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An intelligent approach to supplier evaluation in automotive sector

Zeki Ayağ · **Funda Samanlioglu**

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Abstract During the process of supplier evaluation, selecting the best desirable supplier is one of the most critical problems of companies since improperly selected suppliers may cause losing time, cost and market share of a company. For this multiple-criteria decision making selection problem, in this paper, a fuzzy extension of analytic network process (ANP), which uses uncertain human preferences as input information in the decision-making process, is applied since conventional methods such as analytic hierarchy process cannot accommodate the variety of interactions, dependencies and feedback between higher and lower level elements. The resulting fuzzy ANP enhances the potential of the conventional ANP for dealing with imprecise and uncertain human comparison judgments. In short, in this paper, an intelligent approach to supplier selection problem through fuzzy ANP is proposed by taking into consideration quantitative and qualitative elements to evaluate supplier alternatives, and a case study in automotive sector is presented.

Keywords Supplier selection · Fuzzy logic · Multiple-criteria decision making · Analytic network process

Introduction

Across many industries, companies especially in automotive sector increasingly give more res- ponsibility to their suppliers to design and produce innovative, high quality products at a lower and competitive cost. Drastically increasing customer demands and fierce winds of globalization accelerated competition in the related field, and technological advances in information sharing on internet also increased governmental pressure on worldwide companies toward adoption of the supply chain management (SCM) philosophy.

The SCM covers all business activities associated with the flow and transformation of goods from the raw materials stage through to final-users, as well as the associated information and cash flows. In other words, SCM is the integration of these activities through improved supply chain relationships to achieve a sustainable competitive advantage (CA) (Handfield and Nichols 1999). The great benefit of SCM is that when all of the channel members including suppliers, manufacturers, distributors, and customers behave as if they are part of the same company, they can enhance performance significantly across the board (Copacino 1997). Greater dependence on suppliers increases the need to effectively manage suppliers. Three dimensions underlie supplier management: (1) effective supplier selection; (2) innovative supplier development strategies; and (3) meaningful supplier performance assessment mechanisms (Kannan and Tan 2010).

Recently, supplier selection problem in automotive SCM has become more critical because of the fierce competition among companies. As a result of the pressure of globalization in the last two decades, outsourcing activities has become an important strategic decision and supplier selection is a prime concern. Effective supplier selection and the overall management of supplier evaluation process are critical and complex issues for automotive manufacturers. The issue of the selection of supplies is essentially a problem of selecting the most suitable suppliers for different parts or component. The objective is selecting the ideal combination of suppliers given the criteria that are important for the purchasing decision under a number of secondary conditions (Degraeve and Roodhooft 1999). It can be said that an automotive manufacturer company is as successful as its ability to coordinate the efforts of its key suppliers as steel, glass, plastic, and sophis-

Z. Ayağ · F. Samanlioglu (✉)
Department of Industrial Engineering, Kadir Has University, Kadir Has Campus, Cibali, 34083 Istanbul, Turkey
e-mail: fsamanlioglu@khas.edu.tr

ticated electronic systems are transformed into an automobile that is intended to compete in world markets against the US, the Japanese, the European and the others manufacturers (Spekman et al. 1998).

In short, effective supplier evaluation process in automotive sector has been a major problem for worldwide companies that aim to be successful in the globalizing world. Therefore, the selection of a proper supplier becomes a multiple-criteria decision making (MCDM) problem in the presence of various alternatives and set of evaluation criteria, and needs an analytical tool to efficiently solve.

As one of the most commonly used methods for solving MCDM problems in literature, analytic hierarchy process (AHP) was first introduced by Saaty (1981). In AHP, a hierarchy considers the distribution of a goal amongst the elements being compared, and judges which element has a greater influence on that goal. In reality, a holistic approach like analytic network process (ANP) developed by Saaty (1996) is needed if all attributes and alternatives involved are connected in a network system that accepts various dependencies. Several MCDM problems cannot be hierarchically structured as in AHP because they involve interactions and dependencies in higher or lower level elements. In ANP, not only does the importance of the attributes determine the importance of the alternatives as in AHP, but the importance of alternatives themselves also influences the importance of the attributes.

Furthermore, this application of Saaty's ANP has some shortcomings as follows; this method is mainly used in nearly crisp decision applications and creates and deals with a very unbalanced scale of judgment. In addition, ANP method does not take into account the uncertainty associated with the mapping of one's judgment to a number, and its ranking is rather imprecise. On the other hand, the subjective judgment, selection and preference of decision-makers have great influence on its results.

Naturally, if the conventional ANP method is used for supplier selection, the decision maker's requirements for evaluating a set of possible alternatives may always contain ambiguity and multiplicity of meaning. Additionally, it is also recognized that human assessment on qualitative attributes is always subjective and thus imprecise. Due to the vagueness and uncertainty on judgments of the decision-maker(s), the crisp pair wise comparison in the conventional ANP seems to be insufficient and imprecise to capture the right judgments of decision-maker(s). Therefore, a fuzzy logic is introduced in the pair wise comparison of ANP to make up for this deficiency in the conventional ANP, referred to as fuzzy ANP.

The objective of this paper is to present an intelligent approach to supplier selection problem through fuzzy ANP to help companies determine the best supplier satisfying their needs and expectations among a set of possible alternatives. Furthermore, a case study realized in one of the leading automotive manufacturers in Turkey is presented to prove this approach's applicability and validity in order to make it more understandable, especially for decision-maker(s) who are involved in supplier selection process in a company.

Related literature

Extensive reviews of supplier selection methods with different classifications are presented in Aissaoui et al. (2007); Ho et al. (2010), and Chai and Liu (2012). In some of the articles, mathematical models and heuristics are used to select the best set of the suppliers. Ghodsypour and O'Brien (2001) presented a mixed integer non-linear programming to solve the multiple sourcing problem, which takes into account net price, storage, transportation, and ordering costs. Basnet and Leung (2005) studied a multi-period inventory lot-sizing scenario with multiple products and suppliers. They used enumerative search algorithm and a heuristic for order quantity and schedule decisions and selection of suppliers. Sanayei et al. (2008) combined multi-attribute utility theory and linear programming to rate the suppliers and calculated the optimum order quantities while maximizing the total additive utility. Wu et al. (2010) considered risk factors and used a fuzzy multi-objective programming model to decide on supplier selection. Li and Zabinsky (2011) developed a two-stage stochastic programming model and a chance-constrained programming model to determine suppliers and optimal order quantities when there are business volume discounts. Amin et al. (2011) implemented fuzzy Strengths, Weaknesses, Opportunities and Threats (SWOT) analysis and a fuzzy linear programming model to determine suppliers and order quantities, taking into consideration capacity of warehouses and fuzzy demand. Mendoza and Ventura (2012) proposed two mixed integer nonlinear programming models to select the best set of suppliers and determined the proper allocation of order quantities while minimizing the annual ordering, inventory holding, and purchasing costs under suppliers' capacity and quality constraints. Mansini et al. (2012) developed an integer programming based heuristic to select suppliers when suppliers offer total quantity discounts and transportation costs are based on truckload shipping rates. Arikan (2013) presented a fuzzy linear programming mathematical model for a multiple sourcing supplier selection problem, where minimization of costs and maximization of quality and on-time delivery are studied simultaneously.

In the literature, weighted additive programs are frequently used to handle multiple criteria in supplier selection. Ng (2008) developed a weighted linear program for the multi-criteria supplier selection problem and presented a transformation technique to solve the program without optimization. Amid et al. (2009) worked on a fuzzy weighted additive and mixed integer linear programming model to select suppliers and to determine the order quantities based on price breaks. Yucel and Guneri (2011) expressed linguistic values as trapezoidal fuzzy numbers and developed a weighted additive fuzzy programming model to select suppliers and to determine order quantities to each supplier. Chu and Varma (2012) used triangular fuzzy numbers to represent weights and applied additive weighted ratings to select suppliers.

Different goal programming models are developed in order to select suppliers. Famuyiwa et al. (2008) developed a fuzzy-goal-programming model to select suppliers during the early formation of a strategic partnership. Erol and Ferrell (2009) presented an integrated approach for the supplier selection and performance management and applied their approach in purchasing department of a Turkish steel company. They developed a mixed integer goal programming model to select the suppliers and applied balanced score card approach to the purchasing function to evaluate the performances.

In some research articles, AHP, integrated with other methods, is implemented for supplier selection and order quantity calculations. Ghodsypour and O'Brien (1998) integrated AHP and linear programming to select the best suppliers and place the optimum order quantities among them while maximizing the total value of purchasing. Xia and Wu (2007) combined AHP improved by rough sets theory and multi-objective mixed integer programming to determine the suppliers and the order quantities in the case of multiple sourcing, multiple products, supplier's capacity constraints, and volume discounts. Ha and Krishnan (2008) developed a hybrid method that uses AHP for the weights of qualitative criteria and then data envelopment analysis or neural network to select efficient vendors. Yu and Tsai (2008) integrated AHP with an integer program to rate wafer supplier's performance regarding incoming raw materials and then to allocate periodical purchases in semiconductor industry. Levary (2008) used AHP to rank foreign suppliers based on supply reliability and risks. Wang and Yang (2009) used AHP and fuzzy compromise programming for supplier selection in quantity discount environments. Liao and Kao (2010) integrated the Taguchi loss function, AHP and multi-choice goal programming model to select suppliers. Amid et al. (2011) implemented AHP to determine the weights of criteria and proposed a weighted max–min fuzzy model to find out the appropriate order to each supplier. Bruno et al. (2012) presented a model for supplier evaluation based on AHP and presented a case study of suppliers operating for a customer firm of the railway industry on a particular component of the traction system.

In some journal papers, fuzzy AHP is implemented to capture the vagueness and uncertainty in the selection process. Lee (2009) presented a fuzzy AHP model that includes benefits, opportunities, costs and risks and applied it to select backlight unit supplier for a thin film transistor liquid crystal display (TFT-LCD) manufacturer in Taiwan. Lee et al. (2009) implemented fuzzy AHP to analyze the importance of multiple factors such as cost, yield and number of suppliers and then used a fuzzy multiple goal programming model to select TFT-LCD suppliers. Kilincci and Onal (2011) applied a fuzzy AHP approach for supplier selection in a washing machine company in Turkey. Shaw et al. (2012) presented a combined approach of fuzzy-AHP and fuzzy multi-objective linear programming for supplier selection and quota allocation in a low carbon emission supply chain. Ayag and Ozdemir (2006) applied the integration of fuzzy AHP and goal programming for evaluation of assembly-line systems. Pan et al. (2005) also used the fuzzy expert system for assessing rain impact in highway construction scheduling. Zouggari and Benyoucef (2012) first used fuzzy-AHP for supplier selection according to performance strategy, quality of service, innovation and risk, and then implemented a simulation based fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) technique to evaluate criteria application for order allocation among the selected suppliers.

Technique for Order Preference by Similarity to Ideal Solution, Fuzzy TOPSIS and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) are also used in the literature to evaluate and rank suppliers. Araz and Ozkarahan (2007) used PROMETHEE methodology to evaluate and sort suppliers based on co-design capabilities, and overall performances. Chen (2011) first identified potential suppliers using data envelopment analysis and then ranked them with TOPSIS method. Liao and Kao (2011) presented an integrated fuzzy TOPSIS and multi-choice goal programming approach to solve supplier selection problem and illustrated the method by an example in a watch firm. Chen and Yang (2011) implemented the constrained fuzzy AHP to measure the weights, converted them to deterministic weights using the extent analysis technique, and used fuzzy TOPSIS to rank suppliers. Lin et al. (2011) implemented ANP and TOPSIS to calculate the weights and rank suppliers and a linear program to allocate order quantities to vendors. Govindan et al. (2012) used fuzzy numbers for finding criteria weights and implemented fuzzy TOPSIS to rank suppliers. Sharma and Balan (2013) integrated Taguchi's loss function, TOPSIS and multi criteria goal programming approaches to identify the best performing supplier.

Another method used for supplier evaluation and overall performance of a supply chain is Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH). Clivillé and Berrah (2012) used the SCOR model and integrated the impacting supplier performance into the prime manufacturer scores. They implemented MACBETH with Choquet aggregation in order to take into consideration mutual interactions between processes, and expressed both process and overall performances. They also presented a case study in a bearings company to illustrate the approach. MACBETH is a multi attribute utility theory method that supports interactive learning about the evaluation problem, and that translates qualitative information into quantitative information. It is based on comparison of situations, and describes these situations with elementary performance expressions and aggregated performance expressions. Performance is aggregated with weighted mean but since this requires independence of criteria which might in reality interact, the extension of MACBETH to Choquet integrals is presented by Cliville' et al. (2007).

Analytic network process and fuzzy ANP, integrated with other methods, are used widely in the literature for different applications. Ayag and Ozdemir (2011) implemented fuzzy ANP for evaluation and selection of machine tool alternatives. Vahdani et al. (2012) developed the interval-valued fuzzy-ANP and presented a case study about the performance of property responsibility insurance companies. Ustun and Demirtas (2008) worked on a real life problem of evaluating four different plastic molding firms working with a refrigerator plant. They integrated ANP and a multi-objective mixed integer linear program in order to define the optimum quantities among selected suppliers, maximizing the total value of purchasing, and minimizing the total cost and total defect rate while balancing the total cost among periods. The authors Ustun and Demirtas (2008) also integrated ANP and an additive achievement scalarizing function to select the best suppliers and determine the optimum order quantities. Here, unwanted deviations from budget and aggregate quality goals are balanced by Minmax Goal Programming, and minimized by Achimedean Goal Programming. Lin (2009) combined ANP with fuzzy preference programming to select top suppliers and applied multi-objective linear programming to facilitate optimal allocation of orders. Lin (2012) also combined fuzzy ANP with fuzzy multi-objective linear programming to select the best suppliers for achieving optimal order allocation under fuzzy conditions. Razmi et al. (2009) developed a fuzzy ANP to evaluate the suppliers with respect to vendor related factors and select the best one. They combined the model with a non-linear model to obtain eigenvectors from fuzzy comparison matrices. Ming-Lang et al. (2009) presented an ANP with choquet integral to determine the suppliers for a PCB manufacturing firm. Buyukozkan and Cifci (2011) implemented a fuzzy ANP and studied the sustainability principles for supplier selection operations in supply chains. Vinodh et al. (2011) applied a fuzzy ANP for supplier selection in an Indian electronics switches manufacturing company. Kang et al. (2012) presented a fuzzy ANP model to evaluate various aspects of supplier selection in semiconductor industry with a case study of IC packaging company selection in Tawain. Pang and Bai (2013) integrated fuzzy synthetic evaluation and fuzzy ANP for evaluation and selection of the most suitable suppliers.

In the literature, there are several journal articles specifically focusing on supplier selection in automotive industry. Dogan and Aydin (2011) combined Bayesian Networks and Total Cost Ownership methods and tested their approach by selecting the suppliers of a tier-1 supplier in automotive industry. Zeydan et al. (2011) implemented a methodology for increasing the supplier selection and evaluation quality in a car manufacturing company in Turkey. They used fuzzy AHP to find criteria weights and fuzzy TOPSIS to rank the suppliers of quality car luggage side part (panel) in an automotive factory of Turkey. Aksoy and Ozturk (2011) presented a neural network based supplier selection and supplier performance evaluation system, and tested it with data taken from an automotive factory. Parthiban et al. (2012) studied the interaction of factors influencing the supplier selection process, and used interpretive structural modeling technique to get the weights for the performance factors. They applied AHP to rank the suppliers of an automotive component manufacturing industry in the southern part of India.

At present, there does not appear to be a comprehensive research in the literature that focuses on supplier selection in automotive industry using fuzzy ANP. In reality, an approach like ANP is required if all attributes and alternatives involved are connected in a network system that accepts various interactions and dependencies in higher or lower level elements. Several MCDM approaches such as AHP, PROMETHEE, MACBETH, and TOPSIS lack this network structure, where attributes might influence alternatives and alternatives might influence attributes. Conventional AHP or ANP are insufficient and imprecise to represent the vagueness and uncertainty of judgments of the decision-maker(s), therefore in this research, fuzzy logic is introduced in the pair wise comparison of ANP, and referred as fuzzy ANP.

Proposed approach

In the conventional ANP method, the evaluation of selection attributes is done by using a nine-point scaling system, where a score of 1 represents equal importance between the two elements and a score of 9 indicates the extreme importance of one element, showing that each attribute is related with another. This scaling process is then converted to priority values to compare alternatives. In other words, the conventional ANP method does not take into account the vagueness and uncertainty on judgments of the decision-maker(s). To overcome the inability of ANP to handle the imprecision and subjectiveness in the pair wise comparison process, in this research, fuzzy logic is integrated with the Saaty's ANP. Proposed fuzzy ANP-based methodology to supplier selection problem in automotive industry is presented below step-by-step, and illustrated in Fig. 1.

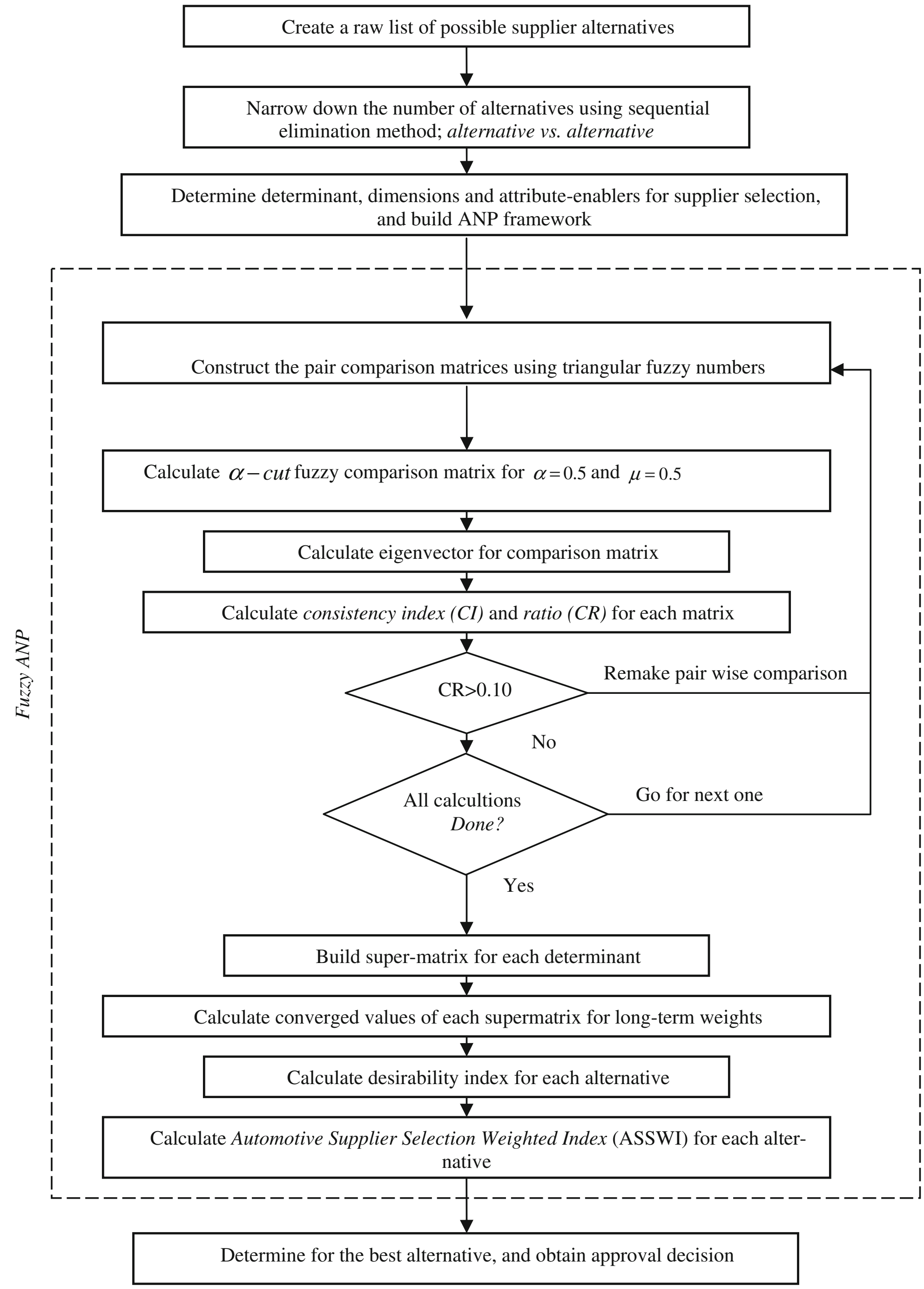

Fig. 1 Fuzzy ANP-based methodology for automotive supplier selection problem

Creating a raw list of possible alternatives and pre-screening process

The company's needs are clearly defined and a list of possible supplier alternatives in the market is prepared. If the number of supplier alternatives in the list is more than expected, a study called *pre-selection process* should be applied to reduce number of alternatives to an acceptable level so the selection process is not time-consuming. S*equential elimination methods* can be used to separate the strong candidates among others. These methods are applicable when one can specify values (outcomes) for all criteria and alternatives. Those values should be scalar (measurable) or at least ordinal (rank orderable). These methods do not consider weighting of attributes, and they are easily understandable and applicable by everyone. There are two kinds of sequential elimination methods:

Alternative versus standard and *alternative versus alternative*. In the first method, if standard value is defined wrong, naturally the results could not be correct. In the second one, more accurate results are obtained by comparing each alternative with others. In other words, weak alternatives are eliminated. Finally, of both methods, the second one is selected for the pre-selection process (Ayag 2002).

Determining the elements for building an ANP framework

To identify the elements (i.e. determinants, dimensions and attribute-enablers) required in an ANP framework and its decision environment related to supplier selection, first a literature research is done and a set of supplier selection criteria are determined, and second, set of companies, practicing similar processes, is analyzed. As a result of this, 3 determinants, 5 different dimensions and 17 attribute-enablers are considered as shown in Table 1.

As an example of the relationships among the determinants; CA, productivity (PR) and profitability (PF) can be given. If the PR, the number of units produced in a certain time (units per day), increases, this results in decreasing unit cost, and naturally increasing PF of the company. If the PR increases, CA of the company on other competitors goes up by selling cheaper. These determinants are taken into consideration in the supplier selection process in order to find out of how the selection criteria and sub-criteria (dimensions and attribute-enablers) of a supplier affect them.

Table 1 List of the determinants, the dimensions and the attribute-enablers for automotive supplier selection problem

Determinants	Dimensions	Definition
Competitive Advantage (CA)	Profile (PRO)	Financial Position (FP)
		Position in Industry (PO)
		Reputation (RE)
	Pricing (PRI)	Discounts Level (DL)
		Payment Conditions (PC)
Productivity (PR)	Delivery (DEL)	Timeliness (TI)
		Cost (CO)
		Lead Time (LT)
		Reliability (RE)
	Quality (QUA)	Rejection Rate (RR)
		Warranties and Claim Policies (WC)
		Return Penalty (RP)
		Certifications (CE)
Profitability (PF)	Service (SER)	Employee Expertise (EE)
		Production Facilities and Capacity (PF)
		R&D Capability (RD)
		Technical Capability (TC)

Fuzzy ANP

Fuzzy logic The main idea of fuzzy set theory is that an element has a degree of membership in a fuzzy set (Negoita 1985; Zimmermann 1996). Therefore, it is defined by a membership function that maps elements in the universe of discourse to elements within a certain interval. The most commonly used range for expressing degree of membership is the unit interval [0, 1]. If the value assigned is 0, the element does not belong to the set. If the value assigned is 1, the element belongs completely to the set. Finally, if the value lies within the interval [0, 1], the element has a certain degree of membership (it belongs partially to the fuzzy set). A fuzzy set, then, contains elements that have different degrees of membership in it. In this study, in order to capture the vagueness, triangular fuzzy numbers (TFNs), $\tilde{1}$ to $\tilde{9}$, are used to represent subjective pair wise comparisons of selection process. TFNs show the participants' judgments or preferences among the options such as equally important, weakly more important, strongly more important, very strongly more important, and extremely more important preferred (see Table 2). On the other hand, $F = \left\{\left(x, \mu_{\tilde{M}}(x)\right), x \in R\right\}$ indicates a fuzzy set, where x takes its values on the real line, $R : -\infty < x < +\infty$ and $\mu_{\tilde{M}}(x)$ is a continuous mapping from R to the closed interval [0, 1]. The element, $x$in the set expresses the real values in the closed interval,$[l, u]$, including mean (m) of each TFN. A TFN denoted as $\tilde{M} = [l, u]$ has the following triangular type membership function (1);

$$\mu_{\tilde{M}}(x) = \begin{cases} 0 & x < l \\ x - l/m - l & l \leq x \leq m \\ u - x/u - m & m \leq x \leq u \\ 0 & x > u \end{cases} \tag{1}$$

If x value is less than lower level of a fuzzy number (l), the function gets the value of 0 (zero), bigger than/equal lower level (l) and less than/equal to mean level (m), the function gets the value of $x - l \big/ m - l$, and bigger than/equal mean level (m) and less than/equal to upper level (u), the function gets the value of $u - x \big/ u - m$. Alternatively, by defining the interval of confidence level α, a TFN can be characterized as:

$$\forall\alpha \in [0, 1],$$
$$\tilde{M}_\alpha = \left[l^\alpha, u^\alpha\right] = (m-1)\alpha + l, -(u-m)\alpha + u \tag{2}$$

Some main operations for positive fuzzy numbers are described by the interval of confidence by Kaufmann and Gupta (1988) as given below;

Table 2 Definition and membership function of fuzzy number (Ayag 2005)

Intensity of importance*	Fuzzy number	Definition	Membership function
1	$\tilde{1}$	Equally important/preferred	(1, 1, 2)
3	$\tilde{3}$	Moderately more important/preferred	(2, 3, 4)
5	$\tilde{5}$	Strongly more important/preferred	(4, 5, 6)
7	$\tilde{7}$	Very strongly more important/preferred	(6, 7, 8)
9	$\tilde{9}$	Extremely more important/preferred	(8, 9, 10)

* Fundamental scale used in pair wise comparison (Saaty 1989)

$$\forall m_l, m_u, n_l, n_u \in R^+, \tilde{M}_\alpha = \left[m_l^\alpha, m_u^\alpha\right],$$
$$\tilde{N}_\alpha = \left[n_l^\alpha, n_u^\alpha\right], \alpha \in [0, 1] \tag{3}$$
$$\tilde{M}_\alpha \oplus \tilde{N}_\alpha = \left[m_l^\alpha + n_l^\alpha, m_u^\alpha + n_u^\alpha\right] \tag{4}$$
$$\tilde{M}_\alpha - \tilde{N}_\alpha = \left[m_l^\alpha - n_l^\alpha, m_u^\alpha - n_u^\alpha\right] \tag{5}$$
$$\tilde{M}_\alpha \otimes \tilde{N}_\alpha = \left[m_l^\alpha n_l^\alpha, m_u^\alpha n_u^\alpha\right] \tag{6}$$
$$\tilde{M}_\alpha / \tilde{N}_\alpha = \left[m_l^\alpha / n_l^\alpha, m_u^\alpha / n_u^\alpha\right] \tag{7}$$

The TFNs, $\tilde{1}$ to $\tilde{9}$, are utilized to improve the conventional Saaty's nine-point scaling scheme. In order to take the imprecision of human qualitative assessments into consideration, the five TFNs ($\tilde{1}$, $\tilde{3}$, $\tilde{5}$, $\tilde{7}$, $\tilde{9}$) are defined with the corresponding membership function. All attributes and alternatives are linguistically depicted by Fig. 2, and Table 2 shows definition and membership function of fuzzy numbers (Ayag 2005). The shape and position of linguistically terms are chosen to illustrate the fuzzy extension of the method.

Computational steps of fuzzy ANP: Application of the fuzzy ANP approach to automotive supplier selection problem is presented below step-by-step. In the approach, the TFNs are utilized to improve the scaling scheme in the judgment matrices, and interval arithmetic is used to solve the fuzzy eigenvector (Cheng and Mon 1994).

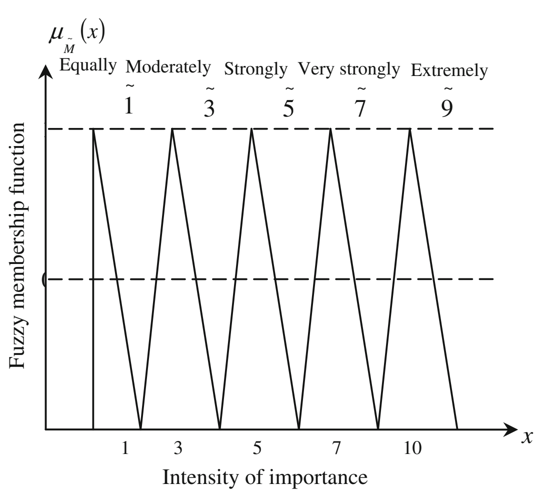

Fig. 2 Fuzzy membership function for linguistic values for attributes or alternatives

Step I: Model construction and problem structuring; the top most elements in the hierarchy of determinants are decomposed into dimensions and attribute-enablers. The decision model development requires identification of dimensions and attribute-enablers at each level and the definition of their inter-relationships. The ultimate objective of hierarchy is to identify alternatives that are significant for finding out best supplier. In this study, three evaluation determinants that are determined are: CA, PR and PF. These determinants are determined based on the idea of how an auto supplier mainly affects a company' performance and they are aggregated in *Automotive Supplier Selection Weighted Index* (ASSWI) selection step.

To construct the ANP hierarchy, Saaty's (1996) suggestions of using a network for categories of benefits, costs, risks and opportunities are utilized. Instead of Saaty's categories, the above-mentioned determinants are used. In order to analyze the combined influence of the determinants on supplier selection process, the value of ASSWI for each alternative is calculated to rank the all. This index also takes the influences of dimensions and attribute-enablers into consideration. Figure 3 shows ANP-based framework to supplier selection problem in automotive industry.

Step II: Pair wise comparison matrices between component/attributes levels; By using TFNs ($\tilde{1}$, $\tilde{3}$, $\tilde{5}$, $\tilde{7}$, $\tilde{9}$), the decision-maker(s) are asked to respond to a series of pair wise comparisons with respect to an upper level "control" criterion. These are conducted with respect to their relevance importance towards the control criterion. In the case of interdependencies, components in the same level are viewed as controlling components for each other. Levels may also be interdependent. Through pair wise comparisons by using TFNs, the fuzzy judgment matrix $\tilde{A}$ $\left(\tilde{a}_{ij}\right)$ is constructed as:

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & .. & .. & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & .. & .. & \tilde{a}_{2n} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ \tilde{a}_{n1} & \tilde{a}_{n2} & .. & .. & 1 \end{bmatrix} \tag{8}$$

where, $\tilde{a}_{ij}^\alpha = 1$, if i is <u>equal</u> j, and $\tilde{a}_{ij}^\alpha = \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$ or $\tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1}$, if i is <u>not equal</u> j.

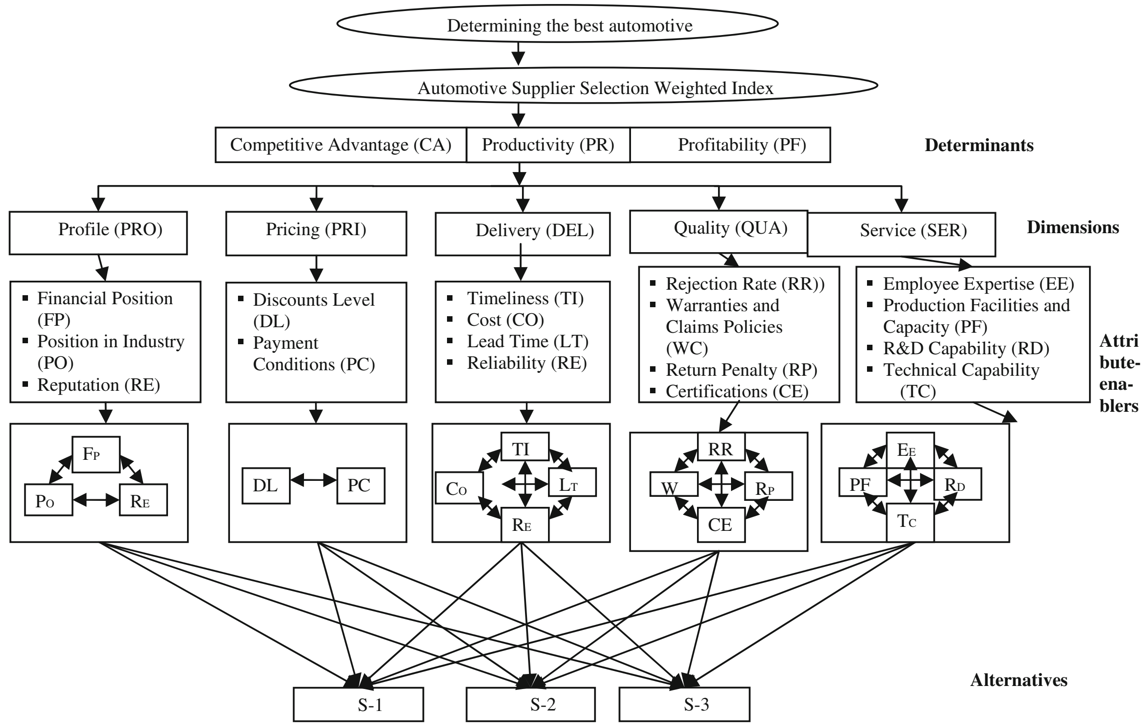

Fig. 3 ANP framework for automotive supplier selection problem

For solving fuzzy eigenvalue: A fuzzy eigenvalue,$\tilde{\lambda}$, is a fuzzy number solution to:

$$\tilde{A}\tilde{x} = \tilde{\lambda}\tilde{x}, \tag{9}$$

where $\tilde{\lambda}_{\max}$ is the largest eigenvalue of $\tilde{A}$. Saaty (1981) provides several algorithms for approximating $\tilde{x}$, where $\tilde{A}$ is $n\,x\,n$ fuzzy matrix containing fuzzy numbers $\tilde{a}_{ij}$, and $\tilde{x}$ is a non-zero $nx1$ fuzzy vector containing fuzzy number $\tilde{x}_i$. To perform fuzzy multiplications and additions by using the interval arithme tic and $\alpha - cut$, the equation $\tilde{A}\tilde{x} = \tilde{\lambda}\tilde{x}$ is equivalent to:

$$\lfloor a^{\alpha}_{i1l}x^{\alpha}_{1l}, a^{\alpha}_{i1u}x^{\alpha}_{1u}\rfloor \oplus \cdots \oplus \lfloor a^{\alpha}_{inl}x^{\alpha}_{nl}, a^{\alpha}_{inu}x_{nu}\alpha\rfloor$$
$$= \left[\lambda x^{\alpha}_{il}, \lambda x^{\alpha}_{iu}\right] \tag{10}$$

where,$\tilde{A} = \left[\tilde{a}_{ij}\right]$, $\tilde{x}_i = (\tilde{x}_1, \ldots, \tilde{x}_n)$, $\tilde{a}^{\alpha}_{ij} = \left[a^{\alpha}_{ijl}, a^{\alpha}_{iju}\right]$, $\tilde{x}^{\alpha}_i = \left[x^{\alpha}_{il}, x^{\alpha}_{iu}\right]$, $\tilde{\lambda}^{\alpha} = \left[\lambda^{\alpha}_l, \lambda^{\alpha}_u\right]$ for $0 < \alpha \leq 1$ and all i, j, where $\mathrm{i} = 1, 2 \ldots n$, $j = 1, 2 \ldots n$.

a^{α}_{ijl}; the lower value (l) of a triangular fuzzy number at i. line and j. column of the fuzzy judgment matrix, $\tilde{A}$ for a given α value

a^{α}_{iju}; the upper value (u) of a triangular fuzzy number at i. line and j. column of the fuzzy judgment matrix, $\tilde{A}$ for a given α value

x^{α}_{il}; the lower value (l) at i. line of the fuzzy vector for a given α value

x^{α}_{iu}; the lower value (u) at i. line of the fuzzy vector for a given α value

$\alpha - cut$ is known to incorporate the experts or decision-maker(s) confidence over his/her preference or the judgments. Degree of satisfaction for the judgment matrix $\tilde{A}$ is estimated by the index of optimism μ. The larger value of index μ indicates the higher degree of optimism. The index of optimism is a linear convex combination (Lee 1999) defined as;

$$\tilde{a}^{\alpha}_{ij} = \mu a^{\alpha}_{iju} + (1 - \mu)\, a^{\alpha}_{ijl}, \forall \mu \in [0, 1] \tag{11}$$

While $\alpha$is fixed, the following matrix can be obtained after setting the index of optimism,μ, in order to estimate the degree of satisfaction. Both of them are defined in the range [0, 1] by decision-makers.

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}^{\alpha}_{12} & .. & .. & \tilde{a}^{\alpha}_{1n} \\ \tilde{a}^{\alpha}_{12} & 1 & .. & .. & \tilde{a}^{\alpha}_{2n} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ \tilde{a}^{\alpha}_{n1} & \tilde{a}^{\alpha}_{n2} & .. & .. & 1 \end{bmatrix} \tag{12}$$

The eigenvector is calculated by fixing the μ value and identifying the maximal eigenvalue. After defuzzification of each pair wise matrix, the consistency ratio (CR) for each matrix is calculated. The deviations from consistency are expressed by the following equation consistency index, and the measure of inconsistency is called the consistency index (CI);

$$CI = \frac{\lambda_{\max} - n}{n - 1}. \tag{13}$$

The consistency ratio (CR) is used to estimate directly the consistency of pair wise comparisons. The CR is computed by dividing the CI by a value obtained from a table of Random Consistency Index (RI);

$$CR = \frac{CI}{RI} \tag{14}$$

If the *CR* less than 0.10, the comparisons are acceptable, otherwise not. *RI* is the average index for randomly generated weights (Saaty 1981).

Step III: Pair wise comparison matrices of inter-dependencies; In order to reflect the interdependencies in network, pair wise comparisons among all the attribute-enablers are calculated.

Step IV: Super-matrix formation and analysis; A super-matrix formation allows a resolution of the effects of interdependence that exists between the elements of the system. The super-matrix is a partitioned matrix, where each sub-matrix is composed of a set of relationships between two levels in the graphical model. Raising the super-matrix to the power $2k + 1$, where k is an arbitrary large number, allows convergence of the interdependent relationships between the two levels being compared. The super-matrix is converged for getting a long-term stable set of weights.

Step V. Selection of the best alternative; The desirability index is calculated for each alternative that is based on the determinants by using the weights obtained from the pair wise comparisons of the alternatives, dimensions and weights of attribute-enablers from the converged super matrix. The equation of *desirability index,* D_{ia} for alternative i and determinant a, *competitive advantage (CA)* is defined as;

$$D_{ia} = \sum_{j=1}^{J} \sum_{k=1}^{K_{ja}} P_{ja} A^{D}_{kja} A^{I}_{kja} S_{ikja} \tag{15}$$

The notations used in this equation are given in Table 3.

Step VI. Calculation of Automotive Supplier Selection Weighted Index (ASSWI); to finalize the analysis of supplier selection, *ASSWI* is calculated for each alternative. The $ASSWI_i$ for an alternative i is the product of the desirability indices, D_{ia}. After calculating *ASSWI* values for each alternative, they are normalized to rank the alternatives to determine the one with the highest value.

Table 3 Notations used to calculate desirability index

Notations	Definition
P_{ja}	The relative importance weight of dimension j on determinant *a*
A^{D}_{kja}	The relative importance weight for attribute-enabler k of dimension j, and determinant *a* for the dependency (D) relationships between attribute-enabler's component levels
A^{I}_{kja}	The stabilized relative importance weight for attribute-enabler k of dimension j, and determinant *a* for the independency (I) relationships within attribute-enabler's component level
S_{ikja}	Is the relative impact of concept alternative i on attribute-enabler k of dimension j of concept selection network
K_{ja}	The index set of attribute-enablers for dimension j of determinant *a*
J	The index set for attribute j

Table 4 Fuzzy comparison matrix for the determinants

Determinant	CA	PR	PF
CA	1	$\tilde{3}$	$\tilde{9}$
PR	$\tilde{3}^{-1}$	1	$\tilde{5}$
PF	$\tilde{9}^{-1}$	$\tilde{5}^{-1}$	1

Table 5 $\alpha - cuts$ fuzzy comparison matrix for the determinants for $\alpha = 0.5$

Determinant	CA	PR	PF
CA	1	[2, 4]	[8, 10]
PR	[1/4, 1/2]	1	[4, 6]
PF	[1/10, 1/8]	[1/6, 1/4]	1

Approval and further actions

The final alternative selected is presented to upper management for approval to proceed with further actions such as developing an implementation schedule, training key users and so on.

Case study

Above, a fuzzy ANP-based approach was presented to evaluate a set of automotive supplier alternatives. In this section, a case study is given to prove this approach's applicability and validity and to make it more understandable especially to decision-makers who are involved in supplier selection process in a company. For the case study, a leading company in Turkey as well as in Europe, specializing in designing and manufacturing various kinds of polyurethane-based products (i.e. polyurethane seat cushion foam, steering wheels and armrests) for main automakers is selected. The company works with suppliers in homeland and abroad, and needs a reliable and practical evaluation system to rank and find the best supplier for each kind of its outsourced products.

The proposed model was developed in partnership with the company, and the company decided to use it for a type of product (i.e. interior trim parts) to evaluate its applicability. Supplier alternatives are determined together with a set of evaluation criteria as shown in Table 1. The elements in the table are specially determined according to the specifications of supplier selection problem in automotive sector, and can be applied to any other kind of automotive product or part.

The number of the suppliers was kept as 3 for simplicity. Moreover, a benchmarking study was also done for their competitors in the same sector to determine supplier alternatives. Since the number of alternatives was 3, the pre-selection process was ignored, and all 3 alternatives were taken into consideration for further work, referred to as fuzzy ANP study. Then, the fuzzy ANP study was done using the TFNs, $\tilde{1}-\tilde{9}$ to express the preference in the pair wise comparisons. Obtained fuzzy comparison matrix for the relative importance of the determinants is shown in Table 4.

The lower limit and upper limit of the fuzzy numbers with respect to the α were defined as follows by applying Eq. (10);

$$\tilde{1}_\alpha = [1, 3-2\alpha], \quad \tilde{3}_\alpha = [1+2\alpha, 5-2\alpha],$$
$$\tilde{3}_\alpha^{-1} = \left[\frac{1}{5-2\alpha}, \frac{1}{1+2\alpha}\right], \quad \tilde{5}_\alpha = [3+2\alpha, 7-2\alpha],$$
$$\tilde{5}_\alpha^{-1} = \left[\frac{1}{7-2\alpha}, \frac{1}{3+2\alpha}\right], \quad \tilde{7}_\alpha = [5+2\alpha, 9-2\alpha],$$
$$\tilde{7}_\alpha^{-1} = \left[\frac{1}{9-2\alpha}, \frac{1}{5+2\alpha}\right], \quad \tilde{9}_\alpha = [7+2\alpha, 11-2\alpha],$$
$$\tilde{9}_\alpha^{-1} = \left[\frac{1}{11-2\alpha}, \frac{1}{7+2\alpha}\right].$$

Later, the values; $\alpha = 0.5$ and $\mu = 0.5$ determined by the decision-maker, were used in the above expression, and the entire$\alpha-cuts$ fuzzy comparison matrix shown in Table 5 was obtained. Equation (11) was used to calculate eigenvector for pair wise comparison matrix given in Table 6.

Table 6 Pair wise comparison matrix for the relative importance of the determinants

Determinants	CA	PR	PF	e-Vector
CA	1.000	3.000	9.000	0.662
PR	0.375	1.000	5.000	0.274
PF	0.113	0.208	1.000	0.064
			λ_{max}	3.082
			CI	0.041
			RI	0.58
			CR	0.070<0.1

Table 7 Fuzzy comparison matrix for the dimensions for the determinant *CA*

Competitive Advantage (CA)					
Dimensions	PRO	PRI	DEL	QUA	SER
PRO	1	$\tilde{3}$	$\tilde{3}$	$\tilde{5}$	$\tilde{9}$
PRI	$\tilde{3}^{-1}$	1	$\tilde{1}$	$\tilde{3}$	$\tilde{3}$
DEL	$\tilde{3}^{-1}$	$\tilde{1}^{-1}$	1	$\tilde{5}$	$\tilde{7}$
QUA	$\tilde{5}^{-1}$	$\tilde{3}^{-1}$	$\tilde{5}^{-1}$	1	$\tilde{1}$
SER	$\tilde{9}^{-1}$	$\tilde{3}^{-1}$	$\tilde{7}^{-1}$	$\tilde{1}^{-1}$	1

Table 8 $\alpha-cuts$ fuzzy comparison matrix for the determinant, *CA* for $\alpha = 0.5$

Competitive Advantage (CA)					
	PRO	PRI	DEL	QUA	SER
PRO	1	[2,4]	[2,4]	[4,6]	[8,10]
PRI	[1/4,1/2]	1	[1,2]	[2,4]	[2,4]
DEL	[1/4,1/2]	[1/2,1]	1	[4,6]	[8,10]
QUA	[1/6,1/4]	[1/4,1/2]	[1/6,1/4]	1	[1,2]
SER	[1/10,1/8]	[1/4,1/2]	[1/8,1/6]	[1/2,1]	1

Table 9 Pair wise comparison matrix for the relative importance of the dimensions for the determinant, *CA*

Competitive Advantage (CA)						
	PRO	PRI	DEL	QUA	SER	e-Vector
PRO	1.000	3.000	3.000	5.00	9.0	0.460
PRI	0.375	1.000	1.500	3.00	3.0	0.192
DEL	0.375	0.750	1.000	5.00	7.0	0.231
QUA	0.208	0.375	0.208	1.00	1.5	0.068
SER	0.113	0.375	0.146	0.75	1.0	0.049
					λ_{max}	5.365
					CI	0.091
					RI	1.12
					CR	0.082<0.100

Table 10 Fuzzy comparison matrix of attribute-enablers under *CA* and *PRO*

CA			
PRO	FP	PO	RE
FP	1	$\tilde{1}$	$\tilde{9}$
PO	$\tilde{1}^{-1}$	1	$\tilde{5}$
RE	$\tilde{9}^{-1}$	$\tilde{5}^{-1}$	1

Then, by using Eq. (9), eigenvalue of the matrix $\boldsymbol{A}$ was calculated by solving the characteristic equation of $\boldsymbol{A}$,det $(A - \lambda I) = 0$ and all λ values for $A(\lambda_1, \lambda_2, \lambda_3)$ were determined. The largest eigenvalue of pair wise matrix,λ_{max}

Table 11 $\alpha - cuts$ fuzzy comparison matrix of attribute-enablers under *CA* and *PRO* for $\alpha = 0.5$

CA			
PRO	FP	PO	RE
FP	1	[1, 2]	[8, 10]
PO	[1/2, 1]	1	[4, 6]
RE	[1/10, 1/8]	[1/6, 1/4]	1

Table 12 Pair wise comparison matrix for the relative importance of the attribute-enablers of the dimension, *PRO* for the determinant, *CA*

CA				
PRO	FP	PO	RE	e-Vector
FP	1.000	1.500	9.000	0.564
PO	0.750	1.000	5.000	0.368
RE	0.113	0.208	1.000	0.068
			λ_{max}	3.067
			CI	0.033
			RI	0.58
			CR	0.057 < 0.100

Table 13 Fuzzy comparison matrix for attribute-enablers for *FP* under *CA* and *PRO*

FP	PO	RE
PO	1	$\tilde{5}$
RE	$\tilde{5}^{-1}$	1

Table 14 $\alpha - cuts$ fuzzy comparison matrix for attribute-enablers for *FP* under *CA* and *PRO* for $\alpha = 0.5$

FP	PO	RE
PO	1	[4, 6]
RE	[1/6, 1/4]	1

was calculated to be 3.082. The dimension of the matrix, n, is 3 and the random index, $RI\ (n)$ is 0.58 (RI - function of the number of attributes) (Saaty 1981). Finally, the consistency index (CI) and the consistency ratio (CR) of the matrix were calculated by using Eqs. (13) and (14) as follows;

$$CI = \frac{\lambda_{max} - n}{n-1} \quad = \frac{3.082 - 3}{2} = 0.041,$$
$$CR = \frac{CI}{RI} = \quad = \frac{0.041}{0.58} = 0.070 < \quad 0.10.$$

As seen in the calculations, the judgments were found as consistent since the calculated CR value, 0.070 is less than 0.100. The same way, fuzzy pair wise comparison matrices of the dimensions for each determinant were built and all fuzzy calculations were made. In Tables 7, 8 and 9, the fuzzy pair wise comparison matrix of the dimensions for the determinant *Competitive Advantage (CA)* is presented.

Then, to reflect the interdependencies in the network, fuzzy pair wise comparison matrices for the attribute-enablers under each dimension for all 3 determinants were built and all fuzzy calculations were completed. In Tables 10, 11, and 12, the fuzzy pair wise comparison matrices for attribute-enablers under *Profile (PRO)* and *Competitive Advantage (CA)* are presented using TFNs.

Next, fuzzy pair wise comparison matrices were built to reflect the interdependencies in network, and fuzzy pair wise comparisons among all the attribute-enablers were con-

Table 15 Pair wise comparison matrix for the relative importance of the attribute-enablers for *FP* under *CA* and *PRO*

FP	PO	RE	e-Vector
PO	1	5.000	0.831
RE	0.208	1	0.169

Table 16 Fuzzy comparison matrix for the alternatives under *CA, PRO* and *FP*

CA, PRO			
FP	S-1	S-2	S-3
S-1	1	$\tilde{5}$	$\tilde{9}$
S-2	$\tilde{5}^{-1}$	1	$\tilde{3}$
S-3	$\tilde{9}^{-1}$	$\tilde{3}^{-1}$	1

Table 17 $\alpha - cuts$ fuzzy comparison matrix for $\alpha = 0.5$, for supplier alternatives under *CA, PRO* and *FP*

CA, PRO			
FP	S-1	S-2	S-3
S-1	1	[4, 6]	[8, 10]
S-2	[1/6, 1/4]	1	[2, 4]
S-3	[1/10, 1/8]	[1/4, 1/2]	1

Table 18 Pair wise comparison matrix for the relative importance of supplier alternatives under *CA, PRO* and *FP*

CA, PRO				
FP	S-1	S-2	S-3	e-Vector
S-1	1.000	5.000	9.000	0.745
S-2	0.208	1.000	3.000	0.182
S-3	0.113	0.375	1.000	0.074
			λ_{max}	3.082
			CI	0.041
			RI	0.58
			CR	0.071 < 0.1

Table 19 Supermatrix for Competitive Advantage (*CA*) after convergence (M^{100})

CA	FP	PO	RE	DL	PC	TI	CO	LT	RE	RR	WC	RP	CE	EE	PF	RD	TC
FP	0.409	0.409	0.409														
PO	0.414	0.414	0.414														
RE	0.177	0.177	0.177														
DL				1.0	0.0												
PC				0.0	1.0												
TI						0.338	0.338	0.338	0.338								
CO						0.317	0.317	0.317	0.317								
LT						0.251	0.251	0.251	0.251								
RE						0.062	0.062	0.062	0.062								
RR										0.336	0.336	0.336	0.336				
WC										0.313	0.313	0.313	0.313				
RP										0.253	0.253	0.253	0.253				
CE										0.061	0.061	0.061	0.061				
EE														0.330	0.330	0.330	0.330
PF														0.284	0.284	0.284	0.284
RD														0.260	0.260	0.260	0.260
TC														0.063	0.063	0.063	0.063

Table 20 Supplier selection desirability indices for Competitive Advantage (*CA*) ($a = 1$)

Dimension	Attribute enabler	P_{j1}	A^D_{kj1}	A^I_{kj1}	S_{1kj1}	S_{2kj1}	S_{3kj1}	Alternatives		
								S-1	S-2	S-3
PRO	FP	0.460	0.564	0.409	0.745	0.182	0.074	0.0791	0.0193	0.0079
	PO	0.460	0.368	0.414	0.116	0.355	0.529	0.0081	0.0249	0.0371
	RE	0.460	0.129	0.177	0.529	0.355	0.116	0.0056	0.0037	0.0012
PRI	DL	0.192	0.586	1.000	0.745	0.182	0.074	0.0838	0.0205	0.0083
	PC	0.192	0.414	1.000	0.660	0.249	0.091	0.0525	0.0198	0.0072
	TI	0.231	0.483	0.338	0.529	0.355	0.116	0.0199	0.0134	0.0044
DEL	CO	0.231	0.328	0.317	0.487	0.433	0.079	0.0117	0.0104	0.0019
	LT	0.231	0.129	0.251	0.643	0.216	0.141	0.0048	0.0016	0.0011
	RE	0.231	0.060	0.062	0.739	0.153	0.108	0.0006	0.0001	0.0001
	RR	0.068	0.510	0.336	0.662	0.274	0.064	0.0077	0.0032	0.0007
QUA	WC	0.068	0.294	0.312	0.487	0.433	0.079	0.0030	0.0027	0.0005
	RP	0.068	0.127	0.253	0.529	0.355	0.116	0.0012	0.0008	0.0003
	CE	0.068	0.068	0.061	0.739	0.153	0.108	0.0002	0.0001	0.0000
SER	EE	0.049	0.573	0.330	0.662	0.274	0.064	0.0061	0.0025	0.0006
	PF	0.049	0.268	0.284	0.660	0.249	0.091	0.0025	0.0009	0.0003
	RD	0.049	0.089	0.260	0.529	0.355	0.116	0.0006	0.0004	0.0001
	TC	0.049	0.070	0.063	0.662	0.274	0.064	0.0001	0.0001	0.0000
Total desirability indices (D_{i1}) of *CA* for supplier alternatives								0.288	0.124	0.072

ducted. A total of 66 matrices were built to obtain 3 supermatrices for all determinants. Only here, fuzzy pair wise comparison matrices of the attribute-enablers for *Upgrade Ability (UA)* under *Flexibility (F)* and*Competitive Advantage (CA)* are presented in Tables 13, 14 and 15.

The final standard fuzzy pair-wise comparison evaluations were required for the relative impacts of each supplier alternative. The number of fuzzy pair wise comparison matrices is dependent of the number of attribute-enablers that are included in the determinant of supplier selection hierarchy.

Table 21 Automotive Supplier Selection Weighted Index (ASSWI) for alternatives

Alternatives	Determinants	Calculated weights for alternatives			
	Competitive Advantage (CA)	Productivity (PR)	Profitability (PF)	ASSWI	Normalization
	0.662	0.274	0.064		
S-1*	0.288	0.287	0.292	0.288	0.599
S-2	0.124	0.121	0.119	0.123	0.255
S-3	0.072	0.066	0.069	0.070	0.146
Total				0.481	1.000

* Best supplier, *S*-1

Next, pair wise comparison matrices of the alternatives (S-1, S-2 and S-3) for each attribute-enabler for all determinants and all fuzzy calculations were completed. Only here, pair wise comparison matrices of the alternatives under *Competitive Advantage (CA)*, *Profile (PRO)* and *Financial Position (FP)* are presented in Tables 16, 17, and 18.

The super-matrix, M, shows the detailing results of the relative importance measures for each of the attribute-enablers for the determinant *Competitive Advantage (CA)* of supplier selection clusters. Since there are 17 fuzzy pair wise comparison matrices, one for each of the interdependent attribute-enablers in the*Competitive Advantage (CA)* hierarchy, there will be 17 non-zero columns in this super-matrix. Each of non-zero values in the column of super-matrix, M, is the relative importance weight associated with the interdependently pair wise comparison matrices. In this model, there are 3 super-matrices, one for each of the determinants (*CA*, *PR* and *PF*) of the best supplier selection hierarchy network, which need to be evaluated. Each super- matrix, M, was converged for getting a long-term stable set of weights. For this, power of super-matrix was raised to an arbitrarily large number. In this case study, convergence was reached at the 100th power for the determinant; CA. Table 19 shows the values after convergence.

To select the best alternative, calculations were made using Eq. (15) as given in Table 10. Table 20 shows the calculations for the desirability indices ($D_i$cost) for supplier alternatives that are based on the *Competitive Advantage (CA)* control hierarchy by using the weights obtained from the fuzzy pair wise comparisons of supplier alternatives, dimensions and attribute-enablers from the converged supermatrix. The weights were used to calculate a score for the determinant of supplier selection desirability for each alternative being considered. For example, the desirability indexes of the alternatives (S-1, S-2, and S-3) under the first determinant *Competitive Advantage (CA)*, where index, a is equal to 1, was calculated respectively by using Eq. (15), as illustrated in Table 20.

To find out the best solution, Automotive*Selection Weighted Index (ASSWI)* was calculated for each supplier alternative. The final results are given in Table 21. The table indicates that the best alternative is S-1.

Conclusions

In this paper, a fuzzy ANP-based methodology for supplier selection problem was proposed by taking into consideration quantitative and qualitative elements to evaluate supplier alternatives. The conventional ANP methodology uses nine-point scale and it is quite new and vastly improved over the AHP method as it allows for feedback between the hierarchical levels. However, due to the vagueness and uncertainty on judgments of the decision-maker(s), the nine-point scale pair wise comparison in the conventional ANP could be insufficient and imprecise to capture the right judgments of decision-maker(s). That is why; a fuzzy logic was integrated with the conventional ANP to overcome this problem.

As compared to fuzzy AHP, the analysis using fuzzy ANP is relatively cumbersome, because a great deal of fuzzy pair wise comparison matrices using triangular fuzzy numbers should be built for a typical study. Acquiring the relationships among deter-minants, dimensions and attribute-enablers required very long and exhaustive effort. So, a software support is needed to carry out all the calculations. In this study, Microsoft EXCEL was used due to the fact that there were a limited number of attributes-enablers, dimensions and determinants. As the number of these components increases, the method becomes more complex to even solve by using EXCEL. On the other hand, fuzzy ANP has an advantage of capturing interdependencies across and along the decision hierarchies, which means that fuzzy ANP provides more reliable solution than fuzzy AHP. For future study, a knowledge-based (KB) system or an expert system (ES) can be integrated to help decision-makers both make fuzzy pair wise calculations more concisely, and interpret the results in each step of the fuzzy ANP.

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