Accelerating the New Product Introduction with Intelligent Data Mining

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Abstract. New product development (NPD) is a vital activity for companies. It is also a very risky process since every development stage involves a high degree of uncertainty and the success of each step depends on how previous steps are successfully accomplished. Hence, there is a clear need to evaluate new product initiatives systematically and make accurate decisions under uncertainty. Another actual concern for the companies is the time pressure to launch a significant number of new products due to the high competition in the market. In this chapter, we first present the available assessment models and techniques that help the evaluators to reduce their risks under uncertainty in NPD process. Then, we propose an integrated framework which is based on fuzzy logic, neural networks and multi criteria decision making and which enables us to make appropriate decisions while accelerating the decision process. We are especially interested in two first stages of new product decision-making: the choice of a new product idea ("go"/"no go" decision) and the choice of the right implementation order of the selected product ideas. We show that this two-staged intelligent approach allows practitioners to roughly and quickly separate good and bad product ideas by making use of previous experiences, and then to analyze in details a more shortened list rigorously.

1 Introduction

New product development (NPD) is the process by which an organization uses its resources and capabilities to create a new product or improve an existing one. Today, product development is seen as "among the essential processes for success, survival, and renewal of organizations, particularly for firms in either fast-paced or competitive markets" ([3] p. 344). Markets are generally perceived to be demanding higher quality and higher performing products, in shorter and more predictable development cycle-times and at lower cost [35]. In order to obtain best performance from NPD, the efficient and effective management of the product development process is vital. However, new product failure rates are substantial and the cost of failure is large, and this

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makes successful NPD rather a complicating task to be exercised with caution [19].

The NPD process is structured around well-defined phases; each phase encloses many decision points, where management decides about the future of the project. The decision maker must take into account the customers' needs, the company's strategies as well as technological opportunities and the company's resources, and deduce the goals based on these factors for a successful NPD. With the support of a successful management system, an enterprise must be able to determine right products or features to be developed, the right time to develop and launch, the right amount of development investments, its effective implementation, etc. As it can be easily understood, no NPD operation can be accomplished without effective and timely decision-making.

An important cornerstone of the new product management is the idea selection and new product project launch decision. Several researchers have suggested that it is difficult for managers to end NPD projects once they are begun [7, 10]. Historical cases suggest that firms can make two types of erroneous decisions when evaluating their new product ideas. First, they might decide to pursue a potentially unsuccessful new product idea. Second, they might decide not to develop a potentially successful new product. In either case, firms accrue big losses, while the former leads to investment loses the latter leads to missed investment opportunities [39]. For this reason, here we focus especially on increasing the accuracy of the necessary decisions before a new product project is launched.

Similar to all decision problems, NPD decisions contain considerable amount of uncertainty causing elements, which confuse the decision-maker to reach the targeted performance. Uncertainty arises from multiple sources including technical, management and commercial issues, both internal and external to the project. It is also widely recognized and accepted that successful management of uncertainty is intimately associated with project success, as the proactive project manager constantly seeks to steer the project towards achievement of the desired objectives [22]. Then, it is critical to use a structured approach that can minimize the risks caused by the uncertainty for NPD projects. In this work, we propose an integrated approach based on fuzzy logic, neural networks and multi criteria decision making (MCDM) to make more rational selection decisions.

The rest of the chapter is organized as follows. In the next section, we briefly expose the uncertainty factors affecting the NPD process. In the third section, we present different decision-making techniques yet available to reduce the risks under uncertainty in NPD. The next two sections give the details on how to incorporate intelligent techniques in NPD and the proposed approach based on intelligent data mining. Finally, the last section contains some concluding remarks and perspectives.

2 Risks under Uncertainty in NPD Process

New product development is a very risky and uncertain process. Risk is defined as the exposure to loss/gain, or the probability of occurrence of loss/gain multiplied by its respective magnitude. Events are said to be certain if the probability of their occurrence is 100% or totally uncertain if the probability of occurrence is 0%. In between these extremes the uncertainty varies quite widely. On projects it is necessary to define one or a number of objective functions to represent the project under consideration and then measure the likelihood of achieving certain target values for them. Examples of such functions include capital expenditure, completion time and so on. Risk management involves modeling the project's objective functions against project variables, which include such variables as cost and quantities of input resources, external factors, etc. Since the project variables are often stochastic in nature and dynamic (i.e., exhibiting varying degrees of uncertainty over time) it is quite natural that the objective functions will also exhibit uncertainty. Project uncertainty is the probability that the objective function will not reach its planned target value [24].

It can be observed that different approaches exist in the literature to define and analyze the uncertainty in NPD projects. [17] combined three dimensions of uncertainty as technical, market and process. They rated and categorized uncertainty along each dimension as being either low or high. For technical uncertainty, when uncertainty is low, the technologies used in the development of the project are well known to the organization and relatively stable. When technical uncertainty is high, technologies used in the development of the project are neither existent nor proven at the start of the project, and/or are rapidly changing over time. For market uncertainty, when uncertainty is low the organization has good market data on both customers and competitors, and product is being sold through familiar channels of distribution. When market uncertainty is high, the organization has little information regarding who the customer is, how the market is segmented and what are the needed channels of distribution. For process uncertainty, when uncertainty is low the engineering, marketing, and communications (both internal and external) processes used in this project are well tested, stable, and embedded in the organization. When process uncertainty is high, a significant portion of any or all of the engineering, marketing, and communications processes are relatively new, unstable, or evolving.

Similarly, [38] identified three levels of uncertainty that confront companies operating in rapidly changing markets. First, potential customers cannot easily articulate needs that a new technology may fulfill. Consequently, NPD managers are uncertain about the market opportunities that a new technology offers. Second, NPD managers are uncertain about how to turn the new technologies into new products that meet customer needs. This uncertainty arises, not only from customers' inability to articulate their needs, but also from managers' difficulties in translating technological advancements into product features and benefits. Finally, senior management faces uncertainty about how much capital to invest in pursuit of rapidly changing markets as well as when to invest.

Reference [36] identified three main risk categories for engineering projects: "completion risks" group formed by technical, construction and operational risks, "market related risks" group formed by demand, financial and supply risks and finally, "institutional risks" group formed by social acceptability and sovereign risks.

We refer also to the recent work of [42] where NPD risks from uncertainty are organized into three general categories such as technical risks, commercial risks and NPD personnel. If we analyze NPD from different perspectives, we can precise risk structure in a more detailed manner. As an example, we can allocate product positioning, pricing and customer uncertainties to marketing; organizational alignment and team characteristics uncertainties to organizations; concept, configuration and performance uncertainties to engineering design; supplier, material, design of production sequence and project management uncertainties to operations management.

Efficient and effective NPD requires the appropriate management of all these uncertainty sources. While considering the decision points in whole NPD process, we expect to minimize the side effects of uncertainties described previously and to increase the effectiveness of the decisions. Numerous decision tools and techniques have been developed to assist managers in making better screening decisions in an uncertain environment. Some of them are summarized in the next section.

3 Risk Analysis Tools and Techniques in NPD

The balance between opportunities and risks has got to be carefully maintained for the performance of the NPD project. There are several, or many, tools and techniques, which are applicable to risk analysis in NPD projects [8, 9, 11, 13, 14, 18, 23, 27, 31, 47, 49]. The summary of them is given as follows.

Probabilistic Models: These include Monte Carlo Simulation and decision trees [48]. Monte Carlo analysis uses the process of simulation to achieve a range of solutions to a problem. Decision tree is a diagram that provides a structured approach to decision making that incorporates uncertainty of outcome and expected revenues.

Options Pricing Theory: It is being proposed as a mean of understanding what level of research investment is justified for a particular project. It treats each stage of the new product project much like purchasing an option on a future investment [16].

Scoring Models and Checklists: Here, projects are rated and scored on a variety of qualitative questions (in some cases, the project score becomes the criterion for project prioritization) [20]. The questions or items often capture proven drivers of new product success such as product advantage, market attractiveness, and synergy with the base business (leverages core competencies), familiarity, etc. [37].

Behavioral Approaches: These are tools designed to bring managers to a consensus in terms of which projects to undertake, and include methods such as the Delphi method that is a qualitative forecasting method which uses a panel of experts [48]. They are particularly useful for the early stages, where only qualitative information is available.

Analytical Hierarchy Process (AHP): These are decision tools based on paired comparisons of both projects and criteria [45]. Software tools such as Expert Choice® enable a team of managers to arrive at the preferred set of projects in a portfolio [54], with relative ease.

Sensitivity Analysis: It examines how the optimal solution and the optimal objective value are affected from the changes of the uncertainty parameters (values and probabilities) that are considered to be important [40].

Scenario Analysis: This technique has been widely preferred and used by many decision makers. Here, a combination of possible values of the uncertainty parameters are assumed regarding to different point of views (e.g., pessimistic, neutral and optimistic), and the resulting scenario is solved. By solving the problem repeatedly for different scenarios and studying the solutions obtained, the decision maker observes sensitivities and heuristically decides on an appropriate solution.

Fuzzy Logic: It deals with problems in which a source of vagueness is involved [53]. In general, the probability concept is related to the frequency of occurrence of events, captured by repeated experiments whose outcomes are recorded, while the fuzzy sets provide the appropriate framework to evaluate the possibility of events rather than their probability [18].

Artificial Intelligence: It is a discipline that is concerned with the study and creation of computer systems that exhibit some form of intelligence. Intelligence is a system that can learn new concepts and tasks; reason and draw useful conclusions about the world around us; understand a natural language; and perceive and comprehend a visual scene [41]. Typical research areas of artificial intelligence include problem solving and planning, expert systems, natural language processing, robotics, computer vision, neural networks, genetic algorithms and machine learning [29]. Case-based reasoning, rough set theory and intelligent agent are the recent emerging areas [42].

These techniques can be used exclusively or in a hybrid way. We must note that there is no best technique. Each of them has some advantages and also disadvantages. For example, the decision tree method is easy to understand where the risk is interpreted as probability and not as a discount rate. In the same time, the risk estimates easily biased and difficult to estimate accurately. The method lacks flexibility since decision points occur continuously and not always at discrete junctions. If too many possibilities are considered, then "tree" becomes a "bush." As another example, Monte Carlo simulation has the advantage to analyze a greater number of scenarios and to estimate the probabilities of these scenarios. But it has also some drawbacks: probability distributions for individual variables and variable correlations may be difficult to calculate. To reflect reality, more variables have to be added which makes the model more complicated and difficult to understand. Moreover, the project value due to the managerial flexibility is not calculated. For these reasons we think that the extent to which different techniques for the NPD idea evaluation can be used will depend upon the nature of the project, the information availability, the company's culture and several other factors. This is clear from the variety of techniques, which are theoretically available, and the extent to which they have been used in practice. In any case, no matter which technique is selected by a company, it should be implemented, and probably adapted, according to the particular needs of that company.

In this study, where we analyze the new product idea evaluation, we propose an intelligent decision-making procedure based on neural networks, fuzzy logic and MCDM that will be described in details in the next section.

4 Use of Intelligent Techniques for New Product Idea Selection

As stated before, being able to consistently and rationally evaluate and justify go/no-go decision-making for each NPD project becomes extremely desirable from both top management as well as project manager's point of view. When there are numerous ideas generating sources, it is almost impossible to rate all new product ideas in a very detailed way and in a reasonable amount of time. In this study, we propose to use a two-stage intelligent decision making approach to accelerate the NPD process and to improve the efficiency of the decisions in an environment of uncertainty. The research in the intersection area of artificial intelligence and NPD is comparatively new. For a comprehensive overview of the application of the related techniques in NPD, we refer the interested readers to [42, 56]. We note that, [56] identified neural networks and genetic search as the predominant techniques for the initial phases of NPD process.

The proposed two-staged new product idea selection approach allows practitioners to roughly and quickly separate good and bad product ideas by making use of previous experiences, and then to analyze in details a more shortened list. The first stage consists of a technique that merges neural networks and fuzzy logic. Artificial Neural Networks (ANN) [21, 34]

- make use of the way that the human brain learns and functions,
- possess the ability to learn from examples,
- have the ability to manage systems from their observed behavior rather than from a theoretical understanding,
- have the capacity to treat large amount of data and capturing complex interactions among the input variables, and thus reducing the development time by learning underlying relationships.

Meanwhile fuzzy logic [28, 53, 57]

- is used to deal with imprecise linguistic concepts or fuzzy terms,
- allows us to make rational decisions in an environment of uncertainty, fuzziness and imprecision without loosing the richness of verbal judgment,
- is highly suitable for approximate reasoning by incorporating fuzzy rules.

So it is likely that substantial improvements on NPD idea selection decisions can be made by merging the ANN and fuzzy set theory. The characteristics of such hybrid architecture can be described as follows:

- It realizes an *automatic procedure* for obtaining in the same time both the consequents and antecedents of a set of fuzzy rules starting from a system's set of input (previous new product idea evaluations) and output data (ideas' grades). Moreover, they allow us to appropriately modify the shape of the membership functions.
- It requires a *small number of parameters* with respect to the number of connections in a Multilayer Perceptron (MLP). Besides, the number of neurons in such architecture is wholly determined by that of membership functions chosen for each new product evaluation input variables.
- It allows us *to incorporate the knowledge* of an expert regarding the choice of new product idea input-output topology.
- It leads us to determine a system model, which is *easily comprehensible*, unlike the model obtained with an MLP. In fact, neural networks reach their own limits precisely because the knowledge acquired by a neural network consists in a set of interconnection weights, which is not simply interpretable. Instead, a fuzzy rules system is always *transparent* in the sense that a practitioner can easily read the knowledge base of the fuzzy system and interpret its behavior when faced by a given new product.

The second stage of the proposed approach is based on MCDM, particularly fuzzy AHP method, which allows a more accurate description of the evaluation and decision making process. Among the different MCDM methods, AHP is the most widely used and easily understandable one [45, 54]. Other researchers also have noted the usefulness of AHP for new product screening [7, 32, 33, 51, 52]. The methodology allows decision makers to model a complex problem like a new product idea selection in a structure showing relationships of the goal, objectives and alternatives. The goal of selecting the best new product idea is defined as a statement of the overall objectives. Therefore, the definition of the goal is that it is the idea that best meets the objectives. With AHP, it is also possible to have a set of ideas that would become the "best choice." AHP allows for decision makers to pull information together for one idea, assess pros and cons for that idea, weight that idea against others using a variety of measurement techniques and finally communicate the decision through synthesis of the new product ideas in relation to the goal. Fuzzy AHP is a natural extension of the traditional AHP where decision makers do not require to express their assessments through crisp values but rather they use fuzzy numbers which is more suitable when uncertainty is high. This is especially true for a decision process like new product idea selection where there are also many qualitative attributes to rate subjectively. Recently, [6] suggested an integrated decision making approach for NPD under uncertainty and they used the fuzzy AHP method to select new product development strategies, which minimize project uncertainties. Fig. 1 illustrates the simplistic view of our proposed two-stage approach

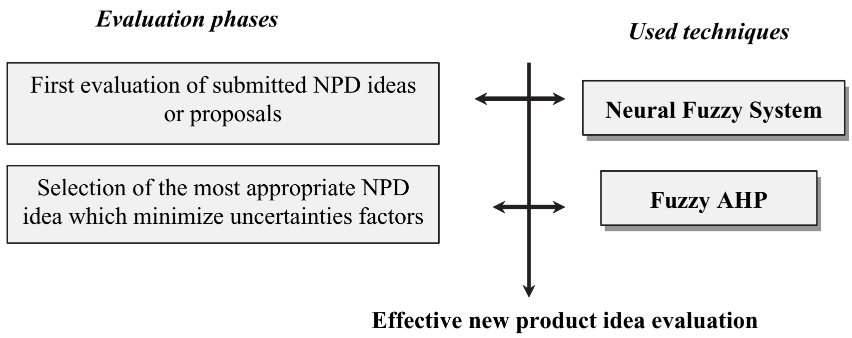

Fig. 1. Proposed intelligent decision-making approach

5 An Intelligent Data Mining Approach for New Product Idea Selection

5.1 Neural Fuzzy System

In this study, new product ideas generated individually or by groups of individuals have been collected by a formal system. The preprocessing of ideas is left to an intelligent neuro-fuzzy inference system, which is trained with precedent decisions. This type of system has clearly an unbiased nature and posses an internal mechanism that can learn the viewpoint of the company management towards products ideas by making use of the extracted rules. This will also reduce the needed effort to make decisions when the number of applications is large.

For our fuzzy inference system (FIS), the input space for the mapping is the information provided by past ideas evaluations and the output space is the status of the idea (i.e., "good" or "bad"). Regarding to NPD, most of the time evaluations are based on a scoring system with determined evaluation criteria. Therefore, translating if necessary these new products' criteria scores to eligibility percentages, one can build the input database for FIS. The mapping then provides a basis from which decisions can be made, or patterns discerned. The details of the FIS are given in [1]. Neural network techniques aid the fuzzy modeling procedure to learn information about a data set, and compute the membership function parameters that best allow the associated FIS to track the given input/output data. ANFIS (adaptive network-based fuzzy inference system) is a class of adaptive networks that are functionally equivalent to FIS [25]. Using a given input/output data set, ANFIS constructs a FIS whose membership function parameters are adjusted using either a back propagation algorithm or a hybrid-learning algorithm. Therefore, using ANFIS, fuzzy systems can learn from the modeling data.

The architecture of ANFIS is a feed-forward network that consists of five layers [25]. Figure 2 shows the equivalent ANFIS architecture for a two-input Sugeno-type fuzzy inference system.

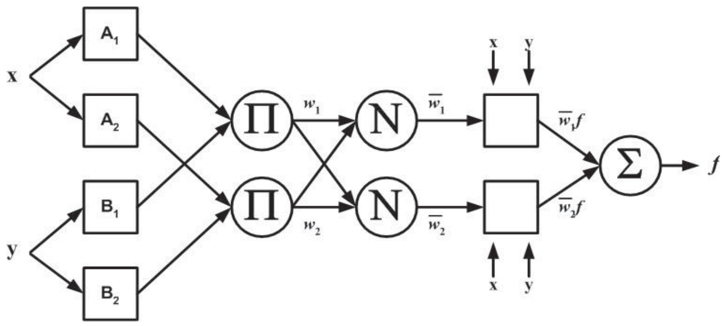

Fig. 2. ANFIS architecture for a two inputs, two rules Sugeno FIS

A rule in the first order Sugeno FIS has the form:

$$\text{If } x \text{ is } A_i \text{ and } y \text{ is } B_i \text{ then } f_i = p_i x + q_i y + r_i$$

The output of a node in the first layer specifies to which degree a given input, x, satisfies a quantifier, A, i.e., the function of the node i in this layer is a membership function for the quantifier, A_i, of the form:

$$O_i^1 = \mu_{A_i}(x) \ . \tag{1}$$

Each membership function has a set of parameters that can be used to control that membership function. For example, a Gaussian membership function that has the form

$$\mu_{A_i}(x) = \exp\left[-\left(\frac{x - c_i}{\sigma_i}\right)^2\right] \tag{2}$$

and has two parameters, c_i and σ_i. Tuning the values of these parameters will vary the membership function, which means a change in the behavior of the FIS. Parameters in this layer are referred to as premise parameters [25].

In the second layer, the output of a node represents a firing strength of a rule. The node generates the output (firing strength) by multiplying the signals that come on its input,

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \; . \tag{3}$$

The function of a node in the third layer is to compute the ratio between the ith rule's firing strength to the sum of all rules' firing strengths:

$$\bar{w}_i = \frac{w_i}{w_1 + w_2} \tag{4}$$

where $\bar{w}_i$ is referred to as the normalized firing strength [25]. In the fourth layer, each node has a function of the form:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i \left(p_i x + q_i y + r_i\right) \tag{5}$$

where $\{p_i, q_i, r_i\}$ is the parameter set. These parameters are referred to as the consequent parameters [25]. The overall output is computed in the fifth layer by summing all the incoming signals, i.e.,

$$O^5 = f = \sum_i \bar{w}_i f_i = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \tag{6}$$

During the learning process, the premise and consequent parameters are tuned until the desired response of the FIS is achieved [25].

5.2 Fuzzy AHP

We propose to use the fuzzy AHP method in the second stage of our study. Traditional AHP [44, 45] uses the principle of comparative judgments to construct pair wise comparisons of the relative importance of elements at some given level of a criteria hierarchy with respect to shared criteria or property at the level above, giving rise to a weight matrix. Priorities are synthesized from the second level down from multiplying local priorities by the priority of their corresponding criterion in the level above and adding for each element in a level according to the criterion it affects. The construction of comparison matrices requires the relative importance among attributes and options being expressed as precise numbers on a standard scale (usually from 1 to 9) where the degree of the preference is proportional with the magnitude of the chosen number. However, precise numbers fail to contain the subjectivity and vagueness in such decision-making. Comparisons between alternatives always contain ambiguity and multiplicity of meaning. Moreover, human assessment on qualitative attributes is always subjective and thus imprecise. We overcome this difficulty of modeling the uncertainty of human assessment by using the fuzzy AHP methodology. The fuzzy AHP approach allows a more accurate description of the decision making process.

The earliest work in fuzzy AHP appeared in [50], which compared fuzzy ratios described by triangular membership functions. Logarithmic least square was used to derive the local fuzzy priorities. Later, using geometric mean, [4] determined fuzzy priorities of comparison, whose membership functions were trapezoidal. By modifying the Van Laarhoven and Pedrycz method, [2] presented a more robust approach to the normalization of the local priorities. In a recent study, [15] used a fuzzy extension of the AHP method in the project selection.

A fuzzy number is a special fuzzy set $F = \{(x,\, \mu_F(x)),\, x \in R\}$, where x takes its value on the real line, $R : -\infty < x < +\infty$ and $\mu_F(x)$ is a continuous mapping from R to the closed interval [0,1] which represents the membership degree of x. A triangular fuzzy number denoted as $\tilde{a} = (l, m, u)$, where $l \leq m \leq u$, has the following triangular type membership function:

$$\mu_{\tilde{a}}(x) = \begin{cases} 0, & \text{if } x \leq l \text{ or } x > u \\ \dfrac{x-l}{m-l}, & \text{if } l < x \leq m \\ \dfrac{u-x}{u-m}, & \text{if } m < x \leq u \end{cases}$$

It can also be characterized alternatively as

$$\tilde{a}^\alpha = [l^\alpha, u^\alpha] = [(m-l)\,\alpha + l, u - (u-m)\,\alpha]$$

for all $\forall\alpha \in [0,1]$. Then, main operations like addition or multiplication can be accomplished by usual interval arithmetic. Here, we use triangular fuzzy numbers $\tilde{1}$ to $\tilde{9}$ as a superior means of representing pair wise comparisons in the AHP judgment matrix and improve the conventional nine-point scaling scheme. These numbers together with their corresponding membership functions are defined in Fig. 3.

A comparison matrix $\tilde{R}$ is constructed for the n-new product idea selection problem, in which pair wise comparisons are assumed to be triangular fuzzy numbers $\tilde{a}_{ij}$ for all $i, j \in \{1, 2, \ldots, n\}$, such that

$$\tilde{R} = \begin{bmatrix} (1,1,1) & \tilde{a}_{12} & \tilde{a}_{13} & \cdots & \tilde{a}_{1(n-1)} & \tilde{a}_{1n} \\ 1/\tilde{a}_{12} & (1,1,1) & \tilde{a}_{23} & \cdots & \tilde{a}_{2(n-1)} & \tilde{a}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1/\tilde{a}_{1(n-1)} & 1/\tilde{a}_{2(n-1)} & 1/\tilde{a}_{3(n-1)} & \cdots & (1,1,1) & \tilde{a}_{(n-1)n} \\ 1/\tilde{a}_{1n} & 1/\tilde{a}_{2n} & 1/\tilde{a}_{3n} & \cdots & 1/\tilde{a}_{(n-1)n} & (1,1,1) \end{bmatrix}$$

The triangular fuzzy number $\tilde{a}_{ij} = (l_{ij},\, m_{ij},\, u_{ij})$ is obtained for each lowest level decision criterion and alternative idea simply by weighted average of different evaluators

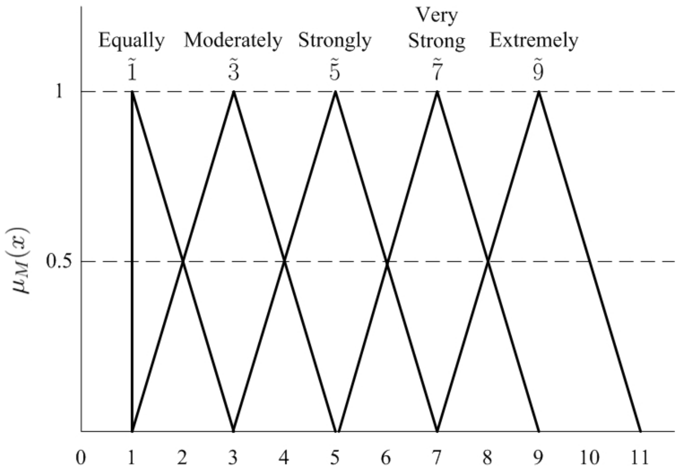

Fig. 3. Membership functions of triangular fuzzy numbers

$$\tilde{a}_{ij} = \tilde{w}_1 \otimes \tilde{a}_{ij1} \oplus \tilde{w}_2 \otimes \tilde{a}_{ij2} \oplus \ldots \oplus \tilde{w}_K \otimes \tilde{a}_{ijK} \text{ for all } i, j \in \{1, 2, \ldots, n\} \quad (7)$$

where $\tilde{w}_k$ is the weight of the evaluator k and there are K evaluators. $\tilde{w}_k$ can be a fuzzy number or just the crisp number (1/K) if one would prefer to treat decision makers equally. Note that, each $\tilde{a}_{ijk} = (l_{ijk}, m_{ijk}, u_{ijk})$ is selected among the triangular fuzzy numbers given in Fig. 3. Equation (8) can also be used to aggregate assessments.

$$\tilde{a}_{ij} = \left(\min_k (l_{ijk}), \left(\prod_{k=1}^{K} m_{ijk} \right)^{1/K}, \max_k (u_{ijk}) \right) \quad (8)$$

Next, the fuzzy eigenvector of the matrix $\tilde{R}$ is estimated. According to [45], the right principal eigenvector of the matrix expresses the importance of the alternatives. The fuzzy eigenvalue, $\tilde{\lambda}$, is a fuzzy number solution to $\tilde{R}\tilde{x} = \tilde{\lambda}\tilde{x}$ where $\tilde{x}$ is a non-zeros $n\times$ 1 fuzzy vector. Using interval arithmetic, this is equivalent to

$$[a^{\alpha}_{i1l} x^{\alpha}_{1l}, a^{\alpha}_{i1u} x^{\alpha}_{1u}] \oplus \ldots \oplus [a^{\alpha}_{inl} x^{\alpha}_{nl}, a^{\alpha}_{inu} x^{\alpha}_{nu}] = [\lambda^{\alpha}_{l} x^{\alpha}_{il}, \lambda^{\alpha}_{u} x^{\alpha}_{iu}]$$

where $\tilde{a}^{\alpha}_{ij} = [a^{\alpha}_{ijl}, a^{\alpha}_{iju}]$, $\tilde{x}^{\alpha}_{i} = [x^{\alpha}_{il}, x^{\alpha}_{iu}]$ and $\tilde{\lambda}^{\alpha} = [\lambda^{\alpha}_{l}, \lambda^{\alpha}_{u}]$ for 0 ¡ $\alpha \leq 1$ and all $i, j = 1, 2, \ldots, n$.

The degree of satisfaction for the matrix $\tilde{R}$ is estimated by the index of optimism μ. Larger value of μ indicates higher degree of optimism. Optimism index is the convex combination defined as [30]

$$\hat{a}^{\alpha}_{ij} = \mu a^{\alpha}_{iju} + (1 - \mu)\, a^{\alpha}_{ijl}, \; \forall \mu \in [0, 1]\,. \quad (9)$$

When α and μ is fixed, the following matrix can be obtained.

$$\tilde{R} = \begin{bmatrix} 1 & \hat{a}^{\alpha}_{12} & \cdots & \hat{a}^{\alpha}_{1(n-1)} & \hat{a}^{\alpha}_{1n} \\ \hat{a}^{\alpha}_{21} & 1 & \cdots & \hat{a}^{\alpha}_{2(n-1)} & \hat{a}^{\alpha}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \hat{a}^{\alpha}_{(n-1)1} & \hat{a}^{\alpha}_{(n-1)2} & \cdots & 1 & \hat{a}^{\alpha}_{(n-1)n} \\ \hat{a}^{\alpha}_{n1} & \hat{a}^{\alpha}_{n2} & \cdots & \hat{a}^{\alpha}_{n(n-1)} & 1 \end{bmatrix}$$

Then, the eigenvector of $\tilde{R}$ corresponding to its maximal eigenvalue can be computed. After a normalization, the importance of alternatives for the given criterion is obtained. The procedure explained so far is repeated for all the lowest level criteria and also others in between criteria. In other words, all alternatives have to be compared one with another for each lowest level criterion so as to find their ratings and meanwhile the importances of criteria have to be determined again by pair wise comparison for each hierarchical level.

Finally, if we denote $x' = \{x'_1, x'_2, \ldots, x'_n\}$ as the adjusted performance measures of new product ideas, then we can construct the following fuzzy decision matrix

$$\tilde{Z} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & C_3 & C_4 \end{array} \\ \begin{bmatrix} x'_{11} & x'_{12} & \cdots & x'_{1m} \\ x'_{21} & x'_{22} & \cdots & x'_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x'_{n1} & x'_{n2} & \cdots & x'_{nm} \end{bmatrix} \end{array}$$

where A and C stand for alternative and criterion, respectively. Note that x'_{ij} is the performance measure of the alternative i for the criteria j. Then, the importance of each alternative is obtained by multiplying each criterion weight v_j (calculated as a crisp number) by the related alternative's performance. In other words, we require

$$p_i = v_1 \times x'_{i1} + v_2 \times x'_{i2} + \ldots + v_m \times x'_{im} \text{ for all } i \in \{1, 2, \ldots, n\}$$

This calculation process continues level by level in the hierarchical structure until the finite performance of alternatives can be obtained.

5.3 Algorithmic Form of Proposed Approach

To summarize our approach, the necessary steps are given in an algorithmic form as follows.

Step 1. Accumulation of the new product ideas through selected collecting techniques (i.e., forms, contest, web, etc.).

Step 2. Rating of individual ideas in percentage for all evaluation criteria by the marketing team.

Step 3. Determination of the input membership functions and related parameters by exercising neural networks techniques on rating data.
Step 4. Building the fuzzy inference system with adjusted membership functions of the previous step.
Step 5. Using the inference system as needed to accept/reject ideas.
Step 6. Given uncertainty factors, each individual member of the expert team is required to evaluate pre-selected ideas by using the linguistic terms.
Step 7. Aggregation of expert results to figure out the right implementation order.

We apply Steps 3–4 if necessary after the idea pool update. The application of this proposed methodology to a specific toy manufacturing firm has been recently reported by [5].

6 Final Remarks and Perspectives

In this study, we aim to improve the quality of decision-making in NPD under uncertainty and to higher the level of success of associated activities by introducing a new iterative methodology. First we describe uncertainty factors affecting the NPD process and cite the essential methods for the decision maker to reduce these factors. Then, we emphasize the motivation behind our approach, which incorporates fuzzy logic, neural networks and MCDM for the new product idea selection.

We believe that the application of our method will be a good practice in terms of the aggregation and purification of the subjective judgments and to clarify the big picture, which is covered by risks and uncertainties. Moreover, it is generic in a sense that although in different sectors, companies exercising similar vast new product idea selection process and having a scoring system can adopt it quite easily. However, we have to also underline two limitations of this study:

- The methodology is proposed to the companies that had already a successful scoring system and want to computerize and speed up the selection process. Without a reliable historical database, the neural network cannot be trained and the FIS can only be equipped with theoretical understanding. This can lead to inconsistent results.
- We underline that the approach is not applicable in all cases. In other words, the method is structured especially for companies/sectors where many new product ideas are stimulated and there is a need for a more efficient evaluation procedure for the initial selection. There is a need for intellectual capital evaluation for high innovative and creative, very few new product developing or highly R&D oriented companies.

No matter which evaluation technique is used, a long period of time is always necessary to observe the results of such a strategic level decision. Additionally, a product success is not only depending on catching the best idea but also on how to manage subsequent development and launch processes. We keep trying to understand the sources of conflict and possible improvements on the approach.

A practical reality is that environmental factors and customer's tendencies towards new products change over time and previously selected genuine ideas cannot be adequate for the actual period. It is then advised to practitioners to update the database in a way that old ideas are discarded (e.g., dating five or more years old) and new ones are added. It is clear that the update frequency highly depends on the targeted market segment.

Based on this work, our future extension is to investigate other decision phases in NPD and to provide similar approaches to enrich the available literature. We will evaluate in a more detailed form, the influence of other methods on the final quality and accuracy of decisions. We would also try to enhance our decision support system with new techniques to enable managers comparing different solutions and making more rigorous decisions.

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