Computers & Industrial Engineering 56 (2009) 368–379

Contents lists available at ScienceDirect

Computers & Industrial Engineering

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

A hybrid approach to concept selection through fuzzy analytic network process

Z. Ayağ [a,*], R.G. Özdemir [b]

[a] Kadir Has University, Faculty of Engineering, Department of Industrial Engineering, Kadir Has Campus, 34083 Cibali, Istanbul, Turkey
[b] Istanbul Kültür University, Faculty of Engineering and Architecture, Department of Industrial Engineering, Atakoy Campus, D-100 Yanyol, 34156 Bakirkoy, Istanbul, Turkey

ARTICLE INFO

Article history:
Received 4 September 2007
Received in revised form 11 June 2008
Accepted 13 June 2008
Available online 20 June 2008

Keywords:
New product development (NPD)
Concept selection
Multiple-criteria decision-making (MCDM)
Fuzzy logic
Analytic network process (ANP)

ABSTRACT

Evaluating conceptual design alternatives in a new product development (NPD) environment has been one of the most critical issues for many companies which try to survive in the fast-growing world markets. Therefore, most companies have used various methods to successfully carry out this difficult and time-consuming evaluation process. Of these methods, analytic hierarchy process (AHP) has been widely used in multiple-criteria decision-making (MCDM) problems. But, in this study, we used analytical network process (ANP), a more general form of AHP, instead of AHP due to the fact that AHP cannot accommodate the variety of interactions, dependencies and feedback between higher and lower level elements. Furthermore, in some cases, due to the vagueness and uncertainty on the judgments of a decision-maker, the crisp pairwise comparison in the conventional ANP is insufficient and imprecise to capture the right judgments of the decision-maker. Therefore, a fuzzy logic is introduced in the pairwise comparison of ANP to make up for this deficiency in the conventional ANP, and is called as fuzzy ANP. In short, in this paper, a fuzzy ANP-based approach is proposed to evaluate a set of conceptual design alternatives developed in a NPD environment in order to reach to the best one satisfying both the needs and expectations of customers, and the engineering specifications of company. In addition, a numerical example is presented to illustrate the proposed approach.

1. Introduction

Today's world is characterized by major changes in market and economic conditions, coupled with rapid advances in technologies. As the natural result of this, companies have been forced to develop new products for current markets, most of all technology-driven or high-tech markets. The changing economic conditions and technologies combined with increased domestic and global competition, changing customer needs, rapid product obsolescence and the emergence of new markets, require very fast innovation process. The innovation process can be divided into three main areas such as fuzzy front-end (FFE) or project planning, new product development (NPD) process, and commercialization.

A NPD process is the sequence of steps or activities which an enterprise employs to conceive, design and commercialize a product. This development process typically includes the following activities: (i) identifying customer needs, (ii) establishing target specifications, (iii) concept generation, (iv) concept selection, (v) concept testing, (vi) setting final specifications, (vii) project planning, (viii) economic analysis, (ix) benchmarking of competitive products, (x) modeling and (xi) prototyping. In the NPD process, in item (v), a set of concepts are introduced and needs to be evaluated in terms of the criteria (i.e. highest performance and lowest cost) to reach to ultimate one. This process is called concept selection (Ayag, 2005b).

Concept selection is often the Rubicon in the design process. It is vital that the best concept is selected, as it determines the direction of the design embodiment stage. It is often said in the literature that nearly 60–80% of the cost is committed at this stage (Duffy, Andreasen, Maccallum, & Reijers, 1993). After this stage has been passed, the design process will diverge towards a detailed solution. Concept selection is therefore a vital part in the design process. It is recognized that the ability to rapidly evaluate design ideas, throughout their development within the design process, is an essential element in the goal to increase design productivity. Given the need for companies to produce more and more innovative products in an increasingly competitive market place, it follows that designers have to consider an increased number of design options. The activity of judging between and selecting from a range of competing design options is referred to as evaluation. As the number of options to evaluate increases and the time available decreases, it is evident that human evaluators will require increasing assistance in selecting the most satisfying design alternative. Due to the fact that the evaluation process of conceptual design alternatives is a multiple-criteria decision-making (MCDM) problem in the presence of many criteria and alternatives, a decision-maker(s) needs to use one of current MCDM methods. In this

* Corresponding author. Tel.: +90 212 533 6532x1409; fax: +90 212 533 5753.
E-mail address: zekia@khas.edu.tr (Z. Ayağ).

0360-8352/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.cie.2008.06.011

paper, we utilized analytic network process (ANP) as presented next.

As one of the most commonly used techniques for solving MCDM problems, analytic hierarchy process (AHP) was first introduced by Saaty (1981). In the 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 ANP is needed if all attributes and alternatives involved are connected in a network system that accepts various dependencies. Several decision problems cannot be hierarchically structured because they involve the interactions and dependencies in higher or lower level elements. Not only does the importance of the attributes determine the importance of the alternatives as in the AHP, but the importance of alternatives themselves also influences the importance of the attributes.

Furthermore, in the conventional ANP method as in the AHP, the pairwise comparisons for each level with respect to the goal of the best alternative selection are conducted using a nine-point scale of Saaty. If this nine-point scale is used to make all pairwise comparions in the ANP, some shortcomings are observed similar to the AHP as follows: (i) it is mainly used in nearly crisp decision applications, (ii) it creates and deals with a very unbalanced scale of judgment, (iii) it does not take into account the uncertainty associated with the mapping of one's judgment to a number, (iv) its ranking is rather imprecise and (v) the subjective judgment, selection and preference of decision-makers have great influence on its results. Due to the vagueness and uncertainty on judgments of the decision-maker(s), the crisp pairwise comparison in the conventional ANP seems to be insufficient and imprecise to capture the right judgments of decision-maker(s). Therefore, in this study, a fuzzy logic is introduced in the pairwise comparison of ANP to make up for this deficiency in the conventional ANP, called as fuzzy ANP.

The objective of this paper is to present a fuzzy ANP-based approach to the concept selection problem using triangular fuzzy numbers in order to reach to the ultimate one satisfying both the expectations of customers, and the engineering specifications of company. Furthermore, a numerical example is presented to illustrate the proposed approach.

2. Related research

A NPD environment is a strategic business activity by intent or by default (Whitney, 1988). It is not only the critical linkage between a business organization and its market, but it is also fundamental to business success. Business organizations need to manage their product development activities strategically to gain competitive advantage in the market place. Firms that fail to manage their product development activities strategically are not only running their business from a position of disadvantage but also risking their future (Fitzsimmons, Kouvelis, & Mallick, 1991). The critical role of NPD in the survival and success of business organizations and the need for managing it strategically is being recognized increasingly in both the academic (Brown & Eisenhardt, 1995; Finger & Dixon, 1989a, 1989b; Griffin & Hauser, 1996; Krishnan & Ulrich, 2001) and practitioner literature (Chesbrough & Teece, 2002; Gates, 1999; Welch & Kerwin, 2003).

In a NPD process, concept selection is an important activity because it strongly influences its upstream and downstream activities in a NPD environment. As the result of this, many methods have been introduced to concept selection. In the literature, five main types of concept selection methods (CSMs) are defined by King and Sivaloganathan (1999) as follows: utility CSMs, AHP CSMs, graphical CSMs, QFD matrices, and fuzzy logic CSMs.

The evaluation of each CSM method is shortly summarized as follows: (i) *Utility theory:* Utility theory has formed the basis for the majority of CSMs in the literature. The method was first developed for economic decision-making and has since been incorporated into a number of systematic design models. The core principle in the theory is a mapping of how criteria will vary across the range of each criterion. This relationship is governed by a utility function. (ii) *AHP:* AHP was first developed by Saaty (1981) for decision-making, and Marsh, Moran, Nakui, and Hoffherr (1991) have developed a more specific method directly for design decision-making. The Marsh AHP has three steps ordering the factors (i.e. attributes) of a decision such that the most important ones receive greatest weight. (iii) *Graphical:* Pugh (1991) gives a simple graphical technique that centers on a matrix with columns (showing concepts), and rows (giving decision criteria). Pugh's evaluation matrix is very simple and fast. However, no measure is given of the importance of each of the criteria and it does not allow for coupled decisions. Therefore, there is a danger that the final concept can be distorted. The simplicity of Pugh's evaluation matrix makes the method a good screening process against highly unfeasible concepts and can allow the designer to focus on the best concepts using a different CSM. (iv) *Quality function deployment* (*QFD*) *matrices:* QFD is a graphical adaptation of utility theory with several additions to assist decision-making building block of the method is a matrix chart known as a "House of Quality (HoQ)" and columns follow the method of utility as given earlier in this paper. While the matrix follows utility theory in many ways, the interaction chart gives a measure of coupled decisions. However, no numerical method is given to this measure into the QFD calculation. Without a numerical method, this become complex for most design situations where many concepts are visual comparison would be almost impossible. (v) *Fuzzy logic:* Fuzzy logic is a concept used when a decision needs to be made near the boundary of two outcomes. Thurston and Carnahan (1992) proposed the application of fuzzy set theory to multiple-criteria engineering design evaluation process. They do not use normalized weights in order that the extended division will not be needed in the calculation. They developed a fuzzy logic CSM.

Comparing the methods above is given as follows: At a conceptual design phase, if information quality may be low and so systematic methods which are the easiest to use, such as those of Pahl and Beitz (1984) Pugh charts (Pugh, 1991) are appropriate. Most methods reviewed allow for multiple attributes to a decision, although the QFD matrix method represents this facility with greatest clarity because of its graphical template. The QFD method provides a qualitative interaction table, but this is used for "optimal conflict information" and does not provide a quantitative analysis of how one decision affects another. A choice to use one technology or component will significantly affect the rest of the design. The fuzzy logic method does require a rather lengthy methodology and is by no means easy to use. It is still necessary to determine the mathematical equation in order to establish a solution. In the field of design decision-making, many decisions are not based upon known (or definable) mathematical equations. The methodology therefore has a very limited advantage when considered as a general methodology for a CSM. In addition, none of the utility methods given in the literature accommodate coupled decisions within the calculation, although they are a reality in most design situations.

As one of the above-mentioned CSMs, the AHP has been widely used for MCDM selection problems in the literature (i.e. Ayag, 2002, 2005a; Scott, 2002; Zahedi, 1986). But, in this study, we used ANP, a more general form of AHP due to the fact that the AHP cannot accommodate the variety of interactions, dependencies and feedback between higher and lower level elements. The ANP approach may be considered as a second generation AHP, which has been designed to overcome more complex problems. It replaces hierarchies with network systems that permit all possible elements and join them together in network structures. With its strength, the modeling of the interactions and dependencies among elements of the problem, ANP may be applied to generate a better in-depth analysis and to deliver a more accurate result than AHP. In other words, the ANP incorporates feedback and interdependent relationships among decision attributes and alternatives (Saaty, 1996). This provides a more accurate approach for modeling complex decision environment (Agarwal & Shankar, 2003; Lee & Kim, 2000; Meade & Sarkis, 1999; Yurdakul, 2003).

In the literature, to the best of our knowledge, a number of studies has been realized in various fields using the ANP since it first was introduced. Some of them are presented here; Hamalainen and Seppalainen (1986) presented ANP-based framework for a nuclear power plant licensing problem in Finland. They used the pairwise comparison process with the consistency index to determine the weightings of the alternatives. ANP is also used to incorporate product lifecycle in replacement decisions. The multi-attribute, multi-period model handles vital dynamic factors as well as interdependence among system attributes. The system attributes' relative importance which vary during the different stages of product life cycle is captured in this model (Azhar & Leung, 1993). Meade and Presley (2002) used the ANP method for R&D project selection. Agarwal and Shankar (2003) presented a framework for selecting the trust-building environment in e-enabled supply chain. Lee and Kim (2000) proposed an integration model by integrating the ANP and goal programming for interdependent information system project selection. Yurdakul (2003) used the ANP method to measure long-term performance of a manufacturing company.

In addition, some design-related works have been done in the literature, a few of them are presented as follows: Thurston and Carnahan (1992) used fuzzy ratings and utility analysis in preliminary design evaluation of multiple attributes. Carnahan, Thurston, and Liu (1994) also used fuzzy ratings for multi-attribute decision-making. Büyüközkan, Ertay, Kahraman, and Ruan (2004) used fuzzy ANP to prioritize design requirements by taking into account the degree of the interdependence between the customer needs and design requirements and the inner dependence among them. Mikhailov and Singh (2003) used fuzzy ANP and its application to the development of decision support systems. Kwong, Chen, Bai, and Chan (2007) emphasized determining the importance weight of engineering characteristics for quality function deployment, and they developed a new methodology of determining aggregated importance of engineering characteristics in a new product development environment. They considered the fuzzy relation measures between customer requirements and engineering characteristics. Hu and Zhang (2007) proposed the use of analytical hierarchy process to determine the house of quality parameters and they employed fuzzy clustering dynamic sort method to classify customer requirements that will be used for obtaining product design features. Büyüközkan, Feyzioğlu, and Ruan (2007) presented a new fuzzy group decision-making approach to fuse multiple preference styles to respond customer needs in product development with quality function deployment. The relationship between user and designer was founded based on integrated technology of quality function deployment and fuzzy multi-objective decision-making method and the optimal principle solution set was obtained using design method of product innovation, with which the technology contradiction problem in product design was solved by Han, Lıu, and Wang (2007). Chen and Weng (2006) proposed a fuzzy goal programming model for evaluation of engineering designs and their model also considers business competition by specifying the minimum fulfillment levels of design requirements and the preemptive priorities between goals. Huang and Gu (2006) considered the product development process modeling based on information feedback and requirement cooperation. In connection with this issue, they developed the reasoning scheme for inferring the relationships between the requirements and information, and the feedback control mechanism by analyzing the conflicting or cooperative relationships among the process requirements. Karsak (2004) defined quality function deployment as a customer-oriented design tool for developing new or improved products to increase customer satisfaction by integrating marketing, design engineering, manufacturing, and other related functions of an organization. The aim of QFD was also described to be maximizing customer satisfaction with considerations (i.e. cost budget, technical difficulty), limiting the number and the extent of the possible design requirements that can be incorporated into a product. The study presented a fuzzy multiple-objective programming approach that incorporates imprecise and subjective information inherent in the QFD planning process to determine the level of fulfillment of design requirements.

In the following section, we propose a fuzzy ANP-based approach to evaluate a set of conceptual design alternatives in order to find out the best concept satisfying the needs and expectations of both customers and company. We also defined a fuzzy ANP-based framework that identifies critical determinants, dimensions and attribute-enablers used in concept selection.

3. Proposed approach

In this section, first fuzzy logic is introduced; second fuzzy ANP-based approach and its steps are presented.

3.1. Fuzzy logic

The key idea of fuzzy set theory is that an element has a degree of membership in a fuzzy set (Negoita, 1985; Zimmermann, 1996). A fuzzy set is defined by a membership function (all the information about a fuzzy set is described by its membership function). The membership function maps elements (crisp inputs) in the universe of discourse (interval that contains all the possible input values) to elements (degrees of membership) within a certain interval, which is usually [0,1]. Then, the degree of membership specifies the extent to which a given element belongs to a set or is related to a concept. 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 (it has no membership). If the value assigned is 1, the element belongs completely to the set (it has total membership). 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, triangular fuzzy numbers, $\tilde{1}$ to $\tilde{9}$, are used to represent subjective pairwise comparisons of selection process (equal to extremely preferred) in order to capture the vagueness (Table 1). A fuzzy number is a special fuzzy set $F = \{(x, \mu_F(x)), x \in R\}$, where x takes it values on the real line, R: $-\infty < x < +\infty$ and $\mu_F(x)$ is a continuous mapping from R to the closed interval [0,1]. A triangular fuzzy number denoted as $\widetilde{M} = (l, m, u)$, where $l \leqslant m \leqslant u$, has the following triangular type membership function:

$$\mu_F(x) = \begin{cases} 0, & x < l \\ x - l/m - l, & l \leqslant x \leqslant m \\ u - x/u - m, & m \leqslant x \leqslant u \\ 0, & x > u \end{cases}$$

The triangular fuzzy numbers, $\tilde{1}$ to $\tilde{9}$, are utilized to improve the conventional nine-point scaling scheme. In order to take the imprecision of human qualitative assessments into consideration, the five triangular fuzzy numbers $(\tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9})$ are defined with the

Table 1
Nine-point fundamental scale used in pairwise comparisons (Saaty, 1989)

Numerical rating	Judgment or preference	Remarks
1	Equally important	Two attributes contribute equally to the attribute at the higher decision level
3	Moderately more important	Experience and judgment slightly favor one attribute over another
5	Strongly more important	Experience and judgment strongly favor one attribute over another
7	Very strongly more important	Experience and judgment strongly favor one attribute over another; its dominance has been demonstrated in practice
9	Extremely more important	Experience and judgment extremely favor one attribute over another; the evidence favoring one attribute over another is of the highest possible order of affirmation

corresponding membership function. All attributes and alternatives are linguistically depicted in Fig. 1. The shape and position of linguistically terms are chosen in order to illustrate the fuzzy extension of the method.

3.2. Fuzzy ANP-based approach

As seen in Fig. 2 in Section 4, a schematic representation of the fuzzy ANP-based framework and its decision environment related to the concept selection problem is given. ANP represents relationships hierarchically but does not require as strict as hierarchical structure and therefore allows for more complex interrelationships among the decision levels and attributes. The overall objective is to find out the best concept. The determinants, dimensions and attribute-enablers used for evaluating a set of conceptual design alternatives are determined based on the needs and expectations of both customers and company. That is why that they may differ from a company to another or from a product to another. They are also so critical elements at the stage of concept evaluation of a NPD environment, because they directly affect to determine the ultimate concept out of the available options.

After constructing flexible hierarchy, the decision-maker is asked to compare the elements at a given level on a pairwise basis to estimate their relative importance in relation to the element at the immediate proceeding level. In conventional ANP, the pairwise comparison is made using a ratio scale. A frequently used scale is

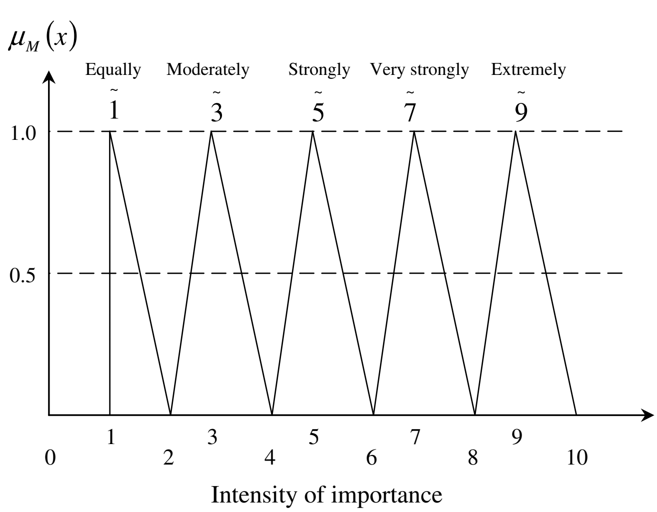

Fig. 1. Fuzzy membership function for linguistic values for attributes or alternatives.

the nine-point scale (Saaty, 1989) which shows the participants' judgments or preferences. Even though the discrete scale of 1–9 has the advantages of simplicity and easiness for use, it does not take into account the uncertainty associated with the mapping of one's perception or judgment to a number.

3.3. Steps of the proposed approach

The fuzzy ANP-based approach is presented step-by-step next.

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 interrelationships. The ultimate objective of hierarchy is to identify alternatives that are significant for finding out best conceptual design. In this study, we determined three evaluation determinants (marketability, competitive advantage and profitability) that are aggregated in *concept selection weighted index* (CSWI) selection step. To define this hierarchy, we also utilized the Saaty's suggestions of using a network for categories of benefits, costs, risks and opportunities (Saaty, 1996). Instead of Saaty's categories, we used evaluation determinants which are very important in concept selection. In order to analyze the combined influence of three determinants on concept selection, a CSWI is calculated to prioritize conceptual design alternatives. This index also takes the influences of dimensions and attribute-enablers into consideration.

Step II. Building pairwise comparison matrices between component/attributes levels: By using triangular fuzzy numbers, the decision-maker(s) are asked to respond to a series of pairwise 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.

Triangular fuzzy numbers $(\tilde{1},\tilde{3},\tilde{5},\tilde{7},\tilde{9})$ are used to indicate the relative strength of each pair of elements in the same hierarchy. Then, the fuzzy judgment matrix, $\widetilde{A}(\tilde{a}_{ij})$ via pair wise comparison is constructed as given below:

$$\widetilde{A}=\begin{bmatrix}1 & \tilde{a}_{12} & \dots & \dots & \tilde{a}_{1n}\\ \tilde{a}_{21} & 1 & \dots & \dots & \tilde{a}_{2n}\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ \tilde{a}_{n1} & \tilde{a}_{n2} & \dots & \dots & 1\end{bmatrix}$$

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

When scoring is conducted for a pair, a reciprocal value is automatically assigned to the reverse comparison within the matrix. That is, if $\tilde{a}_{ij}$ is a matrix value assigned to the relationship of component i to component j, then $\tilde{a}_{ij}$ is equal to $1/\tilde{a}_{ij}$.

Alternatively, by defining the interval of confidence level α, the triangular fuzzy number can be characterized using the following equation:

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

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

$$\forall m_{\mathrm{L}},m_{\mathrm{R}},n_{\mathrm{L}},n_{\mathrm{R}}\in R^{+},\quad \widetilde{M}_{\alpha}=[m_{\mathrm{L}}^{\alpha},m_{\mathrm{R}}^{\alpha}],\quad \widetilde{N}_{\alpha}=[n_{\mathrm{L}}^{\alpha},n_{\mathrm{R}}^{\alpha}],\quad \alpha\in[0,1]$$
$$\widetilde{M}\oplus\widetilde{N}=[m_{\mathrm{L}}^{\alpha}+n_{\mathrm{L}}^{\alpha},m_{\mathrm{R}}^{\alpha}+n_{\mathrm{R}}^{\alpha}],\qquad \widetilde{M}\Theta\widetilde{N}=[m_{\mathrm{L}}^{\alpha}-n_{\mathrm{L}}^{\alpha},m_{\mathrm{R}}^{\alpha}-n_{\mathrm{R}}^{\alpha}]$$
$$\widetilde{M}\otimes\widetilde{N}=[m_{\mathrm{L}}^{\alpha}n_{\mathrm{L}}^{\alpha},m_{\mathrm{R}}^{\alpha}n_{\mathrm{R}}^{\alpha}],\qquad \widetilde{M}/\widetilde{N}=[m_{\mathrm{L}}^{\alpha}/n_{\mathrm{L}}^{\alpha},m_{\mathrm{R}}^{\alpha}/n_{\mathrm{R}}^{\alpha}]$$

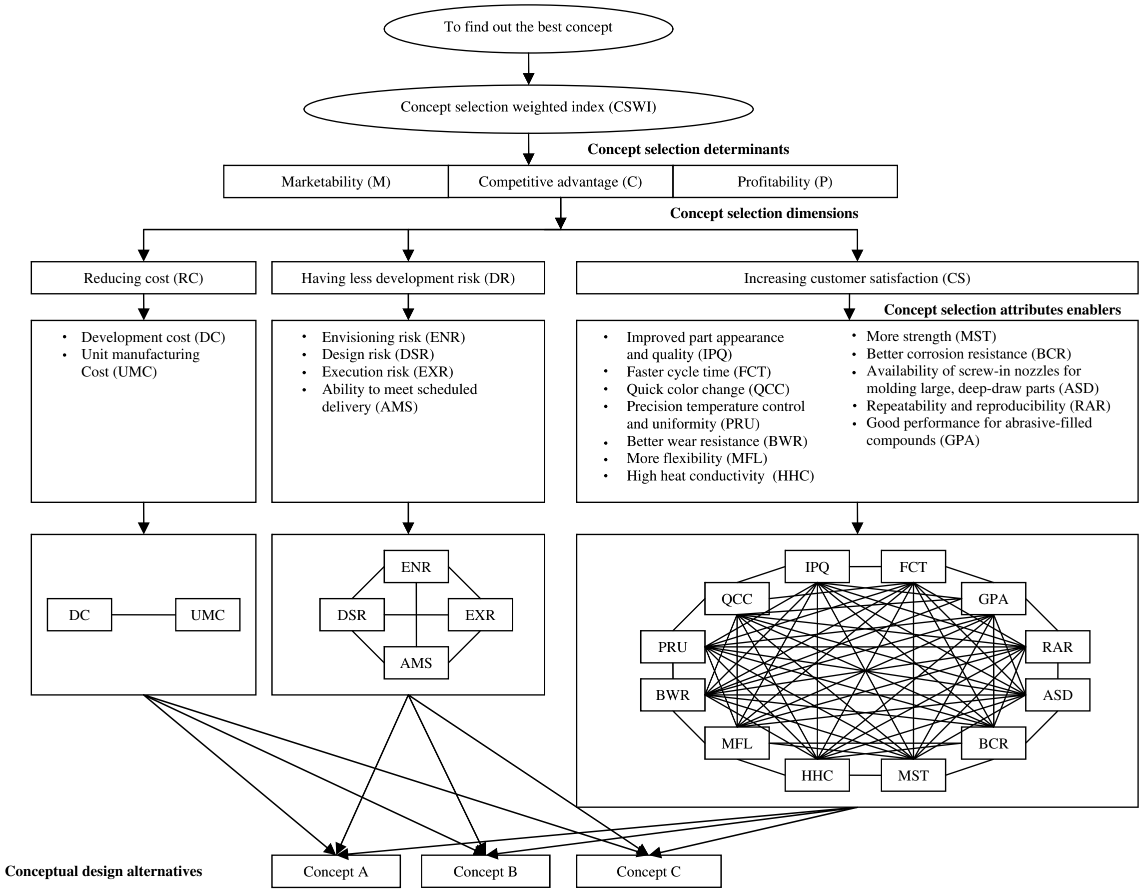

Fig. 2. ANP-based framework for concept selection.

While α is fixed, the following judgment matrix can be obtained after setting the index of optimism, μ, in order to estimate the degree of satisfaction. The eigenvector is calculated by fixing the μ value and identifying the maximal eigenvalue

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{21}^{\alpha} & \dots & \dots & \tilde{a}_{1n}^{\alpha} \\ \tilde{a}_{21}^{\alpha} & 1 & \dots & \dots & \tilde{a}_{2n}^{\alpha} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{a}_{n1}^{\alpha} & \tilde{a}_{n2}^{\alpha} & \dots & \dots & 1 \end{bmatrix}$$

where α-*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 is estimated by the index of optimism μ determined by the decision-maker. The larger value of index μ indicates the higher degree of optimism. The index of optimism is a linear convex combination (Lee, 1999) as defined in the following equation:

$$\tilde{a}_{ij}^{\alpha} = \mu a_{iju}^{\alpha} + (1-\mu) a_{ijl}^{\alpha}, \quad \forall \mu \in [0,1] \tag{2}$$

Once the pairwise comparisons are completed, the local priority vector w (also referred as e-Vector) is computed using the following equation as the unique solution:

$$Aw = \lambda_{\max} w \tag{3}$$

where $\lambda_{\max}$ is the largest eigenvalue of A.

Step III. Calculating consistency ratio (CR) for each pairwise comparison matrix: After constructing all required pairwise judgment matrices between component/attributes levels, for each, the consistency ratio (CR) should be calculated.

The deviation from consistency, the measure of inconsistency is called the consistency index (CI) and calculated using the following equation:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n-1} \tag{4}$$

where n is matrix size.

The CR is used to estimate directly the consistency of pairwise comparisons, and computed by dividing the CI by a value obtained from a table of random consistency index (RI), the average index for randomly generated weights (Saaty, 1981), as shown in the following equation:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{5}$$

If the CR less than 10%, the comparisons are acceptable, otherwise not.

Step IV. Pairwise comparison matrices of inter-dependencies: In order to reflect the interdependencies in network, pairwise comparisons among all the attribute-enablers are constructed and their consistency ratios are calculated as we previously defined in *Step II* and *Step III*.

Step V. Super-matrix formation and analysis: The 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. Three types of relationships may be encountered in this model: (1) independence from succeeding components, (2) interdependence among components and (3) interdependence between levels of components. 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.

First, a super-matrix is constructed as an unweighted one, because in each column it consists of several eigenvectors which of them sums to one (in a column of a stochastic) and hence the entire column of the matrix may sum to an integer greater than one. The super-matrix needs to be stochastic to derive meaningful limiting priorities. So for this reason to get the weighted super-matrix, firstly the influence of the clusters on each cluster with respect to the control criterion is determined. This yields an eigenvector of influence of the clusters on each cluster. Then the unweighted super-matrix is multiplied by the priority weights from the clusters, which yields the weighted super-matrix. Then, the super-matrix will be steady state by multiplying the weighted super-matrix by itself until the super-matrix's row values converge to the same value for each column of the matrix.

Step VI. Selection of the best concept alternative: The equation of *desirability index*, D_{ia} for concept alternative i and determinant a is calculated using the following equation:

$$D_{ia} = \sum_{j=1}^{J} \sum_{k=1}^{K_{ja}} P_{ja} A^D_{kja} A^I_{kja} S_{ikja} \tag{6}$$

where P_{ja} is relative importance weight of dimension j on determinant a; A^D_{kja}, 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}, 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}, relative impact of concept alternative i on attribute-enabler k of dimension j of concept selection network; K_{ja}, index set of attribute-enablers for dimension j of determinant a; and J is index set for attribute j.

Step VII. Calculation of concept selection weighted index (CSWI): To finalize the analysis of concept selection, concept selection weighted index (CSWI) is calculated for each alternative. The CSWI value is the product of the desirability index, D_{ia} for each alternative. Then, the CSWI values are normalized to prioritize the concepts to determine the one with highest value.

4. Case study

Above, a fuzzy ANP-based approach has been presented to evaluate a set of conceptual design alternatives in a NPD environment. In this section, a case study is taken into consideration to clearly explain to readers on how the proposed approach is implemented. This case study was realized at the product engineering department of a hot runner system manufacturer in Ontario, Canada. This company with ISO 9000 certification designs and manufactures all kinds of standard, semi-custom and custom hot runner systems for the world market. Due to the fact that tight competitive conditions in the market, the company's top management decided to develop a new kind of hot runner manifold and horizontal hot tip nozzle system especially for the fast-growing automotive industry in order to keep their competitive advantage up in the following years. The new system would be made of stainless steel as being in existing products. Then, a cross-functional project team consisting of various departments in the company worked to create a set of conceptual design alternatives for four months, and suggested three different concepts named *Concepts A, B and C*, respectively.

To generate the concepts, the team carried out the ways as follows: (1) define the problem (general understanding of a new hot runner system design for automotive industry), (2) external sources (interview with lead mold-makers, consult suppliers for each critical system component, the literature on technical documents (i.e. mold-making, hot runner system design) to find out existing solutions and more, benchmarking study of competitor products and patents for mold and hot runner system design), (3) internal sources (the use of personal and team knowledge and creativity), (4) organization of the possible set of the concepts was done by using a classification tree which divides the entire space of possible solutions into distinct classes which facilitate comparison and pruning and (5) final evaluation (first four steps were evaluated again to make sure that the entire space of concepts are fully-explored).

In Table 2, the determinants, dimensions and attribute-enablers used in the ANP framework is presented in table format, while in Fig. 2, they are illustrated in graphic form.

Reducing cost is only includes development cost and unit manufacturing cost of a product. *Having less development risk* can be categorized as follows (the essence of each risk can be captured in a specific question (Sarbacker & Ishii, 1997)): (1) *Envisioning risk:* will a product with the targeted product attributes of the product vision create value for the customer and the company? (2) *Design risk:* does the product design embody the targeted product attributes of the product vision? (3) *Execution risk:* can the development team execute the conversion of the product design into a delivered product? (4) *Ability to meet scheduled delivery:* especially, the hot runner systems are used for mold-makers which has tight due dates of their injection molds for automotive industry. Delivering on time is quite critical. *Increasing customer satisfaction* or product performance on plastic products for automotive industry for customers (i.e. mold-makers) involves in the product specifications (i.e. improved part appearance and quality, faster cycle time and so on) defined by the mold-makers.

In this paper, three determinants (i.e. marketability, competitive advantage and profitability) with network relationships each other were defined. For example, higher profitability results in increasing competitive advantage of company. On the other hand, if marketability of product increases, then profitability gets higher. For each type of determinant, we also defined the following dimensions and network relationships each other: reducing cost, having less development risk and increasing customer satisfaction. For

Table 2
Determinants/dimensions/attribute-enablers used in the ANP framework

Elements	Code	Definition
Determinants	M	Marketability
	C	Competitive advantage
	P	Profitability
Dimensions	RC	Reducing cost
	DR	Having less development risk
	CS	Increasing customer satisfaction
Attribute-enablers	DC	Development cost
	UMC	Unit manufacturing cost
	ENR	Envisioning risk
	DSR	Design risk
	EXR	Execution risk
	AMS	Ability to meet scheduled delivery
	IPQ	Improved part appearance and quality
	FCT	Faster cycle time
	QCC	Quick color change
	PRU	Precision temperature control and uniformity
	BWR	Better wear resistance
	MFL	More flexibility (i.e. gating options, various nozzle sizes)
	HHC	High heat conductivity
	MST	More strength
	BCR	Better corrosion resistance
	ASD	Availability of screw-in nozzles for molding large, deep-draw parts
	RAR	Repeatability and reproducibility
	GPA	Good performance for abrasive-filled compounds

Table 3
Fuzzy comparison matrix of the determinants using triangular fuzzy numbers

Determinants	*M*	*C*	*P*
M	1	$\tilde{3}$	$\tilde{9}$
C	$\tilde{3}^{-1}$	1	$\tilde{5}$
P	$\tilde{9}^{-1}$	$\tilde{5}^{-1}$	1

example, while reducing cost increases the development risk, on the other hand, it might increase the profitability and customer satisfaction. In addition, we defined attribute-enablers for each dimension under each determinant with their network relationships. For example, faster cycle time results in better customer satisfaction, reducing cost and high profitability.

In order to find out the best concept, we carried out our proposed approach using triangular fuzzy numbers ($\tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$) to express the preference in the pairwise comparisons. First, we obtained the fuzzy pair wise comparison matrix for the relative importance of the determinants, as shown in Table 3.

Second, the lower limit and upper limit of the fuzzy numbers with respect to α were defined by applying Eq. (1) as follows:

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

Then, we substituted the values, $\alpha = 0.5$ and $\mu = 0.5$, where μ is the coefficient of optimism, above expression into fuzzy comparison matrices, and obtained all the α-*cuts* fuzzy comparison matrices using Eq. (2) (Tables 4 and 5). Then, we calculated eigenvalue of the matrix *A* by solving the characteristic equation of *A*, det$(A - \lambda I) = 0$, and found out all λ values for $A(\lambda_1, \lambda_2, \lambda_3)$. The largest eigenvalue of pairwise matrix, λ_{max}, was calculated by using Eq. (3). 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, we also calculated the CI and the CR of the matrix by using Eqs. (4) and (5). Because the CR was less than 0.10, the pairwise comparison was acceptable.

Table 4
α-*Cuts* fuzzy comparison matrix for the determinants ($\alpha = 0.5$, $\mu = 0.5$)

Determinants	*M*	*C*	*P*
M	1	[2,4]	[8,10]
C	[1/4,1/2]	1	[4,6]
P	[1/10,1/8]	[1/6,1/4]	1

Table 5
Eigenvector for comparison matrix of the determinants (CR = 0.070)

Determinants	*M*	*C*	*P*	e-Vector
M	1.000	3.000	9.000	0.662
C	0.375	1.000	5.000	0.274
P	0.113	0.208	1.000	0.064
			λ_{max}	3.082
			CI	0.041
			RI	0.58
			CR	0.070 < 0.100

Table 6
Fuzzy comparison matrix of the dimensions for *marketability* (*M*)

Dimensions	RC	DR	CS
Marketability (M)			
RC	1	$\tilde{3}$	$\tilde{7}$
DR	$\tilde{3}^{-1}$	1	$\tilde{3}$
CS	$\tilde{7}^{-1}$	$\tilde{3}^{-1}$	1

Table 7
α-*Cuts* fuzzy comparison matrix for the relative importance of the dimensions for *marketability* (*M*) ($\alpha = 0.5$, $\mu = 0.5$)

Dimensions	*RC*	DR	CS
Marketability (M)			
RC	1	[2,4]	[6,8]
DR	[1/4,1/2]	1	[2,4]
CS	[1/8,1/6]	[1/4,1/2]	1

By following the same way, three pairwise comparison matrices for the relative importance of the dimensions (RC, DR, and CS) for the determinants (M, C and P) were constructed and checked out their consistencies, which were less than 0.10 and acceptable. Tables 6 and 7 show only the fuzzy related matrices for the relative importance of the dimensions for the determinant *marketability* (*M*).

Additionally, nine all fuzzy related matrices for the relative importance of the attribute-enablers for the dimensions (RC, DR and CS) and the determinants (M, C and P) were constructed and checked out their consistencies, which were less than 0.10 and acceptable. Tables 8–10 shows only fuzzy pairwise comparison matrices for relative importance of the attribute-enablers for the dimension, *reducing cost* (*RC*) and the determinant *marketability* (*M*).

Then, 54 fuzzy pairwise comparison matrices for the relative importance of each concept alternative (A, B and C) for each attribute-enabler of the dimensions for three determinants were constructed and checked out their consistencies, which were less than 0.10 and acceptable.

Tables 11–13 show the fuzzy pairwise comparison matrix of concept alternatives for the attribute-enabler *development cost* (*DC*) of the dimension *reducing cost* (*RC*) for the determinant *marketability* (*M*).

Table 8
Eigenvector for comparison matrix for the relative importance of the dimensions for *marketability* (*M*) (CR = 0.078)

Dimensions	*RC*	DR	CS	e-Vector
Marketability (M)				
RC	1.000	3.000	7.000	0.660
DR	0.375	1.000	3.000	0.249
CS	0.146	0.375	1.000	0.091
			λ_{max}	3.091
			CI	0.045
			RI	0.58
			CR	0.078 < 0.100

Table 9
Fuzzy comparison matrix for the relative importance of the attribute-enablers of *reducing cost* (*RC*) for *marketability* (*M*)

Reducing cost (RC)	DC	UMC
Marketability (M)		
DC	1	$\tilde{5}$
UMC	$\tilde{5}^{-1}$	1

Table 10
α-Cuts fuzzy comparison matrix for the relative importance of the attribute-enablers of *reducing cost* (*RC*) for *marketability* (*M*) ($\alpha = 0.5$, $\mu = 0.5$)

Reducing cost (RC)	DC	UMC
Marketability (M)		
DC	1	[4,6]
UMC	[1/6,1/4]	1

Table 11
Eigenvector for comparison matrix for the relative importance of the attribute-enablers of *reducing cost* (*RC*) for *marketability* (*M*)

Reducing cost (RC)	DC	UMC	e-Vector
Marketability (M)			
DC	1.000	5.000	0.831
UMC	0.208	1.000	0.169

Table 12
Fuzzy comparison matrix for the relative importance of concept alternatives under *marketability* (*M*), *reducing cost* (*RC*) and *development cost* (*DC*)

Development cost (DC)	Concept A	Concept B	Concept C
Marketability (M)			
Concept A	1	$\tilde{1}$	$\tilde{7}$
Concept B	$\tilde{1}^{-1}$	1	$\tilde{5}$
Concept C	$\tilde{7}^{-1}$	$\tilde{5}^{-1}$	1

Table 13
α-Cuts fuzzy comparison matrix for the relative importance of concept alternatives of *reducing cost* (*RC*) for *marketability* (*M*) ($\alpha = 0.5$, $\mu = 0.5$)

Development cost (DC)	Concept A	Concept B	Concept C
Marketability (M)			
Concept A	1	[1,2]	[6,8]
Concept B	[1/2,1]	1	[4,6]
Concept C	[1/8,1/6]	[1/6,1/4]	1

Then, to reflect the inter-dependencies in network, we also built pairwise comparison matrices for each of the attribute-enablers for three determinants of concept selection clusters. A total of 54 matrices were built. Tables 14–16 show the fuzzy pairwise comparison matrix of the attribute-enablers under *marketability* (*M*), *reducing cost* (*RC*) and *development cost* (*DC*).

Similarly, fuzzy pairwise comparison matrices for other attribute-enablers were constructed as shown in Tables 14–16, and all resultant e-Vectors are presented as given in Table 17, to build a super-matrix.

The final standard fuzzy pair wise comparison evaluations are required for the relative impacts of each concept alternative. The number of fuzzy pairwise comparison matrices is dependent of

Table 14
The eigenvector for comparison matrix for the relative importance of concept alternatives under *marketability* (*M*), *reducing cost* (*RC*) and *development cost* (*DC*) (CR = 0.053)

Development cost (DC)	Concept A	Concept B	Concept C	e-Vector
Marketability (M)				
Concept A	1.000	1.500	7.000	0.540
Concept B	0.750	1.000	5.000	0.383
Concept C	0.146	0.208	1.000	0.077
			λ_{max}	3.061
			CI	0.031
			RI	0.58
			CR	0.053 < 0.100

Table 15
Fuzzy comparison matrix for the relative importance of the attribute-enablers under *marketability* (*M*), *reducing cost* (*RC*) and *development cost* (*DC*)

Development cost (DC)	UMC
UMC	$\tilde{3}^{-1}$

Table 16
α-Cuts fuzzy comparison matrix for the relative importance of the attribute-enablers under *marketability* (*M*), *reducing cost* (*RC*) and *development cost* (*DC*)

Development cost (DC)	UMC
UMC	[2,4]

Table 17
The eigenvector for comparison matrix for the relative importance of the attribute-enablers under *marketability* (*M*), *reducing cost* (*RC*) and *development cost* (*DC*)

Development cost (DC)	UMC	e-Vector
UMC	3.000	1

the number of the dimensions and the attribute-enablers that are included in the determinant of concept selection hierarchy. In this case study, we constructed 94 fuzzy pairwise comparison matrices at all levels of relationships in the concept selection hierarchy.

Table 18 shows the super-matrix, *M*, detailing results of the relative importance measures for each of the attribute-enablers for the determinant *marketability* of concept selection clusters. Since there are 18 pairwise comparison matrices, one for each of the interdependent attribute-enablers in the *marketability* hierarchy, there will be 18 non-zero columns in this super-matrix. Each of non-zero values in the column in super-matrix, *M*, is the relative importance weight associated with the interdependently pairwise comparison matrices. In this study, there are three super-matrices, one for each of the determinants (M, C and P) of the best concept selection hierarchy network. Then, all the super-matrices were converged for getting a long-term stable set of weights. For this power of super-matrix was raised to an arbitrarily large number. In our case study, convergence for the super-matrix constructed under the determinant *marketability* (*M*) was reached at 16th power. Table 19 shows the values of super-matrix after convergence.

To determine the best concept alternative, we used Eq. (6) and made the calculations for the desirability indices (D_{ia}, where a is equal to 1 for the determinant *marketability*) for concept alternatives based upon the determinant *marketability* control hierarchy using the weights obtained from the pairwise comparisons of concept alternatives, dimensions and attribute-enablers from the converged super-matrix. The weights were used to calculate a score for the determinant *marketability* of concept selection desirability for each concept alternative being considered. For example, the desirability indices of Concepts A, B and C under the first determinant *marketability* (M), where index, a is equal to 1, was calculated, respectively, by using Eq. (5) as illustrated in Table 20.

Finally, to reach to the best concept, we calculated concept selection weighted index (CSWI) for each concept alternative (A, B and C). The final results are presented in Table 21. As easily seen in the table, the best concept alternative among S-type hot runner manifold and horizontal hot tip nozzle system alternatives, is *Concept A*.

We also made a sensitivity analysis, the details of which is given next.

The final priorities of the conceptual design alternatives are mainly dependent on the weights of three determinants (or risk

Table 18
Super-matrix for *marketability* (*M*) before convergence

M	DC	UMC	ENR	DSR	EXR	AMS	IPQ	FCT	QCC	PRU	BWR	MFL	HHC	MST	BCR	ASD	RAR	GPA
DC	0.000	1.000																
UMC	1.000	0.000																
ENR			0.000	0.544	0.564	0.544												
DSR			0.739	0.000	0.368	0.397												
EXR			0.153	0.397	0.000	0.058												
AMS			0.108	0.058	0.068	0.000												
IPQ							0.000	0.313	0.284	0.283	0.328	0.311	0.334	0.331	0.286	0.272	0.288	0.269
FCT							0.294	0.000	0.216	0.216	0.206	0.212	0.201	0.202	0.209	0.213	0.211	0.228
QCC							0.236	0.211	0.000	0.156	0.138	0.140	0.140	0.141	0.165	0.167	0.156	0.165
PRU							0.118	0.150	0.157	0.000	0.107	0.109	0.092	0.094	0.099	0.102	0.101	0.101
BWR							0.100	0.111	0.113	0.112	0.000	0.063	0.064	0.064	0.062	0.063	0.062	0.063
MFL							0.052	0.051	0.061	0.068	0.061	0.000	0.049	0.043	0.045	0.045	0.045	0.045
HHC							0.045	0.044	0.045	0.045	0.048	0.048	0.000	0.032	0.032	0.037	0.037	0.037
MST							0.041	0.031	0.031	0.027	0.027	0.028	0.032	0.000	0.033	0.032	0.031	0.028
BCR							0.036	0.028	0.029	0.029	0.028	0.028	0.028	0.029	0.000	0.029	0.029	0.022
ASD							0.035	0.025	0.024	0.025	0.021	0.021	0.022	0.022	0.028	0.000	0.022	0.025
RAR							0.027	0.020	0.021	0.023	0.021	0.023	0.022	0.024	0.022	0.022	0.000	0.017
GPA							0.017	0.017	0.017	0.016	0.016	0.016	0.017	0.017	0.018	0.018	0.018	0.000

Table 19
Super-matrix for *marketability* (*M*) after convergence (A^{16})

M	DC	UMC	ENR	DSR	EXR	AMS	IPQ	FCT	QCC	PRU	BWR	MFL	HHC	MST	BCR	ASD	RAR	GPA
DC	1.000	0.000																
UMC	0.000	1.000																
ENR			0.353	0.353	0.353	0.353												
DSR			0.364	0.364	0.364	0.364												
EXR			0.203	0.203	0.203	0.203												
AMS			0.073	0.073	0.073	0.073												
IPQ							0.232	0.232	0.232	0.232	0.232	0.232	0.232	0.232	0.232	0.232	0.232	0.232
FCT							0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191
QCC							0.158	0.158	0.158	0.158	0.158	0.158	0.158	0.158	0.158	0.158	0.158	0.158
PRU							0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
BWR							0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089
MFL							0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052
HHC							0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042
MST							0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032
BCR							0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029
ASD							0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026
RAR							0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022
GPA							0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017

Table 20
Concept selection desirability index for *marketability* (*M*) ($a = 1$)

Dimension	Attribute enabler	P_{j1}	A^D_{kj1}	A^I_{kj1}	S_{1kj1}	S_{2kj1}	S_{3kj1}	Concept alternatives		
								A	B	*C*
RC	DC	0.660	0.831	1.000	0.540	0.383	0.077	0.2962	0.2101	0.0422
	UMC	0.660	0.169	0.000	0.636	0.290	0.074	0.0000	0.0000	0.0000
DR	ENR	0.249	0.551	0.353	0.643	0.216	0.141	0.0311	0.0105	0.0068
	DSR	0.249	0.267	0.364	0.506	0.402	0.091	0.0122	0.0097	0.0022
	EXR	0.249	0.124	0.203	0.540	0.383	0.077	0.0034	0.0024	0.0005
	AMS	0.249	0.058	0.073	0.564	0.368	0.068	0.0006	0.0004	0.0001
CS	IPQ	0.091	0.232	0.232	0.165	0.705	0.130	0.0008	0.0035	0.0006
	FCT	0.091	0.214	0.191	0.218	0.582	0.200	0.0008	0.0022	0.0007
	QCC	0.091	0.129	0.158	0.683	0.237	0.080	0.0013	0.0004	0.0001
	PRU	0.091	0.091	0.112	0.745	0.182	0.074	0.0007	0.0002	0.0001
	BWR	0.091	0.080	0.089	0.636	0.290	0.074	0.0004	0.0002	0.0000
	MFL	0.091	0.048	0.052	0.720	0.194	0.086	0.0002	0.0000	0.0000
	HHC	0.091	0.034	0.042	0.218	0.582	0.200	0.0000	0.0001	0.0000
	MST	0.091	0.035	0.032	0.540	0.383	0.077	0.0001	0.0000	0.0000
	BCR	0.091	0.034	0.029	0.506	0.402	0.091	0.0000	0.0000	0.0000
	ASD	0.091	0.031	0.026	0.564	0.368	0.068	0.0000	0.0000	0.0000
	RAR	0.091	0.041	0.022	0.540	0.383	0.077	0.0000	0.0000	0.0000
	GPA	0.091	0.031	0.017	0.720	0.194	0.086	0.0000	0.0000	0.0000
Total desirability indices (D_{i1}) of *marketability* (*M*) for concept alternatives								0.348	0.240	0.054

Table 21
Concept selection weighted index (CSWI) for concept alternatives

Concept alternatives	Determinants			Calculated weights for alternatives	
	Marketability (M)	Competitive advantage (C)	Profitability (P)	CSWI	Normalization
	0.662	0.274	0.064		
A*	0.348	0.194	0.153	0.293	0.551
B	0.240	0.075	0.098	0.186	0.349
C	0.054	0.051	0.063	0.054	0.101
Total				0.533	1.000

factors). Small changes in the related weights might cause major changes of the final ranking of the alternatives. Because the weights of the determinants are usually based on subjective judgments of the decision-maker, the stability of the final ranking under varying the determinant weights should be checked out. For this reason, we performed a sensitivity analysis based on a set of scenarios that reflect alternative future developments or different views on the relative importance of the determinants. By increasing the weight of each determinant, we observed the resulting changes of the priorities and the final ranking of the alternatives. Therefore, we changed the weight of each determinant by increasing its current weight by a certain value. For remember, the weights of the determinants are calculated through a pairwise comparison matrix using triangular fuzzy numbers. This matrix reflects the subjective judgments of the decision-maker. Also the consistency index and ratio analysis is done to make sure that the judgments are consistent. For example, to obtain the incremental value, 3% for the determinant, M, respectively, we constructed a new pairwise comparison matrix (new evaluation rising from changing conditions) using triangular fuzzy numbers, and made its further calculations to observe how this positive change (3%)

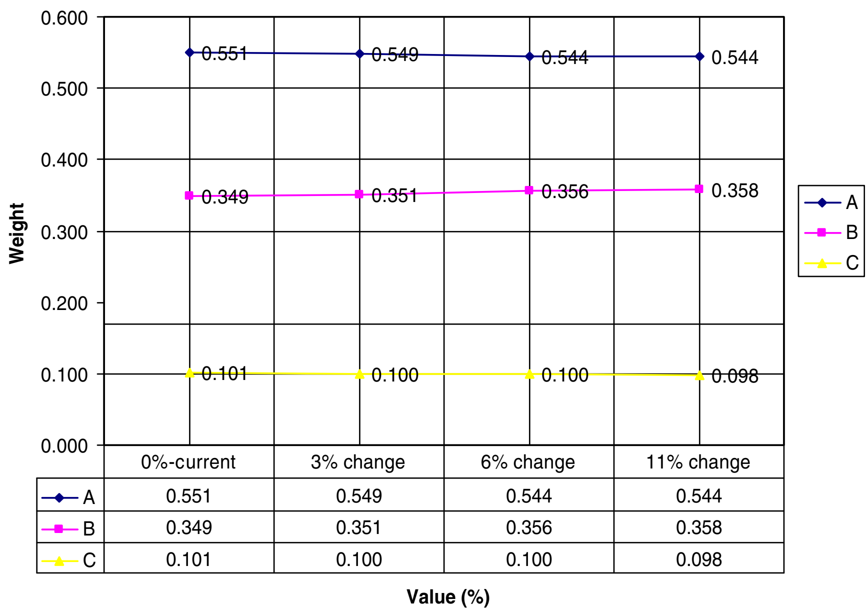

Fig. 3. Changes in the weight of the determinant, M (3%, 6% and 11%) in relation to the final weights of the alternatives (A, B and C).

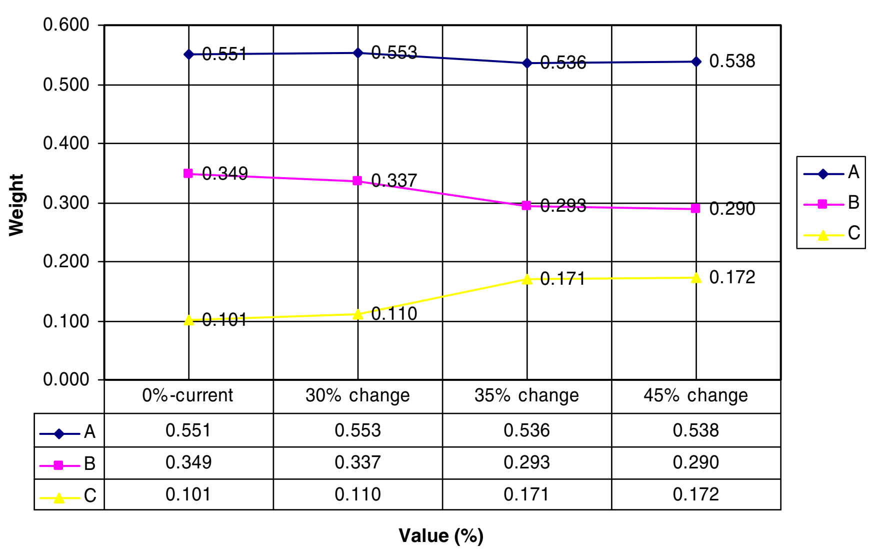

Fig. 4. Changes in the weight of the determinant, C (30%, 35% and 45%) in relation to the final weights of the alternatives (A, B and C).

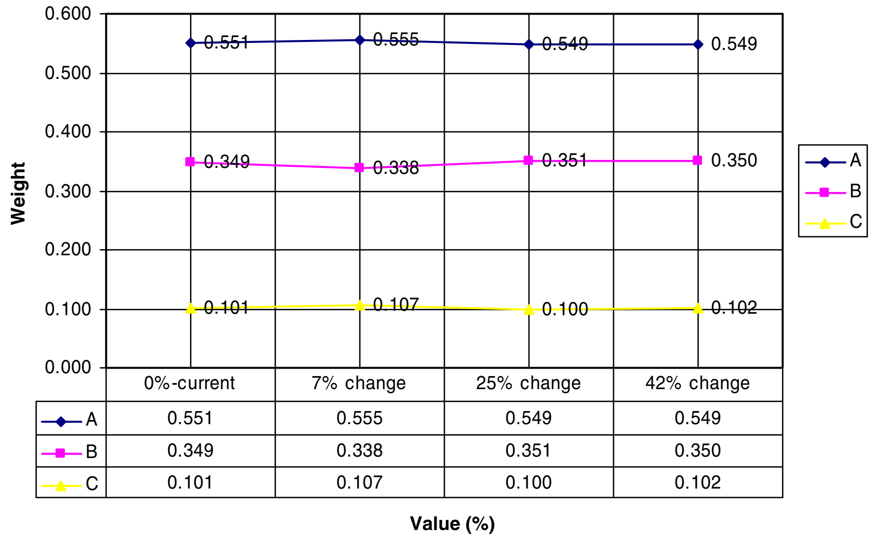

Fig. 5. Changes in the weight of the determinant, *P* (7%, 25% and 42%) in relation to the final weights of the alternatives (A, B and C).

in the current weight of *M* affect to the weights of the others, of course the final ranking of the alternatives (A, B and C). The process is also applied to determine other values (6% and 11%) as seen in Fig. 3, as well as the values used for the other determinants (Figs. 4 and 5). We also develop a Microsoft Excel template to easily calculate the variations in the priority weights of selected determinant.

The relevance change, about 3%, for the determinant, *M* is calculated by using the following formula (the value of 0.683 for the determinant, *M* was calculated from new pairwise comparison matrix using triangular fuzzy numbers):

$$\text{Increment } (\%) = \frac{\text{new\_weight} - \text{current\_weight}}{\text{current\_weight}} \times 100$$
$$= \frac{0.683 - 0.662}{0.662} \times 100 \cong 3\%$$

Finally, we can say that any change of the weight of each determinant in various levels does not change the final ranking of the alternatives. It means that the final ranking has stability.

After the team found out that the best concept is *Concept A*, they carried out the following steps to translate the chosen concept using the necessary information (i.e. BOM information, process plan, assembly chart and so on) to reality: (1) estimate the manufacturing costs (i.e. component costs, assembly costs and overhead costs), (2) reduce the costs of components (understanding the process constraints and cost drivers, redesigning components to eliminating processing steps, choosing the appropriate economic scale for the part process, standardizing components and processes), (3) reduce the costs of assembly (keeping score, integrate parts and maximize ease of assembly), (4) reduce the costs of production-related activities, (5) design and organize the necessary hardware (i.e. machines, fixtures and tools) for some components of the new system, (6) make a ramp-up or pilot manufacturing and (8) schedule a serial production. Then, they introduced the new system to the world markets at a limited number in order to firstly see its performance. After a couple of months, a customer survey showed that the new system perfectly met the needs and expectations of both customers and company. And, it is now very competitive product in the world market.

5. Conclusions

The objective of the research was, to use a fuzzy ANP-based approach to evaluate a set of conceptual design alternatives in a NPD environment in order to reach to ultimate conceptual alternative that satisfies the needs and the expectations of both customers and company.

The back-end and front-end of product development mainly affects to defining determinants, dimensions and attribute-enablers used in the ANP method. Because the ANP needs well-defined the elements in a decision network, which are obtained from customer expectations, technical specifications and more information created during development project in a NPD environment.

As compared to the AHP, the analysis using the ANP is relatively cumbersome, because a great deal of pairwise comparison matrices should be constructed for a typical study. In our study, we built great deal of pairwise matrices. Acquiring the relationships among determinants, dimensions and attribute-enablers required very long and exhaustive effort. On the other hand, advantage of the ANP method is to capture interdependencies across and along the decision hierarchies. It means that the ANP provides more reliable solution than the AHP. The full support of management in the ANP will help to use their long experience and thus eliminate the biases in the weights for conceptual design alternatives. Although the AHP is easier to apply than the ANP, in this study, we selected the ANP, both due to the fact that its holistic view and interdependencies accounted in the ANP, and due to the fact that it generates more reliable solution than the AHP. Making wrong decision in selecting the best concept can put a company into undesired risk in terms of losing market share, cost and time.

The ANP approach illustrated in this paper has a few limitations as well. For example, the outcome of the model is dependent on the inputs provided by the decision-maker(s). The possibility of bias of the decision-maker towards any particular alternative cannot be ruled out while applying this model. Inconsistency may also occur in the pairwise comparison of matrices, which may give wrong results. There are a number of opportunities for expanding the research presented herein. Its potential applicability in real-world problems raises practical challenges that include issues such as the problem structuring phase, the uncertainty analysis, and its usefulness in a group decision-making environment, among others. In addition, the number of criteria and their related sub-criteria can affect to the applicability of fuzzy ANP method due to the fact that the decision-maker(s) might have to make great deal of judgments in constructing pair wise matrices.

For future work, it would be better to divide each kind of risk into sub-factors in order to capture more reliable comparison judgments of the decision-makers. Furthermore, a knowledge-based (KB) or an expert system (ES) can be integrated to help the decision-maker(s) both make fuzzy pair wise calculations more concisely, and interpret the results in each step of the fuzzy ANP.

References

Agarwal, A., & Shankar, R. (2003). On-line trust building in e-enabled supply chain. *Supply Chain Management: An International Journal, 8*(4), 324–334.

Ayag, Z. (2002). An analytic-hierarchy-process simulation model for implementation and analysis of computer-aided systems. *International Journal of Production Research, 40*(13), 3053–3073.

Ayag, Z. (2005a). An integrated approach to evaluating conceptual design alternatives in a new product development environment. *International Journal of Production Research, 43*(4), 687–713.

Ayag, Z. (2005b). A fuzzy AHP-based simulation approach to concept evaluation in a NPD environment. *IIE Transactions, 37*, 827–842.

Azhar, T. M., & Leung, L. C. (1993). A multi-attribute product life-cycle approach to replacement decisions: An application of Saaty's system-with-feedback method. *The Engineering Economist, 38*(4), 321–343.

Brown, S. L., & Eisenhardt, K. M. (1995). Product development: Past research, present findings and future directions. *Academy of Management Review, 4*, 343–378.

Büyüközkan, G., Ertay, T., Kahraman, C., & Ruan, D. (2004). Determining the importance weights for the design requirements in the house of quality using the fuzzy analytic network approach. *International Journal of Intelligent Systems, 19*, 443–461.

Büyüközkan, G., Feyzioğlu, O., & Ruan, D. (2007). Fuzzy group decision-making to multiple preference formats in quality function deployment. *Computers in Industry, 58*, 392–402.

Carnahan, J. V., Thurston, D. L., & Liu, T. (1994). Fuzzing ratings for multiattribute design decision-making. *Journal of Mechanical Design, 116*, 511–521.

Chen, L.-H., & Weng, M.-C. (2006). An evaluation approach to engineering design in QFD processes using fuzzy goal programming models. *European Journal of Operational Research, 172*, 230–248.

Chesbrough, H. W., & Teece, D. J. (2002). Organizing for innovation: When is virtual virtuous? *Harvard Business Review*, 127–135.

Duffy, A. H. B., Andreasen, M. M., Maccallum, K. J., & Reijers, L. N. (1993). Design co-ordination for concurrent engineering. *Journal of Engineering Design, 4*, 251–261.

Finger, S., & Dixon, J. R. (1989a). A review of research in mechanical engineering design. Part I: Descriptive, prescriptive and computer-based models of design processes. *Research Engineering Design, 1*, 51–68.

Finger, S., & Dixon, J. R. (1989b). A review of research in mechanical engineering design. Part II: Representations, analysis, and design for the life cycle. *Research Engineering Design, 1*, 121–137.

Fitzsimmons, J. A., Kouvelis, P., & Mallick, D. N. (1991). Design strategy and its interface with manufacturing and marketing strategy: A conceptual framework. *Journal of Operations Management, 10*, 398–415.

Gates, W. (1999). *Business@the speed of sound*. Warner Books.

Griffin, A., & Hauser, J. R. (1996). Integrating R&D and marketing: A review and analysis of the literature. *Journal of Product Innovation Management, 13*, 191–215.

Hamalainen, R. P., & Seppalainen, T. O. (1986). The analytic network process in energy policy planning. *Socio-Economic Planning Science, 20*, 399–405.

Han, G.-P., Lıu, K., & Wang, X.-H. (2007). Micro force sensor design for friction test based on integrated technology of QFD/TRIZ/FUZZY. *Chinese Journal of Sensors and Actuators, 20*, 287–292.

Hu, Q.-G., & Zhang, P. (2007). Improved QFD based on group-decision AHP and fuzzy clustering. *Computer Integrated Manufacturing Systems (CIMS), 13*, 1374–1380.

Huang, H.-Z., & Gu, Y.-K. (2006). Product development process modeling based on information feedback and requirement cooperation. *Concurrent Engineering Research and Applications, 14*, 87–98.

Karsak, E. E. (2004). Fuzzy multiple objective programming framework to prioritize design requirements in quality function deployment. *Computers and Industrial Engineering, 47*, 149–163.

Kaufmann, A., & Gupta, M. M. (1988). *Fuzzy mathematical model in engineering and management science*. Amsterdam: Elsevier.

King, A. M., & Sivaloganathan, S. (1999). Development of a methodology for concept selection in flexible design strategies. *Journal of Engineering Design, 10*, 329–349.

Krishnan, V., & Ulrich, K. T. (2001). Product development decisions: A review of the literature. *Management Science, 47*, 1–21.

Kwong, C. K., Chen, Y., Bai, H., & Chan, D. S. K. (2007). A methodology of determining aggregated importance of engineering characteristics in QFD. *Computers and Industrial Engineering, 53*, 667–679.

Lee, A. R. (1999). *Application of modified fuzzy AHP method to analyze bolting sequence of structural joints*. UMI Dissertation Services, A Bell & Howell Company.

Lee, J. W., & Kim, S. H. (2000). Using analytic network process and goal programming for interdependent information system project selection. *Computers and Operations Research, 27*, 367–382.

Marsh, S., Moran, J. V., Nakui, S., & Hoffherr, G. (1991). *Facilitating and training in quality function deployment*. Methuen, MA: GOAL/QPC.

Meade, L., & Presley, A. (2002). R&D project selection using AHP. *IEEE Transactions on Engineering Management, 49*, 22–28.

Meade, L., & Sarkis, J. (1999). Analyzing organizational project alternatives for agile manufacturing process: An analytical network approach. *International Journal of Production Research, 37*, 241–261.

Mikhailov, L., & Singh, M. G. (2003). Fuzzy analytic network process and its application to the development of decision support systems. *IEEE Transactions on Systems, Man and Cybernetics, 33*, 33–41.

Negoita, C. V. (1985). *Expert Systems and Fuzzy Systems*. Menlo Park, California: The Benjamin/Cummings.

Pahl, G., & Beitz, W. (1984). *Engineering Design*, 119–138.

Pugh, S. (1991). *Total design* (pp. 67–85). Reading, MA: Addison-Wesley.

Saaty, T. L. (1981). *The analytical hierarchy process*. New York: McGraw-Hill.

Saaty, T. L. (1989). Decision making, scaling, and number crunching. *Decision Science, 20*, 404–409.

Saaty, T. L. (1996). *Decision making with dependence and feedback: The analytic network process*. Pittsburgh, PA: RWS Publication.

Sarbacker, S. D., Ishii, K. (1997). A framework for evaluating risk in innovative product development. In *Proceedings of the ASME DETC'97: ASME design engineering technical conference*, September 14–17, Sacramento, CA.

Scott, M. (2002). Quantifying certainty in design decisions: Examining AHP. In *Proceedings of the DETC2002/DTM-34020*, Montreal, Canada.

Thurston, D. L., & Carnahan, J. V. (1992). Fuzzy ratings and utility analysis in preliminary design evaluation of multiple attributes. *Journal of Mechanical Design, 114*, 648–658.

Welch, D., & Kerwin, K. (2003). Rick Wagoner's game plan. *Business Week*, 52–60.

Whitney, D. T. (1988). Manufacturing by design. *Harvard Business Review, 66*, 83–91.

Yurdakul, M. (2003). Measuring long-term performance of a manufacturing firm using analytic network process (ANP) approach. *International Journal of Production Research, 41*(11), 2501–2529.

Zahedi, F. (1986). The analytic hierarchy process: A survey of the method and its application. *Interfaces, 16*, 96–108.

Zimmermann, H. J. (1996). *Fuzzy set theory and its applications*. Massachusetts: Kluwer.