major design aspects that affect all DSSs: (a) language system, (b) presentation system, (c) knowledge system, (d) problem processing system.

There are five specific Decision Support System types which has been proposed by Power (2015); 1) communications-driven, 2) data-driven, 3) document-driven, 4) knowledge-driven, and 5) model-driven systems. Communications technologies are centered in communications-driven DSS for supporting decision-making (Kou, Shi, & Wang, 2011). Data-driven DSS provides access to large data stores and analytics to create information. Document-driven DSS uses documents to provide information for decision making. Knowledge-driven DSS are connected to expert systems or recommender systems. A knowledge-driven DSS emphasizes solving a decision making problem using facts, cased-based reasoning, rules, procedures, and similar structures (Zarate & Dargam, 2015). A communication-driven DSS facilitates working on a shared task by allowing sending and receiving data among a group of decision makers. A data-driven DSS assists decision makers by providing access to data and sometimes manipulation options (Sharma, Sarker, & Romagnoli, 2011). Model-driven DSS handles quantitative models for functionality and works on data manipulation and analysis using mathematical methods for optimization, simulation, etc. (Lei & Moon, 2015; Zhang & Goddard, 2007). Most model-driven DSSs are one individual user only; on the other hand, data-driven DSSs are used by multiple users across organizations. A document-driven DSS concentrates on managing, and manipulation of data in various electronic formats (Baumeister & Striffler, 2015).

A collaborative knowledge base system is a communication module composing of several elements which represents various functions that the module should perform for the problem solving stages. The elements are controlling function, application controller, communication manager and a user update module. This collaborative knowledge base system illustrates a base for development of a cooperative DSS (Hernández, Lyons, Zarate, & Dargam, 2014).

2.3. Knowledge significance

A supply chain management can be called sustainable if it is applied to all relevant supply chain aspects: environmental product design, natural resource and energy efficiency, final product guarantee, after sale service, employment ethical issues, reusing/recycling design and reverse logistics (Tavana et al., 2017). These items are basically configured from a customer viewpoint. All those supply chain aspects are subjects that must be consulted and negotiated with aid of customers/stakeholders. In this manner, arguing customer values and then converting them into the supply chain factors in this paper not even pushes forward supply chain toward a global and sustainable appearance; it enhances the significance of the research from a customer-based perspective. Moreover, even though many studies emphasize the influence of traditional supply chain criteria on the logistic provider's process, none of them deals with a decision support system with inclusion of customer variables, their affection on each other and on supply chain attitudes. This is the reason we try to adopt quality function deployment which is a structured and well-known customer-driven product design technique whose basic task is to translate customer ideals to technical logistic and supply chain criteria (Chen, Ko, & Yeh, 2017; Zaim, Sevkli, Camgöz-Akdağ, Demirel, Yayla et al., 2014). Although some studies showed interest on involving customer values in supply chain systems, however, in the case of integrating customer dimensions into the logistic provider decision process and to obtain criteria importance, there was not significant research in terms of logistic provider's evaluation and selection.

We believe that our research is unique and brings sufficient contributions in area of supply chain due to the following reasons: Despite of many articles employed integrated and intelligent tools in order to compare the performance of suppliers and logistic providers, none of them designed a platform or prototype of a DSS for their objectives. Whilst the existing literature noticed no particular study assigned to the modelling of a DSS for the evaluation of logistic providers, we announce that our GRUS system would allow a more holistically successful direction on logistic decision making and therefore a more sustainable supply chain can be achieved. In addition of that, none of the decision support tools in the past studies, to best of our knowledge, reported a customer/stakeholder-driven approach with utilization of QFD. Previous research projects reported logistic provider's assessment by different perspective and far from customer satisfaction. Therefore, these shortcomings existed in the current supply chain investigations will be captured and resolved in this paper. We adopted a decision support system through the integration of quality function deployment aided by fuzzy TOPSIS. A group decision making structure with a systematic procedure can reduce the effect of arbitrary decisions by managing tension among decision makers and accelerate the evaluation process using a rational aggregation of group decisions and application of information technology and computer programming. With confidence, it can be interpreted that this is the first DSS which combines QFD and fuzzy TOPSIS in order to evaluate logistic service providers by a real-world project.

3. Decision model application in the agriculture domain

Risk and Uncertain Conditions for Agriculture Production Systems (RUC-APS, 2016) aims to provide knowledge advancing in agricultural based-decision making process to realize the key impacts of every stage of the agriculture-related processes. The project title is "Enhancing and implementing Knowledge based ICT solutions within high Risk and Uncertain Conditions for Agriculture Production Systems" . This implies the development of a high impact research project in order to integrate real-life based agriculture requirements, alternative land management scenarios, as well as supporting 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 stands in a European Commission project and aims to model decision support systems to deal with a sustainable agriculture supply chain with respect to risk and uncertainty. It implies twenty three partners coming from seven countries. The call of project is *H2020-MSCA-RISE-2015* in the economic sciences panel. The domain of the project covers theoretical studies, investigation as well technical achievements and several universities and research institutes are in collaboration. The contribution of the proposed method is to implement the proposed decision support model on a web-based decision making and voting tool called GRUS. This action widely facilitates decision making process and integrates role of information technology in supply chain management modeling. The project has defined some scientific objectives (SOs) that among them SO_5 is assigned to model and optimize innovative transport-logistics solutions of horticulture products across the full value chain structure. Hence, our proposed model is being implemented in RUC-APS project to grasp high level of efficiency in supply chain.

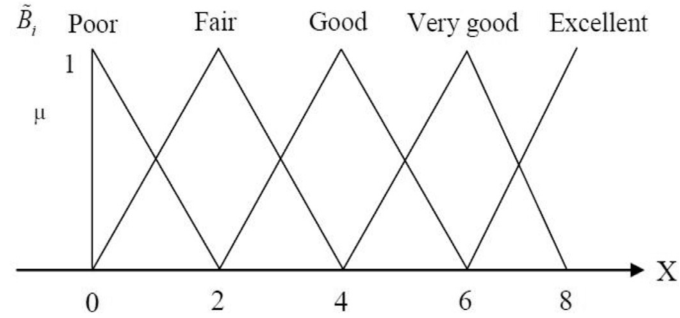

Fig. 1. Fuzzy linguistic terms for house of quality evaluation.

4. Proposed methodologies

In the proposed group decision model, several tasks are defined. Initially, weights of the decision criteria (e.g. weights of technical supply chain requirements) are determined using fuzzy QFD. The second task is to generate the ranking of alternative logistic providers using fuzzy TOPSIS. The suggested algorithm is explained as these sub-sections:

4.1. A fuzzy quality function deployment model

The major steps toward a QFD (Karsak & Dursun, 2014; Yazdani, Chatterjee, Zavadskas, & Zolfani, 2017) model can be represented here:

Step 1 – Identify customer requirements (CRs) and related technical requirements (TRs) that influence the performance of logistic providers in supply chain (Table 1). Table 1 schematically explains the allocation of the corresponding values of customers to the most related supply chain technical factor. As it is observed, the first row considers CRs and the column is referred to the TRs. This operation is carried out using linguistic variables provided by Table 2 and 3.

Step 2 – Understanding the importance of the customer requirement by using fuzzy triangular linguistics variables and fuzzy weighted average together with the correlation between CRs and technical requirements. A fuzzy set is composed by a membership function that maps elements to degrees of membership within interval of [0, 1]. If the value assigned lies within the interval, the element has a certain degree of membership (it belongs partially to the fuzzy set). Fig. 1 exhibits the structure of triangular fuzzy numbers that are utilized in this paper (Tseng, Lim, Wu, Zhou, & Bui, 2017).

Step 3 – Computation of fuzzy QFD weights for supply chain technical requirements. A normalization rule is used to deliver normalized weights of main decision criteria for final selection process.

The proposed approach conducts the QFD model, the House of quality matric to convert customer and external variables into the technical factors. The detail of QFD model can be found in (Germani, Mengoni, & Peruzzini, 2012; Tavana et al., 2017). Fuzzy QFD (Zaim et al., 2014) model in a group decision making environment has been established to connect customer needs to product design steps. In step 1, decision-makers are selected; alternatives, evaluation criteria, customer/stakeholders factors and their characteristics are defined. In this stage, the entire requirement for the evaluation of a logistic provider in view of stakeholders and customers

Table 1
A sample fuzzy QFD matric and the relevant variables.

Customer req. / Technical req.	R_1	R_2	…….	R_{n-1}	R_n	Importance of customer requirements
C_1						Wc_1
C_2						Wc_2
.						.
.			Fuzzy interrelationship matrix			.
.						.
.						
C_{m-1}						
C_m						Wcm
Weights of criteria						

Table 2
Linguistic preference and the corresponding fuzzy numbers.

Linguistic terms	Fuzzy number
Very poor (VP)	(0,0,2)
Poor (P)	(0,2,4)
Neutral (N)	(2,4,6)
Good (G)	(4,6,8)
Excellent (E)	(6,8,8)

Table 3
Linguistic values for weight of CRs.

Linguistic terms	Fuzzy number
Very low (VL)	(0,2,4)
Low (L)	(2,4,5)
Medium (M)	(4,6,8)
High (H)	(6,8,10)
Very high (VH)	(8,9,10)

are determined and reviewed. It should be declared that the technical requirements are the instrument to achieve customer satisfaction.

Step 4 - A survey is performed in order to realize perception of customers and end users regarding satisfaction level and degree of importance of customer requirement in the second step. Fuzzy linguistic values as shown in Table 2 are defined to assign the degree of importance of customer attitudes and technical requirements. Thereafter those linguistic values are transferred to fuzzy triangular numbers to be usable for computation steps. Using this conversion form linguistic variables to fuzzy numbers allows decision makers to deal with ambiguity and conflicted environments of decision process. We have provided a set of five-linguistic labels to facilitate participation of decision makers. The decision makers have the role to choose linguistic variables in order to launch a reliable and high quality decision. The linguistic terms (Table 2) (Lee, Ru, Yeung, Choy, & Ip, 2015) such as “very poor”, “poor”, “neutral”, “good” and “Excellent” are utilized to present the level of satisfaction of the customer requirement and technical supply chain criteria. It is evident that decision makers treat alternatives and rate them different from decision factors. Therefore, to weight CRs, the following linguistic variables adopted from Kannan, de Sousa Jabbour, & Jabbour, 2014 can be taken into account (Table 3).

In GRUS system we have established facilitator and participant roles (we call DM or experts in supply chain). Facilitator is the leader in each decision stage to handle the system and coordinate with the participants. One of the advantages of GRUS system is that the process of voting and presenting the opinion of DMs can be anonymous, so each DM is asked to use this option during the decision making. As usual, there are some conflicts and issues like when DMs have different opinion about a subject, so this anonymity in GRUS can cause them freely follow the evaluation process and not to be afraid of further negative feedback, punishment or reactions.

To complete the questionnaire and run the decision making, we have invited three experts, one from agriculture section, another expert from supply chain and purchasing and a professor of operations management. They have been invited and assigned a user and profile to go through the GRUS online web application and perform the questionnaire. When they finish the questionnaire, automatically facilitator can observe the aggregated opinion, calculations, and required solutions. We have been assured that experts are completely neutral and the process of evaluating logistic providers is completely impartial.

Step 5 - Due to participation of group of decision makers, an average triangular fuzzy numbers from q fuzzy numbers is required. As the degree of importance of customer requirements is being measured by sample of q individual members based on their area of expertise. The q_j member expresses the weights of ith customer requirement, $w_{\tilde{c}_{ij}}=(w^{ij}_{c_1}, w^{ij}_{c_2}, w^{ij}_{c_3})$. Using these weights and also the correlation judgment between customer requirements and technical criteria the final weights for technical factors are obtained (Lee et al., 2015).

$$\tilde{w}_{\tilde{c}_{ij}} = \frac{\sum_{j=1}^{q} w_{cij}}{q} = \frac{\left(\sum_{j=1}^{q} w^{ij}_{c_1}, \sum_{j=1}^{q} w^{ij}_{c_2}, \sum_{j=1}^{q} w^{ij}_{c_3}\right)}{q} = \left(w^{i}_{c_1}, w^{i}_{c_2}, w^{i}_{c_3}\right) \quad (1)$$

Where q is the total number of decision makers and $\tilde{w}_{\tilde{c}_{ij}}$ addresses the importance weights of the ith customer requirement. The task of QFD team members is to present their judgments by assigning degree of correlation between CRs and TRs, $\tilde{c}_{ij} = (c_{ij1}, c_{ij2}, c_{ij3})$. Moreover,

$$\tilde{c}_{ij} = \frac{\sum_{k=1}^{q} c_{ij}^{k}}{q} = \frac{\left(\sum_{j=1}^{q} c_{ij1}^{k}, \sum_{j=1}^{q} c_{ij2}^{k}, \sum_{j=1}^{q} c_{ij3}^{k}\right)}{q} = \left(c_{ij1}, c_{ij2}, c_{ij3}\right) \tag{2}$$

In this equation c_{ij} is the strength of the contribution of jth technical requirement on the ith CR determined by QFD group. Triangular fuzzy values can be converted into crisp numbers (defuzzification process) using the formula below (Cheng, 1999), if $\tilde{B} = (b_1, b_2, b_3)$:

$$x = \frac{(b_1 + 2b_2 + b_3)}{4} \tag{3}$$

In this stage, fuzzy weighted average is applied to compute the technical requirement weightings for customer satisfaction $(w_{\widetilde{CS}})$ by the following equation:

$$(w_{\widetilde{CS}}) = \frac{\sum_{i=1}^{m} \tilde{w}_{\tilde{c}_{ij}} \tilde{c}_{ij}}{\sum_{i=1}^{m} \tilde{w}_{\tilde{c}_{i}}} \tag{4}$$

4.2. Fuzzy technique for order preference by similarity to ideal solution

In decision making systems there are situations that the solution should be analyzed based on negative (worse) and positive (best or ideal) solutions. Then the distance from the ideal solution can realize the optimal option. TOPSIS is a user-friendly and common decision making tool that has this advantage. As a well-known classical MCDA/MCDM method, it has received enormous attention from academic and industrial communities. The global interest in the TOPSIS method has exponentially grown. The underlying logic of TOPSIS is to measure the positive ideal solution (PIS) and negative ideal solution (NIS) and the optimal solution should have the shortest distance from the PIS and the farthest from the NIS (Tavana, Li, Mobin, Komaki, & Teymourian, 2016). TOPSIS has been combined, extended and integrated to other decision tools and/or engineering concepts to support decision process in various applications and case studies (Asadi, Sansoleimani, Fatehi, & Carranza, 2016; Vinodh et al. 2016; Wang, Zhu, & Wang, 2016). However, due to imprecise environments of the frequent decisions, fuzzy TOPSIS model (Kannan et al., 2014; Zavadskas, Mardani, Turskis, Jusoh, & Nor, 2016) requires preliminarily information about the relative importance of the criteria by fuzzy variables. The stepwise procedure for fuzzy TOPSIS model is followed here:

Step 1: Identify an initial fuzzy decision table including preference judgment of supply chain experts. Let us consider a fuzzy decision matrix with a group of k decision makers (D_1,D_2,D_3,...D_k) considering m alternatives (A_1,A_2,A_3,...A_m) and n criteria (c_1,c_2,c_3,...c_n) for a MCDM problem. Therefore, the first fuzzy decision table is expressed as a matrix:

$$X = \begin{array}{c} A_1 \\ A_1 \\ \vdots \\ A_1 \end{array} \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{11} & r_{11} & \dots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m1} & \dots & r_{mn} \end{bmatrix} \tag{5}$$

In this equation r_{mn} is the rating of alternative A_m with respect to criteria c_n which is expressed as a linguistic triangular fuzzy number. Each evaluator (decision expert) can evaluate the alternatives considering to the criteria using the ratings given in Table 1. To make an aggregated matric of all the decision makers, Assume that a decision making committee consists of k decision makers and the fuzzy rating of each decision maker can be represented as a positive triangular fuzzy number $\tilde{R}_k (k = 1, 2, ..., K)$with a membership function. In this way, the aggregated fuzzy rating is measured as:

$$\tilde{R} = (a, b, c) \text{ and } k = 1, 2, ..., K \text{ where } a = Min\{a_k\},$$

$$b = \frac{1}{k}\sum_{k=1}^{K} b_k \text{ and } c = Max\{c_k\} \tag{6}$$

Step 2: This step performs the normalization process of the aggregated fuzzy decision matrix. The data in the aggregated fuzzy decision matrix are normalized to unify different measurement scales. The normalized aggregated fuzzy-decision matrix can be notified as:
$\tilde{R} = [\tilde{r}_{ij}]_{m \times n}$
Therefore, the normalized values for benefit and cost related criteria are calculated using the following equations:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), \quad j \in B$$
$$c_j^* = \max c_{ij}, \quad j \in B \tag{7}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \quad j \in C$$
$$a_j^- = \min a_{ij}, \quad j \in C \tag{8}$$

As it has been stated TOPSIS and generally MCDM tools consider conflicting factors with different direction and optimization objectives. So, B and C are the sets of benefit and cost criteria respectively.

Step 3: The weighted normalized fuzzy decision matrix v_{ij} is calculated by multiplying the normalized matrix with the weights of the evaluation criteria. The weighted normalized fuzzy decision matrix V is defined as follows:

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m \times n} \text{ where } i = 1, 2, .., m \text{ and } j = 1, 2, .., n \tag{9}$$

By this equation weights of decision criteria are included in decision process; while $\tilde{w}_j$ is the fuzzy weights of j th criteria. In this paper the final weights of technical requirements (main criteria) have been already discussed and computed using QFD process and formula (4);

$$\tilde{v}_{ij} = \tilde{r}_{ij}.\tilde{w}_j \tag{10}$$

Step 4: Measure the positive and negative ideal solutions (PIS, NIS) which are shown by: (A^*, A^-)

$$\tilde{A}^* = (v_1^*, v_2^*, ..., v_n^*) \quad v_j^* = \max\left\{v_{ij}\right\} \tag{11}$$

$$\tilde{A}^- = \left(v_1^-, v_2^-, ..., v_n^-\right) \quad v_j^- = \min\left\{v_{ij}\right\} \tag{12}$$

Where $i = 1, 2, .., m$ and $j = 1, 2, .., n$

Step 5: To achieve an optimal solution and make a compromise ranking, the distances of each alternative from NIS and PIS should be considered;

$$d_i^* = \sqrt{\sum_{j=1}^{n} \left(\tilde{v}_{ij} - \tilde{v}_j^*\right)^2} \quad i = 1, 2, .., m \tag{13}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(\tilde{v}_{ij} - \tilde{v}_j^-\right)^2} \quad i = 1, 2, .., m \tag{14}$$

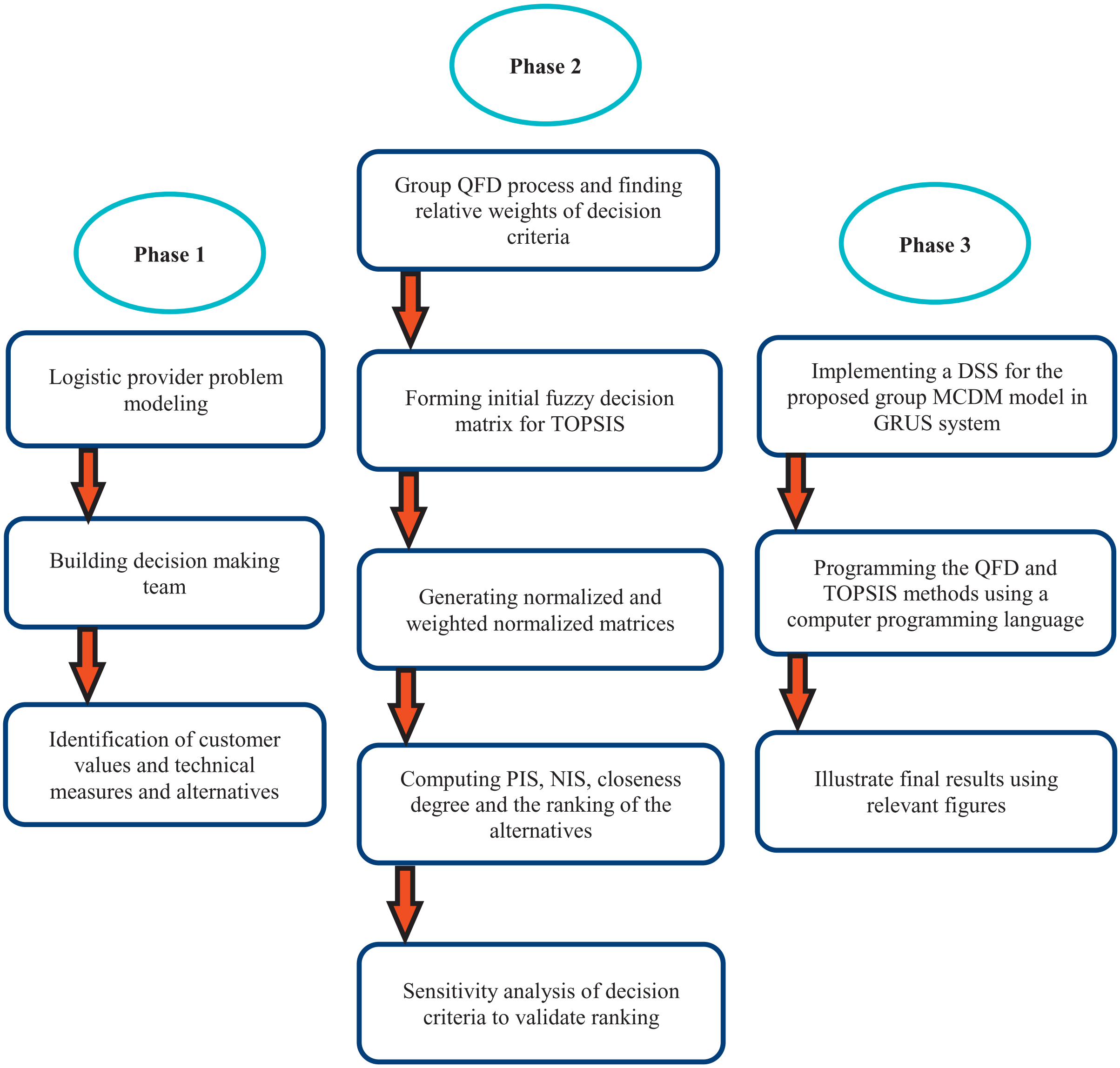

Fig. 2. Decision making process for third party logistic providers' evaluation.

Step 6: To produce ranking of alternatives and getting final solution the closeness coefficient of each alternatives must be calculated:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*}, \quad i = 1, 2, .., m \tag{15}$$

The ranking order of all alternatives is determined according to the descending order of CC_i. The alternative A_i will be the best only if its CC_i indicates higher value.

5. Proposed decision framework and case study explanation

A decision making model for current study is pictured in Fig. 2. The fuzzy QFD-TOPSIS phase of the proposed method provides a window to implement costumer driven weighting procedure for decision criteria. This function permits the satisfaction of external stakeholders and customers to the decision process. We have considered three decision makers to deliver us their judgments over the above logistic providers with respect to the relevant factors to compose a decision system. Proposed model in Fig. 2 is composed of the following phases:

Phase 1 - In this phase, the essential CRs and the corresponding technical criteria for assessment of the third party logistic providers is interpreted and introduced. Moreover, the alternatives of the decision problem (logistic providers) shall be recognized. The alternatives are real logistics and transportation companies which are active in France and whole Europe. The decision making team, experts and users that must participate in this project are introduced and called.

Phase 2 **–** Group of experts (DMs) express their preference using the fuzzy linguistic variables provided in Table 2 and 3 by house of quality matrix and to rate performance of alternatives based on a questionnaire. The house of quality matrix is composed and three decision makers present the judgments to determine importance of customers' requirement utilizing fuzzy values. They are asked to consider relationship and effect customer attitudes on technical criteria of logistic providers in order to realize the core relation and its degree by means of fuzzy tools.

In general there are three types of the weighting process in MCDM; subjective, objective and hybrid approach. Objective weighting like Entropy determine weights by making use of mathematical models or statistical methods. Subjective approaches like AHP or SMART methods rely entirely on the subjective judgments or intuition of DMs. Then it will be required to apply some mathematic methods such as the eigenvector method to calculate overall evaluation of each decision maker. In many MCDM conditions where there are no obvious DMs, subjective approaches are not applicable because no subjective judgments can be demonstrated on the relative importance of attributes. Hybrid approach takes the advantages of both subjective and objective approaches (Wang & Lee, 2009; Yang, Yang, Xu, & Khoveyni, 2017).

In the proposed model we have used fuzzy linguistic variables to recognize whether CR and TR are in connection and then how much. The significant point in our proposal about subjective weights is that we used QFD method to calculate the overall weight for TRs. Indeed the weight of each CR is subjective that are translated to TRs. However, the weights for TR (which are called decision criteria for MCDM process in this paper) are recalculated and so, it can be said that we have acted based on a hybrid approach. In practice, we integrated a new layer in evaluation of criteria weights by using customer requirements. This enhances the quality of the weighing procedure and whole decision process.

Based on formulas (1) and (2), the aggregated matric of fuzzy QFD and fuzzy customer weights (Using Table 3) are obtained. Thereafter the normalized weights of technical criteria (such as input for main decision matric) can be achieved through formula 4.

The fuzzy TOPSIS methodology proposed in Section 2.2 is carried out to rank LPs. The criteria weights in previous phase and rating performance of decision makers on alternatives are integrated to the F-TOPSIS procedure. The information and linguistic fuzzy values are accessed through questionnaire derived from group of DMs. The aggregated fuzzy rating is generated using eq. 6. The normalized decision table for cost or benefit criteria are formed (Eqs. 7 and 8). Computation of the weighted normalized fuzzy decision matrix is the next task at this stage aided by eq. 10. At this stage fuzzy PIS and fuzzy NIS according eqs. (11) and (12) must be verified. Thereafter, PIS and NIS (eqs. 13 and 14) are measured and finally CC is attained as formula 15 indicates. A sensitivity analysis is performed to indicate the different ranking and flexibility of the proposed model by weights replacement.

Phase 3 – Working on a programming platform and database to structure a decision making support system. To develop a model driven DSS, this section provides the implementation of the proposed methodology in a group decision making support system. The system is called GRUS and acts as an electronic meeting system which provides a set of tools and meetings processes. Each meeting process which is designed or modified by a user of GRUS, automatically and anonymously can be shared by the other users. With GRUS, one can organize public and private meetings. Anyone can participate to all of the public meetings, but only invited participants can participate to private meetings. Meetings are created by a facilitator who is able to invite persons in her/his private meetings. Facilitators are responsible for managing meetings but also may participate as everyone. The content of private meetings is only accessible to their participants. Conversely, public meetings content is accessible to everyone. This system has been invented and configured by IRIT laboratory at University of Toulouse Capitole 1 (Toulouse, France).

Designing, manufacturing and delivering the right product to the right location at the right time at the right price is the lifeblood of companies. The economic environment is changing, borders are opening up, and international competition is intensifying. The life cycle of products is reduced; the pressure on delays is becoming stronger. The continuous improvement of logistical organization is today an essential element of business strategy. Agility and flexibility via clients and adaptability in the face of social and environmental economic constraints are the leverage to achieve sustainable progress.

Questions like how to manage our information flows? Where to place our warehouses? Which transport and logistics system should be implemented? A controlled and agile supply chain becomes paramount not only due to collaboration among all the company departments (marketing, production, logistics, procurement etc.) but also to extend the collaboration beyond its borders (suppliers, subcontractors, logistic providers, etc.).

In the RUC-APS project the importance of logistic process is very particularly considerable in order to support companies. In this way the French association of supply chain and logistics (ASLOG) since 1972 has been established and activated. It has encouraged companies to involve logistics and supply chain directions in the top level of the management decisions. Multi activity with over 400 companies, nearly 1500 people network, ASLOG is now the leading French network of professionals in the supply chain area. Its objectives are to provide forward-looking visions, to generate standards and qualifications, to measure and evaluate logistics performance, and ultimately to produce research dissemination in partnership with the academic sector and benchmark best practices (www.aslog.org). For this research, five logistic based companies are selected to be assessed by the proposed fuzzy model; Mathez, BANSARD, GEFCO, SCHNEIDER transport, and GETMA.

Mathez group is a family run company specializing in logistics coordination and international transportation (air, sea and road freight). Main activities of this group can be extended from transport management by airfreight, sea freight, road haulage, storage, packing, Supply and distribution management and optimization, port agent, management of cargo and cruise ships. Bansard International offers a complete service for sea, air and road transportation through partnerships with major airlines to cover the needs of our customers. Thus, major ports and airports are served by Bansard International. In addition, this company provides a door to door service and assistance to facilitate customs operations. They offer kind of service like; air transport, sea transport, road transport, logistics, and industrial projects. A leading name in industrial and automotive logistics, GEFCO provides complete, efficient logistics solutions for its industrial customers throughout the world. The group combines standards of quality and performance with the responsible management of its logistics activities. GEFCO incorporates and complies with all the elements of sustainable development. The group is able to respond to all supply chain optimization requirements, upstream or downstream from production sites: land transport, logistics, container management, vehicle distribution, and management of maritime and air flows. SCHNEIDER is a medium-sized international freight forwarding company providing specialized services in clearly defined markets. The Schneider Group combines high service quality with flexibility and commitment to delivery dates. The company plans and coordinates transportation of all kind of goods between Switzerland, Europe, the Far East and the USA. This group delivers sort of activates from road transport, sea and air transport and inventory and procurement management, Reverse logistics, food logistic etc. Getma operates cargo handling in African ports, central Africa and coastal line. Through its network, Getma offers a range of services tailored

Table 4
Correlation matric for house of quality process made by DM_1.

WHATs (preference of customer/stakeholder)	HOWs (Technical requirement) DM_1							Weight of CRs
	TR_1	TR_2	TR_3	TR_4	TR_5	TR_6	TR_7	
Confidence in safe & durable product (CR_1)		G	N		P			H
Emission of pollution & hazardous materials (CR_2)				G		N	G	M
Social responsibility (CR_3)		N					E	H
Availability and access (CR_4)			N		N			L
Recycling (CR_5)				N		G	N	H
Commit to health of employee (CR_6)							G	M
Affordable price (CR_7)	G							H

Table 5
Correlation matric for house of quality process made by DM_2.

WHATs	HOWs (Technical requirement) DM_2							Weight of CRs
	TR_1	TR_2	TR_3	TR_4	TR_5	TR_6	TR_7	
CR_1		G	N	N	P			L
CR_2				N		G	N	H
CR_3						N	G	VH
CR_4		N	G	P				H
CR_5	G			N			N	M
CR_6	N						G	M
CR_7				G			E	H

Table 6
Correlation matric for house of quality process made by DM_3.

WHATs	HOWs (Technical requirement) DM_3							Weight of CRs
	TR_1	TR_2	TR_3	TR_4	TR_5	TR_6	TR_7	
CR_1	N	G		N				H
CR_2				G		N	G	H
CR_3	P			N				M
CR_4		G		G				M
CR_5	N		P			G		L
CR_6	G						E	M
CR_7		P			N	N	G	H

to your business needs: port management, port handling, shipping agency, freight forwarding, and inland logistics.

6. Results, sensitivity analysis and validation

6.1. Results

This paper focuses on application of decision support model in supply chain that aims to show how it may choose a third party logistics provider as a partner from the pool of possible providers. The five proposed phases are demonstrated step by step here:

Phase 1 - The aim of the model is to involve customer and stakeholders' preferences into the decision process in order to provide a global and comprehensive structure. The proposed DSS elements include three decision makers (DM_1, DM_2 and DM_3), the seven customer requirements (CRs), the seven technical factors (decision criteria) which satisfy CRs, and also the 5 alternatives logistic provides (LPs). The decision alternatives include: LP_1 (Mathez), LP_2 (GETMA), LP_3 (GEFCO), LP_4 (SCHNEIDER), and LP_5 (BANSARD). The customer factors are: confidence in safe and durable product (CR_1), Emission of pollution & hazardous materials (CR_2), Social responsibility (CR_3), Availability and access (CR_4), Recycling process (CR_5), Commitment to health of employee (CR_6) and offering affordable price (CR_7). In other side, financial stability (TR_1), quality (TR_2), delivery condition (TR_3), services (TR_4), flexibility of the system (TR_5), environmental management system (TR_6) and corporate social responsibility (CSR) (TR_7) are listed as technical requirements for logistic provider evaluation.

Phase 2 - As defined in five phase's process, primarily group of decision makers presents their judgments about correlation between customer factors and decision criteria. That information made by decision makers are seen in Tables 4–6. To do the computation users are in front of operating system and they can fill anonymously questionnaires as well. Also they are asked to assign weights of each CR by linguistic variables which are in last column of Tables 4–6.

Phase 3 - Then linguistic forms are converted to fuzzy triangular values and aggregated QFD table is provided referring formulas 1–4. Linguistic terms in Table 6 are converted to numerical fuzzy values and then the correlated computations are carried out. The fuzzy triangular values can be diffuzzfied using formula 3. For instance decision maker 1 gives importance of availability and access (CR_4) as L. The value of L is achieved as this; $\frac{2\,+\,2(4)+5}{4} = 3.75$. The final relative, normalized and aggregated weights of technical requirements are obtained as seen in Table 7. According to this table corporate social responsibility (the bolded value) has received more attention based on DMs approach. Those weights can be counted as inputs for TOPSIS process.

Phase 4 – To rate alternatives, again decision makers are asked to fill the questionnaire or by operating system on-line forms. DMs must provide judgments based on experience and should rate alternatives with respect to each criterion using fuzzy linguistic values. The whole information is gathered and can be found in Table 8. For instance, DM_2 considered "Normal" and "Good" values for quality and delivery criteria in assessing LP_3. The aggregated fuzzy matrix is obtained with help of formula 6 which can be checked in Table 9.

Phase 5 - Thereafter normalized fuzzy matric is generated using Eqs. 7 and 8. Table 10 shows the normalized fuzzy matric. To compute weighted normalized decision matrix a defuzzification muse be done by Eq. 3, then using formula 10 a defuzzified weighted matric is attainable as Table 11 presents. In this table, NIS, PIS are extracted and appeared. These two measures NIS and PIS are computed using formulas 11 and 12. Then distances from PIS and NIS must be derived (based on Eqs. 13 and 14) which are shown in Table 12 and Table 13, in order. As it is observed the distances from PIS are too small which shows almost all of them can be feasible. However, TOPSIS anatomy releases the best choice. TOPSIS closeness coefficient values and ranking of logistic providers are produced by formula 15 which is tabulated in Table 14. According to this information BANSARD logistic company is the best service provider with $CC_i = 0.917$ while the weakest logistic provider is GETMA ($CC_i = 0.172$) as LP_2. In total the final priority of logistic providers based on combined fuzzy QFD-TOPSIS are:

BANSARD> SCHNEIDER > Mathez > GEFCO > GETMA

Table 7
The aggregated weights calculation by QFD.

CRs (**DM$_1$**)	TRs							Weight of CRs
	TR$_1$	TR$_2$	TR$_3$	TR$_4$	TR$_5$	TR$_6$	TR$_7$	
CR$_1$		6	4		2			8
CR$_2$				6		4	6	6
CR$_3$		4					7.5	8
CR$_4$			4		4			3.75
CR$_5$				4		6	4	8
CR$_6$							6	6
CR$_7$	6							8
CRs (**DM$_2$**)	TRs							Weight of CRs
	TR$_1$	TR$_2$	TR$_3$	TR$_4$	TR$_5$	TR$_6$	TR$_7$	
CR$_1$		6	4	4	2			3.75
CR$_2$				4		6	4	8
CR$_3$						4	6	9
CR$_4$		4	6	2				8
CR$_5$	6			4			4	6
CR$_6$	4						6	6
CR$_7$				6			7.5	8
CRs (**DM$_3$**)	TRs							Weight of CRs
	TR$_1$	TR$_2$	TR$_3$	TR$_4$	TR$_5$	TR$_6$	TR$_7$	
CR$_1$	4	6		4				8
CR$_2$				6		4	6	8
CR$_3$	2			4				6
CR$_4$		6		6				6
CR$_5$	4		2			6		3.75
CR$_6$	6						7.5	6
CR$_7$		2			4	4	6	8
Relative weights	203	234.5	117.5	343	70.5	242.5	511	1722
Normalized & aggregated weights	0.1179	0.1362	0.0682	0.1992	0.0409	0.1408	**0.2967**	

Table 8
Linguistic fuzzy preferences of decision makers for logistic providers.

Alternatives	Decision makers	Financial stability (TR$_1$)	Quality (TR$_2$)	Delivery (TR$_3$)	Services (TR$_4$)	Flexibility (TR$_5$)	EMS (TR$_6$)	CSR (TR$_7$)
LP$_1$	DM$_1$	N	N	G	G	P	N	G
	DM$_2$	E	G	N	N	N	N	G
	DM$_3$	P	N	N	N	G	G	N
LP$_2$	DM$_1$	N	G	G	N	N	N	P
	DM$_2$	N	G	G	G	G	N	G
	DM$_3$	N	VP	P	G	G	G	N
LP$_3$	DM$_1$	G	G	N	N	N	E	G
	DM$_2$	N	N	G	N	G	P	N
	DM$_3$	G	N	N	VP	G	G	N
LP$_4$	DM$_1$	G	N	N	G	N	N	N
	DM$_2$	G	G	G	N	P	N	N
	DM$_3$	N	N	G	G	N	N	E
LP$_5$	DM$_1$	G	G	P	P	N	G	G
	DM$_2$	N	N	G	N	G	G	G
	DM$_3$	N	N	E	N	N	G	G

Table 9
Aggregated fuzzy decision matrix.

Alternatives	TR$_1$	TR$_2$	TR$_3$	TR$_4$	TR$_5$	TR$_6$	TR$_7$
LP$_1$	(0,4.7,8)	(2,4.7,8)	(2,4.7,8)	(2,4.7,8)	(0,4,8)	(2,4.7,8)	(2,5.4,8)
LP$_2$	(2,4,6)	(0,4,8)	(4,4.7,8)	(2,5.4,8)	(2,5.4,8)	(2,4.7,8)	(0,4,8)
LP$_3$	(2,5.4,8)	(2,4.7,8)	(2,4.7,8)	(0,2.7,6)	(2,5.4,8)	(0,5.4,8)	(2,4.7,8)
LP$_4$	(2,5.4,8)	(2,4.7,8)	(2,5.4,8)	(2,5.4,8)	(0,3.4,6)	(2,4,6)	(2,5.4,8)
LP$_5$	(2,4.7,8)	(2,4.7,8)	(0,5.4,8)	(0,3.4,6)	(2,4.7,8)	(4,6,8)	(4,6,8)

Table 10
Normalized fuzzy matrix.

Alt.	TR$_1$	TR$_2$	TR$_3$	TR$_4$	TR$_5$	TR$_6$	TR$_7$
LP$_1$	(0,0.588,1)	(0.25,0.588,1)	(0.25,0.588,1)	(0.25,0.588,1)	(0,0.5,1)	(0.25,0.588,1)	(0.25,0.675,1)
LP$_2$	(0.25,0.5,1)	(0,0.5,1)	(0.5,0.588,1)	(0.25,0.675,1)	(0.25,0.675,1)	(0.25,0.588,1)	(0,0.5,1)
LP$_3$	(0.25,0.675,1)	(0.25,0.588,1)	(0.25,0.588,1)	(0,0.45,1)	(0.25,0.675,1)	(0,0.675,1)	(0.25,0.588,1)
LP$_4$	(0.25,0.675,1)	(0.25,0.588,1)	(0.25,0.675,1)	(0.25,0.675,1)	(0,0.57,1)	(0.34,0.67,1)	(0.25,0.675,1)
LP$_5$	(0.25,0.588,1)	(0.25,0.588,1)	(0,0.675,1)	(0,0.57,1)	(0.25,0.588,1)	(0.5,0.75,1)	(0.5,0.75,1)

Table 11
Weighted normalized matric for TOPSIS.

Alternatives	TR_1	TR_2	TR_3	TR_4	TR_5	TR_6	TR_7
LP_1	0.06413	0.08259	0.04138	0.12081	0.02047	0.08541	0.19289
LP_2	0.06631	0.06809	0.04572	0.12947	0.02661	0.08541	0.14837
LP_3	0.07663	0.08259	0.04138	0.09461	0.02661	0.08309	0.17998
LP_4	0.07663	0.08259	0.04435	0.12947	0.0219	0.09435	0.19289
LP_5	0.0715	0.08259	0.04026	0.10657	0.02483	0.10562	0.22256
PIS (V^+)	0.0766	0.0826	0.0457	0.1295	0.0266	0.1056	0.2226
NIS (V^-)	0.0641	0.0681	0.0403	0.0946	0.0205	0.0831	0.1484

Table 12
Distance from PIS.

Alternatives	TR_1	TR_2	TR_3	TR_4	TR_5	TR_6	TR_7
LP_1	0.000156	0	0.0000188	0.0000751	0.0000377	0.0004084	0.0008806
LP_2	0.000106	0.0002103	0	0	0	0.0004084	0.0055037
LP_3	0	0	0.0000188	0.0012151	0	0.0005077	0.0018133
LP_4	0	0	0.0000019	0	0.0000222	0.0001269	0.0008806
LP_5	0.000026	0	0.0000298	0.0005247	0.0000032	0	0

Table 13
Distances from NIS.

Alternatives	TR1	TR2	TR3	TR4	TR5	TR6	TR7
LP1	0	0.000210	0.000001	0.000686	0	0.000005	0.001981
LP2	0.000005	0	0.000030	0.001215	0.000038	0.000005	0
LP3	0.000156	0.000210	0.000001	0	0.000038	0	0.000999
LP4	0.000156	0.000210	0.000017	0.001215	0.000002	0.000127	0.001981
LP5	0.000054	0.000210	0	0.000143	0.000019	0.000508	0.005504

Table 14
Final solution of TOPSIS.

Alternatives	CC_i	Ranking
LP_1	0.647	3
LP_2	0.172	5
LP_3	0.284	4
LP_4	0.783	2
LP_5	0.917	1

Fig. 3. Sensitivity analysis illustration.

6.2. Sensitivity analysis

Sensitivity analysis is a technique to observe the affection of change from some parameters of the model on other elements. This action generally is completed by replacing the weight of each criterion; the resulting changes of the priorities and the final ranking of the alternatives are pictured. The strategy to operate sensitivity analysis in this paper is to change randomly position of criteria weights. Therefore, ten different set of tests are arranged to produce different ranking for TOPSIS. The tests are shown in Table 15.

Table 16 depicts the changes in final ranking of logistic providers when criteria weights are altered. However, those changes are slightly similar and as seen the same rankings are obtained in Test 1, 8 and 10. The results declare that ranking of sensitivity analysis are in good agreement based on closeness. So, managers can infer that BANSARD and SCHNEIDER are the most confident logistic service providers. In addition in 6 tests (test 1,2,4,7,8 and 10) the ranking score of 1st and second logistics providers remain the same. This claims final ranking is not affected by those weight replacements and the stability of the model is approved. Fig. 3 illustrates the ranking changes. The notable point is that GETMA (LP_2) (the worst option) has the most stable ranking and keeps its ranking position.

6.3. Validation of the results

During the design of the survey and questionnaire, we have asked all the experts to value the items below in their preference comparison. This lead to model a robust logistic provider assessment plan;

- Feasibility and applicability; does the logistic providers approach evaluate the most relevant logistic companies which are feasible and practical for a long-term relationship?
- Preference based evaluation; does the LP assessment approach select them based on incorporation of all the preferences supplied by the DM?
- Competency; does the proposed approach select LPs competitively superior to others?
- Sustainability; does the LP selection approach offer a selection mechanism which are sustainable and efficient to the environmental?

Table 15
Tests for sensitivity analysis.

	W_1	W_2	W_3	W_4	W_5	W_6	W_7
Test 1	0.1362	0.1179	0.1992	0.0682	0.0409	0.2967	0.1406
Test 2	0.1992	0.0682	0.0409	0.1179	0.1362	0.2967	0.1406
Test 3	0.2967	0.1406	0.0409	0.1992	0.0682	0.1362	0.1179
Test 4	0.2967	0.1406	0.0682	0.1179	0.0409	0.1992	0.1362
Test 5	0.0682	0.2967	0.1179	0.1992	0.0409	0.1406	0.1362
Test 6	0.0682	0.2967	0.1992	0.1406	0.0409	0.1179	0.1362
Test 7	0.0682	0.2967	0.1362	0.0409	0.1406	0.1992	0.1179
Test 8	0.0682	0.2967	0.0409	0.1362	0.1179	0.1406	0.1992
Test 9	0.1406	0.1992	0.2967	0.0682	0.0409	0.1179	0.1362
Test 10	0.1406	0.1992	0.0409	0.1179	0.1362	0.0682	0.2967

Table 16
Sensitivity analysis ranking outcomes.

Alternatives	Ranking									
	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7	Test 8	Test 9	Test 10
LP_1	**3**	4	4	4	3	3	4	**3**	3	**3**
LP_2	**5**	5	5	5	5	5	5	**5**	5	**5**
LP_3	**4**	3	3	3	4	4	3	**4**	4	**4**
LP_4	**2**	**2**	1	**2**	1	1	**2**	**2**	1	**2**
LP_5	**1**	**1**	2	**1**	2	2	**1**	**1**	2	**1**

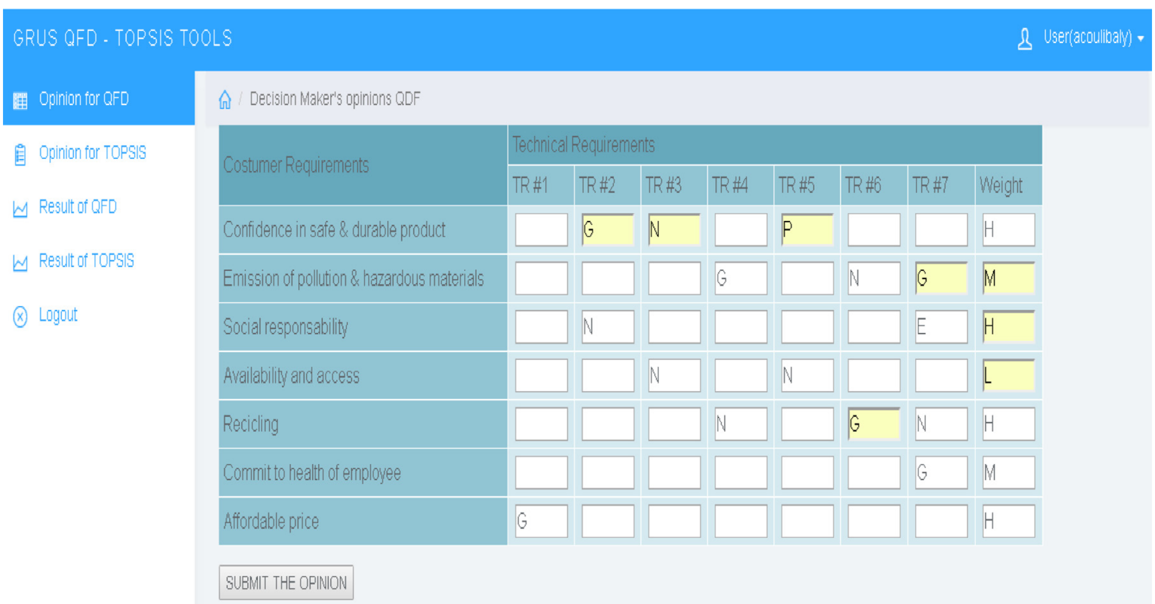

Fig. 4. QFD implementation for DM_1 in GRUS system.

Apart of that, we have formulated an integrated logistic provider selection model with the application of QFD and TOPSIS. Initially, it has been started to provide a case example and solve the multi criteria decision problem by Excel software. Although we can rely on the model and its efficiency, however the validity of the methodology must be studied and clarified. Thus, for some main reasons we develop a decision support system and implement the QFD-TOPSIS algorithm which is vital;

1- The proposed DSS gives accuracy and stability to the study. Because all the calculations are monitored by a machine and mathematical algorithm
2- For larger scale decision problem and high volume of computations, the DSS acts faster and in second all the results are extracted.
3- For decision makers and experts always is more convenient to work on a computer system and offer their opinion or judgment rather than filing printed questionnaire which sometimes will cause errors and mistakes. They are able to check all the process of decision making (brainstorming, arguments and discussion). It is much more economic to use a DSS rather than paper questionnaire in terms of printing ethics as well.

To ensure that the model is usable and applicable for the RUC-APS project, a real-world case study of selecting logistic provider (five companies in France) for transportation of agriculture products to the storage or distribution centers is regulated with a genuine decision support system (Section 7). We pushed our efforts to handle uncertainty existed in evaluation process and to face a complex and influential customer/stakeholder group.

In the previous section, a set of sensitivity analysis test, which has been done with changing different criteria weight position and weight combination, denotes that the decision makers can trust on the proposed QFD-TOPSIS approach due to stable ranking results for 3PL providers. This is another way to verify and validate our proposed algorithm.

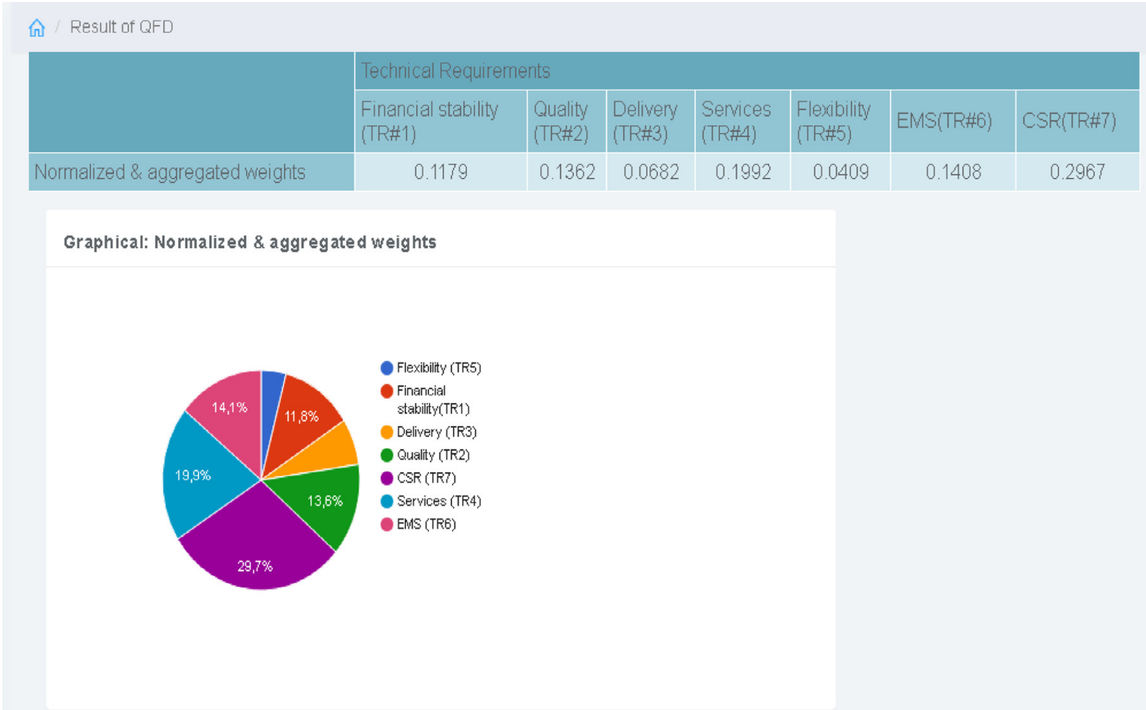

Fig. 5. Final weights obtained by the QFD and graphical chart.

Fig. 6. Alternative performance on each TR made by DM_1.

7. Group DSS implementation

To implement the proposed model, we divide it by the two sections. Initially the QFD process is established and the weights of technical requirements are computed. In the second part fuzzy TOPSIS methodology will be implemented to reach the ranking of logistic providers. Each user (decision maker) can register to the system, make a profile, sign in and present the preferences based on fuzzy linguistic variables. For instance, we have shown that the first evaluation matrix (Table 4) which is given by decision maker (DM_1). Fig. 4 reflects the picture of GRUS system. The software must be connected to the internet and at the same time each user can submit the preferences as well. In this software, there are options for presenting preference of the decision makers assigned to both TOPSIS and QFD tools. When a user submits his/her opinion, the calculation and aggregation is carried out automatically based on the written algorithm. The final aggregated weights from the three DMs are generated in Fig. 5. A pie chart also visualizes the importance of technical requirements as well. It is observed that CSR is the most effective item followed by services by the 0.199 of significance.

In this step like QFD process again each decision maker is requested to submit his/her judgment anonymously using the system input. In Fig. 6, the performance of logistic providers is evaluated

Result of TOPSIS

Normalized fuzzy matrix

Alternatives	Technical Requirements						
	Financial stability (TR#1)	Quality (TR#2)	Delivery (TR#3)	Services (TR#4)	Flexibility (TR#5)	EMS(TR#6)	CSR(TR#7)
LP1	[0.0, 0.58, 1.0]	[0.25, 0.58, 1.0]	[0.25, 0.58, 1.0]	[0.25, 0.58, 1.0]	[0.0, 0.5, 1.0]	[0.25, 0.58, 1.0]	[0.25, 0.67, 1.0]
LP2	[0.25, 0.5, 1.0]	[0.0, 0.5, 1.0]	[0.0, 0.58, 1.0]	[0.25, 0.67, 1.0]	[0.25, 0.67, 1.0]	[0.25, 0.58, 1.0]	[0.0, 0.5, 1.0]
LP3	[0.25, 0.67, 1.0]	[0.25, 0.58, 1.0]	[0.25, 0.58, 1.0]	[0.0, 0.33, 1.0]	[0.25, 0.67, 1.0]	[0.0, 0.67, 1.0]	[0.25, 0.58, 1.0]
LP3	[0.25, 0.67, 1.0]	[0.25, 0.58, 1.0]	[0.25, 0.58, 1.0]	[0.0, 0.33, 1.0]	[0.25, 0.67, 1.0]	[0.0, 0.67, 1.0]	[0.25, 0.58, 1.0]
LP4	[0.25, 0.67, 1.0]	[0.25, 0.58, 1.0]	[0.25, 0.67, 1.0]	[0.25, 0.67, 1.0]	[0.0, 0.42, 1.0]	[0.25, 0.5, 1.0]	[0.25, 0.67, 1.0]
LP5	[0.25, 0.58, 1.0]	[0.25, 0.58, 1.0]	[0.0, 0.67, 1.0]	[0.0, 0.42, 1.0]	[0.25, 0.58, 1.0]	[0.5, 0.75, 1.0]	[0.5, 0.75, 1.0]

Fig. 7. Normalized fuzzy decision matrix.

Weighted normalized matrix for TOPSIS

Alternatives	Technical Requirements						
	Financial stability (TR#1)	Quality (TR#2)	Delivery (TR#3)	Services (TR#4)	Flexibility (TR#5)	EMS(TR#6)	CSR(TR#7)
LP1	0.063666	0.0820605	0.0410905	0.120018	0.02045	0.084832	0.19211325
LP2	0.06631875	0.0681	0.036828	0.128982	0.02648275	0.084832	0.14835
LP3	0.07634025	0.0820605	0.0410905	0.082668	0.02648275	0.082368	0.17876175
LP3	0.07634025	0.0820605	0.0410905	0.082668	0.02648275	0.082368	0.17876175
LP4	0.07634025	0.0820605	0.0441595	0.128982	0.018814	0.0792	0.19211325
LP5	0.07103475	0.0820605	0.039897	0.091632	0.02464225	0.1056	0.222525
PIS (V^+)	0.0766	0.0826	0.0457	0.1295	0.0266	0.1056	0.2226
NIS (V^-)	0.0641	0.0681	0.0403	0.0946	0.0205	0.0831	0.1484

Fig. 8. Weighted normalized matrix.

with respect to each technical requirement by DM_1. Each decision maker starts to give the preference by a fuzzy linguistic table. By clicking submit button all the process of the TOPSIS is completed and step by step it is possible to check details of computations.

For example the normalized and aggregated fuzzy decision matrix can be shown as Fig. 7 indicates. In this matrix is equal to the computations of Table 10 in previous sections. Through each stage the system has the capability to be tested and verified and it is part of the strength of the software. The weighted normalized decision matrix in the next step must be determined. All the matrix elements thereafter are defuzzified and the outcome is captured as shown by Fig. 8. To prevent of producing several table and figures, we have withdrawn to bring all those computations. In order to get the final results of the TOPSIS, closeness coefficient must be identified. In final the priority of each logistic provider is detected as Fig. 9 claims. The system allows us to generate a graphical picture of the performance of each alternative such in Fig. 10. It is evident that LP_5 (Bansard company) is the only option who is eligible to be selected by the supply chain experts.

8. Conclusion and suggestion for future project directions

This paper resolves the issue of evaluating and ranking logistics providers by utilizing an integrated decision making formulation. It evaluates and elucidates the interaction relationships and impact levels between the customer attitudes and logistics providers' criteria. A fuzzy approach is designed to eliminate uncertainty among factors and decision variables. QFD facilitates building up the un-

Final solution of TOPSIS

Alternatives	CC_i	Ranking
LP_1	0.647	3
LP_2	0.172	5
LP_3	0.284	4
LP_4	0.783	2
LP_5	0.917	1

Fig. 9. TOPSIS ranking for logistic providers.

derlying relationship among customer and technical requirements. The findings of this paper put forward very significant insights on different attributes which considerably contribute to LPs performance and in this case the efficiency of inefficient providers can be improved. Through design of a decision support model, a logistic provider problem has been defined, required factors under viewpoint of experts and customer identified, and finally, a solution has been generated using fuzzy MCDM. It must be pointed out that house of quality matric allows the project users and designers to capture customer preferences, and convert them simply to multi criteria process. The outputs of QFD are incorporated into the MCDM as weights of the main decision criteria. Sensitivity analysis strategies confirm that the applied model is stable and cannot be affected by the changes in criteria weights. Hence, it is approved that the BANSARD Company can be counted as optimal logistic provider.

Based on the results, it is recommended to focus on flexibility and delivery factors because they have been rated by decision makers with lower importance. So, those factors need some improvement and corrective actions. It is figured out the best alternative (BANSARD) has earned very good rating on CSR (as most important criterion) and so it can be key driving force to the developments of infrastructure of the service provider. It is also the responsibility of the management to strongly control main drivers of the supply chain and logistics to improve manufacturing and logistics processes and production planning activities as well.

We believe that the proposed decision making formula is acceptable and robust and can be easily executed practically for group multi-criteria decision-making problems. The top ranked logistic provider scores can be outlined for the rest to comprehend their weaknesses and fulfill logical pattern for future plans. We have tried to develop a basis for generous relation of logistic companies to reduce their weaknesses. So, managers can rely on this structure effectively to reach global objectives. Through the released model, groups of experts can participate to the core of the decision making process focusing on customer and external parameters to deliver effective performance among logistics partners. Evaluation of the LP performance indirectly improves performance and behavior of LPs regarding weak attribute and also allocate more credit to the stronger providers to appreciate all practices to the next level.

The proposed model has objected at bridging two existing gaps in the literature on LPs evaluation; the lack of a systematic approach to analyze specific decision elements and the consideration of customer satisfaction factors in fuzzy environment. Although the proposed framework is not hard to be implemented in logistics problem by any other users whose features are similar to those delineated for the company of the case study, it requires serious efforts on the side of the managers. For example, the wrong choice of experts by the manager as well as the inaccurate analysis of just one expert may cause the selection of less than efficient alternatives, imposing an opportunity cost on the company in terms of efficiency losses and foregone profits.

The implementation of a group fuzzy MCDM approach in a supply and logistics management is the achievement of the RUC-APS project. In the decision support system (GRUS), we developed and implemented an integrated MCDM formula to help supply chain and agricultural partners in facilitation of their judgments and grasp a practical framework. The article supplied an effort to discuss about selection of suppliers under supervision and satisfaction of customers. Basically we obtain a new trend in supporting group decision making technologies in the supply chain with the utilization of information technology. We have argued the interaction and linkage between decision makers and computer applications by an integrated multi criteria decision making framework.

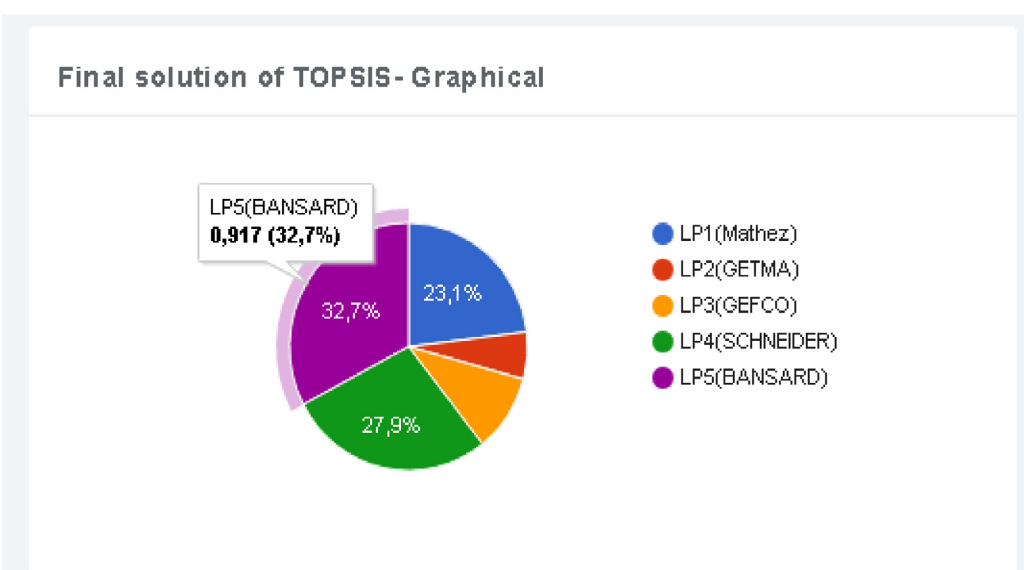

Fig. 10. Graphical presentation of alternative ranking.

In this sense, we deem that the utilization of computers and programming to structure a decision support model pushes managers and executives of the RUC-APS to come closer and participate in a common perspective. The paper attempts to establish a foundation for further works and it highly appreciates newer works and/or extension.

The decision support system we designed and introduced is based on Grails web application framework and supports an open source framework. We have proposed a fuzzy multi criteria decision making system including QFD and TOPSIS, to weight decision factors and to rank LPs, respectively. The proposed DSS has some advantages: first of all it gives a comfortable and reliable interface with the decision making system through a computer facility. Secondly, sometimes it is hard to gather participants (users or decision makers) and ask them to fill questionnaire about a problem. By using GRUS, a user can be everywhere and by an online system the meeting is made and the results automatically are registered and saved in the DSS environment. Thirdly, by such DSS the time of decision making decreases and a decision making facilitator does not put too much time to handle decision process. Forth, this system with the same formulas and programming can be operated for other decision making or voting situation like selecting a fertilizer with different variables for the agricultural production system. Five, the system can be extended and generalized according to the requirement of the decision problem by some modification on the programming, parameters and etc. Accordingly, the developed DSS not even is applicable for supply chain and logistic objectives, it is possible to implement other integrated decision making tools or programming in it with specific adjustment based on the defined decision problem.

Acknowledgment

The paper is supported by the University of Toulouse and IRIT (Institut de Recherche en Informatique de Toulouse). Authors are thankful for all the encouragement and kind notification. Authors of this publication acknowledge the contribution of the Project 691249, RU-CAPS: Enhancing and implementing Knowledge based ICT solutions within high Risk and Uncertain Conditions for Agriculture Production Systems (www.ru-caps.eu), funded by the European Union under their funding scheme H2020-MSCA-RISE-2015.

References

Accorsi, R., Manzini, R., & Maranesi, F. (2014). A decision-support system for the design and management of warehousing systems. *Computers in Industry, 65*(1), 175–186.

Aguezzoul, A. (2014). Third-party logistics selection problem: A literature review on criteria and methods. *Omega, 49*, 69–78.

Akman, G., & Baynal, K. (2014). Logistics service provider selection through an integrated fuzzy multicriteria decision making approach. *Journal of Industrial Engineering, 2014*, 1–16.

Alter, S., & Alter, S. (1980). Decision support systems: Current practice and continuing challenges (No. 04; HD30. 23, A5.).

Asadi, H. H., Sansoleimani, A., Fatehi, M., & Carranza, E. J. M. (2016). An AHP–TOPSIS Predictive Model for District-Scale Mapping of Porphyry Cu–Au Potential: A Case Study from Salafchegan Area (Central Iran). *Natural Resources Research*, 1–13.

Bhattacharya, A., Mohapatra, P., Kumar, V., Dey, P. K., Brady, M., & Tiwari, M. K. ,&Nudurupati,S. S. (2014). Green supply chain performance measurement using fuzzy ANP-based balanced scorecard: A collaborative decision-making approach. *Production Planning & Control, 25*(8), 698–714.

Baumeister, J., & Striffler, A. (2015). Knowledge-driven systems for episodic decision support. *Knowledge-Based Systems, 88*, 45–56.

Bonczek, R. H., Holsapple, C. W., & Whinston, A. B. (2014). *Foundations of decision support systems*. Academic Press.

Bosona, T., & Gebresenbet, G. (2013). Food traceability as an integral part of logistics management in food and agricultural supply chain. *Food Control, 33*(1), 32–48.

Brandenburg, M., Govindan, K., Sarkis, J., & Seuring, S. (2014). Quantitative models for sustainable supply chain management: Developments and directions. *European Journal of Operational Research, 233*(2), 299–312.

Carvalho, J. B., Varela, M. L. R., Putnik, G. D., Hernández, J. E., & Ribeiro, R. A. (2014). A Web-Based Decision Support System for Supply Chain Operations Management Towards an Integrated Framework. *Decision Support Systems III-Impact of Decision Support Systems for Global Environments (pp. 104-117)*. Springer International Publishing.

Chandra, C., & Kumar, S. (2000). An application of a system analysis methodology to manage logistics in a textile supply chain. *Supply Chain Management: An International Journal, 5*(5), 234–245.

Cheng, C. H. (1999). Evaluating weapon systems using ranking fuzzy numbers. *Fuzzy sets and systems, 107*(1), 25–35.

Chen, L. H., Ko, W. C., & Yeh, F. T. (2017). Approach based on fuzzy goal programing and quality function deployment for new product planning. *European Journal of Operational Research, 259*(2), 654–663.

Diabat, A., Khreishah, A., Kannan, G., Panikar, V., & Gunasekaran, A. (2013). Benchmarking the interactions among barriers in third-party logistics implementation: An ISM approach. *Benchmarking: An International Journal, 20*(6), 805–824.

Dweiri, F., Kumar, S., Khan, S. A., & Jain, V. (2016). Designing an integrated AHP based decision support system for supplier selection in automotive industry. *Expert Systems with Applications, 62*, 273–283.

Erfani, M., Afrougheh, S., Ardakani, T., & Sadeghi, A. (2015). Tourism positioning using decision support system (case study: Chahnime—Zabol, Iran). *Environmental Earth Sciences, 74*(4), 3135–3144.

Fahimnia, B., Sarkis, J., & Davarzani, H. (2015). Green supply chain management: A review and bibliometric analysis. *International Journal of Production Economics, 162*, 101–114.

Germani, M., Mengoni, M., & Peruzzini, M. (2012). A QFD-based method to support SMEs in benchmarking co-design tools. *Computers in Industry, 63*(1), 12–29.

Gorry, A. G., & Morton, M. S. (1971). A framework for management information systems.

Govindan, K., Palaniappan, M., Zhu, Q., & Kannan, D. (2012). Analysis of third party reverse logistics provider using interpretive structural modeling. *International Journal of Production Economics, 140*(1), 204–211.

Guo, Z. X., Ngai, E. W. T., Yang, C., & Liang, X. (2015). An RFID-based intelligent decision support system architecture for production monitoring and scheduling in a distributed manufacturing environment. *International Journal of Production Economics, 159*, 16–28.

Gupta, A., & Walton, R. O. (2016). Interpretive structural modelling to assess third party logistics providers. *World Review of Intermodal Transportation Research, 6*(1), 59–73.

Hashemian, S. M., Behzadian, M., Samizadeh, R., & Ignatius, J. (2014). A fuzzy hybrid group decision support system approach for the supplier evaluation process. *The International Journal of Advanced Manufacturing Technology, 73*(5-8), 1105–1117.

Hernández, J. E., Lyons, A. C., Zarate, P., & Dargam, F. (2014). Collaborative decision–making and decision support systems for enhancing operations management in industrial environments. *Production Planning & Control, 25*(8), 636–638.

Holt, C. C., & Huber, G. P. (1969). A computer aided approach to employment service placement and counseling. *Management Science, 15*(11), 573–594.

İç, Y. T., & Yurdakul, M. (2009). Development of a decision support system for machining center selection. *Expert systems with Applications, 36*(2), 3505–3513.

Ignatius, J., Rahman, A., Yazdani, M., Šaparauskas, J., & Haron, S. H. (2016). An integrated fuzzy ANP–QFD approach for green building assessment. *Journal of Civil Engineering and Management, 22*(4), 551–563.

Karsak, E. E., & Dursun, M. (2014). An integrated supplier selection methodology incorporating QFD and DEA with imprecise data. *Expert Systems with Applications, 41*(16), 6995–7004.

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. *European Journal of Operational Research, 233*(2), 432–447.

Khademolqorani, S., & Hamadani, A. Z. (2013). An adjusted decision support system through data mining and multiple criteria decision making. *Procedia-Social and Behavioral Sciences, 73*, 388–395.

König, A., & Spinler, S. (2016). The effect of logistics outsourcing on the supply chain vulnerability of shippers: Development of a conceptual risk management framework. *The International Journal of Logistics Management, 27*(1), 122–141.

Kou, G., Shi, Y., & Wang, S. (2011). Multiple criteria decision making and decision support systems—Guest editor's introduction. *Decision Support Systems, 51*(2), 247–249.

Kristianto, Y., Gunasekaran, A., Helo, P., & Sandhu, M. (2012). A decision support system for integrating manufacturing and product design into the reconfiguration of the supply chain networks. *Decision Support Systems, 52*(4), 790–801.

Lee, C. K. M., Ru, C. T. Y., Yeung, C. L., Choy, K. L., & Ip, W. H. (2015). Analyze the healthcare service requirement using fuzzy QFD. *Computers in Industry, 74*, 1–15.

Lei, N., & Moon, S. K. (2015). A Decision Support System for market-driven product positioning and design. *Decision Support Systems, 69*, 82–91.

Liu, S., Wang, Z., & Liu, L. (2012). An Integrated Sustainability Analysis Approach to Support Holistic Decision Making in Sustainable Supply Chain Management. In *DSS* (pp. 391–402).

Marakas, G. M. (2003). *Decision support systems in the 21st century (Vol. 134)*. Upper Saddle River, NJ: Prentice Hall.

Ngai, E. W. T., Peng, S., Alexander, P., & Moon, K. K. (2014). Decision support and intelligent systems in the textile and apparel supply chain: An academic review of research articles. *Expert Systems with Applications, 41*(1), 81–91.

Piltan, M., & Sowlati, T. (2016). A multi-criteria decision support model for evaluating the performance of partnerships. *Expert Systems with Applications, 45*, 373–384.

Power, D. J., Sharda, R., & Burstein, F. (2015). *Decision support systems*. John Wiley & Sons, Ltd.
Rajesh, R., Pugazhendhi, S., Ganesh, K., Ducq, Y., & Koh, S. L. (2012). Generic balanced scorecard framework for third party logistics service provider. *International Journal of Production Economics, 140*(1), 269–282.
RUC-APS, (2016). http://cordis.europa.eu/project/rcn/204775_en.html, https://ruc-aps.eu/,
Scott, J., Ho, W., Dey, P. K., & Talluri, S. (2015). A decision support system for supplier selection and order allocation in stochastic, multi-stakeholder and multi-criteria environments. *International Journal of Production Economics, 166*, 226–237.
Seuring, S. (2013). A review of modeling approaches for sustainable supply chain management. *Decision support systems, 54*(4), 1513–1520.
Sharma, P., Sarker, B. R., & Romagnoli, J. A. (2011). A decision support tool for strategic planning of sustainable biorefineries. *Computers & Chemical Engineering, 35*(9), 1767–1781.
Shi, P., Yan, B., Shi, S., & Ke, C. (2015). A decision support system to select suppliers for a sustainable supply chain based on a systematic DEA approach. *Information Technology and Management, 16*(1), 39–49.
Shi, J., Guo, J. E., & Fung, R. Y. (2017). Decision support system for purchasing management of seasonal products: A capital-constrained retailer perspective. *Expert Systems with Applications, 80*, 171–182.
Sprague, R., & Carlson, E. D. (1982). *Building effective decision support systems*. Englewood Cliffs NJ: Prentice Hall.
Taticchi, P., Tonelli, F., & Pasqualino, R. (2013). Performance measurement of sustainable supply chains: A literature review and a research agenda. *International Journal of Productivity and Performance Management, 62*(8), 782–804.
Tavana, M., Yazdani, M., & Di Caprio, D. (2017). An application of an integrated ANP–QFD framework for sustainable supplier selection. *International Journal of Logistics Research and Applications, 20*(3), 254–275.
Turban, E., & Watkins, P. R. (1986). Integrating expert systems and decision support systems. *Mis Quarterly, 10*(2), 121–136.
Tavana, M., Li, Z., Mobin, M., Komaki, M., & Teymourian, E. (2016). Multi-objective control chart design optimization using NSGA-III and MOPSO enhanced with DEA and TOPSIS. *Expert Systems with Applications, 50*, 17–39.
Tseng, M. L., Lim, M., Wu, K. J., Zhou, L., & Bui, D. T. D. (2017). A novel approach for enhancing green supply chain management using converged interval-valued triangular fuzzy numbers-grey relation analysis. *Resources, Conservation and Recycling*. doi:10.1016/j.resconrec.2017.01.007.
Vinodh, S., Balagi, T. S., & Patil, A. (2016). A hybrid MCDM approach for agile concept selection using fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS. *The International Journal of Advanced Manufacturing Technology, 83*(9-12), 1979–1987.
Wang, T. C., & Lee, H. D. (2009). Developing a fuzzy TOPSIS approach based on subjective weights and objective weights. *Expert Systems with Applications, 36*(5), 8980–8985.
Wang, P., Zhu, Z., & Wang, Y. (2016). A novel hybrid MCDM model combining the SAW, TOPSIS and GRA methods based on experimental design. *Information Sciences, 345*, 27–45.
Wong, W. K., & Leung, S. Y. S. (2008). Genetic optimization of fabric utilization in apparel manufacturing. *International Journal of Production Economics, 114*(1), 376–387.
Yang, G. L., Yang, J. B., Xu, D. L., & Khoveyni, M. (2017). A three-stage hybrid approach for weight assignment in MADM. *Omega, 71*, 93–105.
Yayla, A. Y., Oztekin, A., Gumus, A. T., & Gunasekaran, A. (2015). A hybrid data analytic methodology for 3PL transportation provider evaluation using fuzzy multi-criteria decision making. *International Journal of Production Research, 53*(20), 6097–6113.
Yazdani, M., Hashemkhani Zolfani, S., & Zavadskas, E. K. (2016). New integration of MCDM methods and QFD in the selection of green suppliers. *Journal of Business Economics and Management, 17*(6), 1097–1113.
Yazdani, M., Chatterjee, P., Zavadskas, E. K., & Zolfani, S. H. (2017). Integrated QFD-MCDM framework for green supplier selection. *Journal of Cleaner Production, 142*, 3728–3740.
Zarate, P. (2013). *Tools for collaborative decision-making*. John Wiley & Sons.
Zarate, P., & Dargam, F. (2015). Featured issue on collaborative decision processes and analysis. *EURO Journal on Decision Processes, 3*(3-4), 215–218.
Zaim, S., Sevkli, M., Camgöz-Akdağ, H., Demirel, O. F., Yayla, A. Y., & Delen, D. (2014). Use of ANP weighted crisp and fuzzy QFD for product development. *Expert Systems with Applications, 41*(9), 4464–4474.
Zavadskas, E. K., Turskis, Z., Vilutienė, T., & Lepkova, N. (2017). Integrated group fuzzy multi-criteria model: Case of facilities management strategy selection. *Expert Systems With Applications, 82*, 317–331 (2017).
Zavadskas, E. K., Mardani, A., Turskis, Z., Jusoh, A., & Nor, K. M. (2016). Development of TOPSIS Method to Solve Complicated Decision-Making Problems—An Overview on Developments from 2000 to 2015. *International Journal of Information Technology & Decision Making, 15*(03), 645–682.
Zha, X. F., Sriram, R. D., Fernandez, M. G., & Mistree, F. (2008). Knowledge-intensive collaborative decision support for design processes: A hybrid decision support model and agent. *Computers in Industry, 59*(9), 905–922.
Zhang, S., & Goddard, S. (2007). A software architecture and framework for Web-based distributed Decision Support Systems. *Decision Support Systems, 43*(4), 1133–1150.