Evaluation of New Product Development Projects using Artificial Intelligence and Fuzzy Logic

Orhan Feyzioğlu, and Gülçin Büyüközkan

Abstract—As a vital activity for companies, new product development (NPD) is also a very risky process due to the high uncertainty degree encountered at every development stage and the inevitable dependence on how previous steps are successfully accomplished. Hence, there is an apparent need to evaluate new product initiatives systematically and make accurate decisions under uncertainty. Another major concern is the time pressure to launch a significant number of new products to preserve and increase the competitive power of the company. In this work, we propose an integrated decision-making framework based on neural networks and fuzzy logic to make appropriate decisions and accelerate the evaluation process. We are especially interested in the two initial stages where new product ideas are selected (go/no go decision) and the implementation order of the corresponding projects are determined. 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, analyze a more shortened list rigorously.

Keywords—Decision Making, Neural Networks, Fuzzy Theory and Systems, Choquet Integral, New Product Development.

I. 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. 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" [1]. 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 [2]. With the support of a successful management system, an enterprise will be able to determine right products or features to be developed, the right time to develop and launch and the right amount of investments.

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New product idea selection and project launch are important cornerstones of the new product management. In practice, it is observed that it is difficult to end NPD projects once they are begun [3], [4] and firms can make two types of erroneous decisions when evaluating their new product ideas: pursuing an unsuccessful idea and not developing a potentially successful new product. In either case, firms accrue big losses, and while the former leads to investment loses, the latter leads to missed investment opportunities [5]. Consequently, we especially focus in this study on increasing the accuracy of the necessary decisions before the project is launched.

NPD decisions, especially necessary at early stages of the development, contain considerable amount of uncertainty causing elements, which confuse the decision-maker to reach the target performance. The uncertainty arises from multiple sources including technical, management and commercial issues, both internal and external to the project. Meanwhile, successful management of uncertainty is intimately associated with the project success, as the proactive project manager constantly seeks to steer the project towards achievement of the desired objectives [6]. Hence, 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 Choquet integral to make more rational selection decisions.

The rest of the paper is organized as follows. In the next section, we present a new intelligent decision making method that aims to accelerate the new product project evaluation process while taking into account the uncertainty factors that affect it. The application of the approach is given in section 3 and the last section includes some concluding remarks and perspectives.

II. AN INTELLIGENT EVALUATION APPROACH FOR NPD PROJECTS

NPD has a vast working area and it address different strategic, tactic and operational managerial abstraction levels in the organization. Although different organizations can make different choices and may use different methods, all of them make decisions about a collection of issues such as the product concept, architecture, configuration, procurement and distribution arrangements, project schedule, etc.

Consequently, NPD can be defined as a process including many ''generic decision'' points, where each of them must be evaluated, selected, and prioritized. Similar to all decision problems, NPD decisions contain considerable amount of uncertainty causing elements, which confuse the decision-maker to reach the targeted performance. Efficient and effective NPD requires the appropriate management of all these uncertainty sources. While considering the decision points in whole NPD process, numerous decision tools and techniques have been developed to assist managers in making better screening decisions in an uncertain environment. Some of them are probabilistic models, options pricing theory, scoring models and checklists, behavioral approaches, analytical hierarchy process, sensitivity analysis, scenario analysis and intelligent techniques. 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. 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 project evaluation, we propose an intelligent decision-making procedure based on neural networks, fuzzy logic and Choquet integral. 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 [7], [8]. We note that, Zaremba and Morel [8] identified neural networks and genetic search as the predominant techniques for the initial phases of NPD process. Fig. 1 illustrates the simplistic view of our proposed two-stage approach and the next sub-sections give the details. This approach is especially relevant when there are numerous new ideas generating sources and it is difficult to rate all related products in a very detailed way and in a reasonable amount of time. It 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.
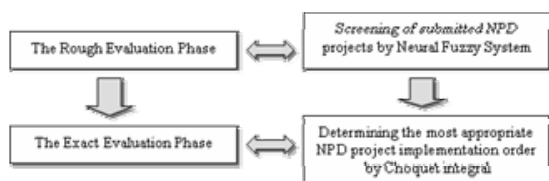
ability to manage systems from their observed behavior, have the capacity to treat large amount of data and capturing complex interactions among the input variables. Meanwhile fuzzy logic [11], [12], [13] is used to deal with imprecise linguistic concepts or fuzzy terms, allows making rational decisions in an uncertain environment without loosing the richness of verbal judgment, and is highly suitable for approximate reasoning by incorporating fuzzy rules. Hence substantial improvements on NPD project selection can be made by merging the ANN and fuzzy set theory.

In this study, new product ideas generated individually or by groups of individuals have been collected by a formal system. Then, the preprocessing of ideas is left to an intelligent neuro-fuzzy inference system. Regarding to NPD, evaluations are mostly based on a scoring system with determined evaluation criteria. Therefore, translating if necessary these scores to eligibility percentages, one can build an input database. Our fuzzy inference system (FIS) maps the input space consisting of the information provided by past evaluations to the output space formed by the status of the ideas (i.e., "good" or "bad"). The system posses an internal mechanism that can learn the viewpoint of the company management towards products by making use of the extracted rules. It also reduce the decision-making effort when the number of applications is large. The details of the FIS are given in [14].

Neural network techniques aid the fuzzy modeling procedure to learn information about a historical 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 [15]. 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 [15]. Fig. 2 shows the equivalent ANFIS architecture for a two-input Sugeno-type fuzzy inference system.

Fig. 1 Proposed intelligent decision-making approach

A. The Rough Evaluation Phase

This stage consists of a technique that merges neural networks and fuzzy logic. Artificial Neural Networks (ANN) [9], [10] make use of the way that the human brain learns and functions, possess the ability to learn from examples, have the
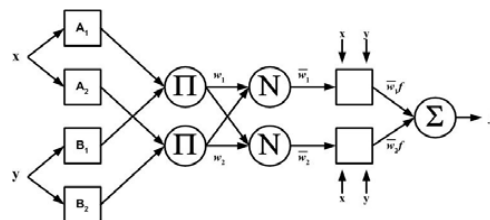

Fig. 2 ANFIS architecture for a two inputs, two rules Sugeno FIS

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

If x is A_i and y is B_i 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

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

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 [15].

In the second layer, a node output 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:

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

where $\bar{w}_i$ is referred to as the normalized firing strength [15]. In the fourth layer, each node has a function of the form:

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

where $\{p_i, q_i, r_i\}$ is the parameter set. These parameters are referred to as the consequent parameters [15]. The overall output is computed in the fifth layer by summing all the incoming signals, i.e.,

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

During the learning process, the premise and consequent parameters are tuned until the desired response of the FIS is achieved [15].

B. The Exact Evaluation Phase

The exact evaluation phase consists of rating of project alternatives versus different and various criteria and the aim is to find a trade-off solution for these criteria. Therefore, a compromise operator should naturally be selected. We propose to use Choquet integral in this phase. The key feature of the Choquet integral is that it can incorporate interaction among criteria into the evaluation process, an issue that has been generally overlooked in earlier NPD project evaluation studies. Researchers generally tend to ignore the frequently encountered problem of interacting criteria by assuming that criteria are independent. Contrary to widely-used multiple criteria decision aids, the Choquet integral enables the decision makers to incorporate the interaction between criteria into the analysis. We thus select this type of decisional aggregation in NPD project evaluation, especially the two-additive Choquet integral that considers only interactions by pair.

Let us define the two-additive Choquet integral, which is based on two types of parameters [16]:

- The weight v_i of each evaluation criterion (Shapley parameters) that satisfy $\sum_{i=1}^{n} v_i = 1$, which is a natural condition for decision-makers.

- Interaction parameters I_{ij} of any pair of evaluation criteria, that range in [0,1]; a value of 1 means positive synergy, a value of -1 means negative synergy and a value of 0 means no influence.

Noting P_i as the satisfaction degree of a project for criterion $i = 1, \ldots, n$ and the overall score of that alternative as $Sc(P_1, \ldots, P_n)$, the associated combination function is given by:

$$Sc(P_1, P_2, \ldots, P_n) = \sum_{i=1}^{n} P_i \left(v_i - \frac{1}{2} \sum_{j \neq i} |I_{ij}| \right) + \sum_{I_{ij} > 0} \min(P_i, P_j) I_{ij} + \sum_{I_{ij} < 0} \max(P_i, P_j) |I_{ij}| \tag{7}$$

with the property that

$$\left(v_i - 1/2 \sum_{i \neq j} |I_{ij}| \right) \geq 0 \quad \text{for all } i = 1, \ldots, n \tag{8}$$

Thus, this combination function is decomposed in a conventional linear part modified by a conjunctive and a disjunctive part.

- Positive I_{ij} implies that the simultaneous satisfaction of criteria i and j is significant for the aggregated evaluation, but a unilateral satisfaction has no effect.

- Negative I_{ij} implies that the satisfaction of either i and j is sufficient to have a significant effect on the aggregated evaluation.

- Null I_{ij} implies that no interaction exists; thus v_i acts as the weights in a common weighted mean.

The coefficients of importance v_m and $I_{mm'}$ being more natural to the decision maker, their determination by asking the decision maker is possible, but it must be verified that the monotonicity conditions in Eq. 8 is satisfied to use the transformation relation with the conventional fuzzy measure representation. Other methods based on the identification of these coefficients from experimental data exists but it is another problematic (see [17]), that is not the object of this article.

C. 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 project 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: Identifying the hierarchical structure of criteria in new product project evaluation

Step 7: Determining the weight of the evaluation criteria

and their possible interactions.

Step 8: Aggregation of expert results to figure out the right implementation order.

We apply step 3-4 if necessary after the idea pool update. The application of this proposed methodology is given in the next section.

III. AN ILLUSTRATION OF THE PROPOSED APPROACH

The subject company of our work is the local branch of an international toy-manufacturing firm. The new product database contains ideas generated from company designers, product managers, and also from employees and customers. Ideas are collected through a web based proposal system externally and also through an internal system where product managers introduce their proposals based on competitor products, benchmarking reports and marketing analysis reports. Therefore, large amount of data tend to accumulate over time. The marketing management team evaluates these ideas based on different tangible and intangible points. Note that evaluating only the risks and revenues of the investment is not sufficient for NPD projects since they have special characteristics, which may establish intangible profits depending on their creativity and innovative features. We therefore summarized the available data into three indicators, namely risk ratio, benefit ratio and strategic impact index. These indicators form the input of our FIS and are expressed in terms of percentage. Their severity increases with the allocated value.

Since the objective is to classify ideas as "good" or "bad", two ANFIS models are built to recognize the corresponding idea status. The resulting architecture is sometimes called many ANFIS (MANFIS). One ANFIS model will be trained to provide a value close to 1 if the idea is good, the other model will perform the same for a bad idea. The discrimination process is done by presenting the features of the idea to be classified to each of the two ANFIS models. The result is two different responses and a voting scheme is applied to determine the class to which the idea belongs. The class (idea status) that is associated with the ANFIS model with the response closest to the value of 1 is chosen as the class to which the idea under investigation belongs. Obviously, only good ideas are kept for further analysis. Fig. 3 shows the discrimination of ideas using MANFIS.
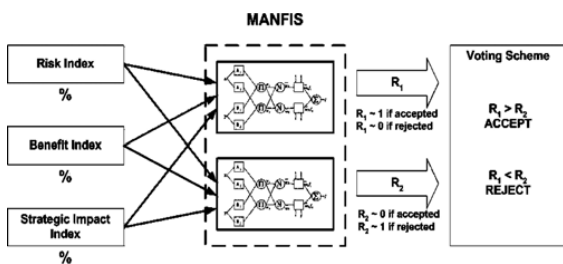

Fig. 3 Discrimination of new product ideas using MANFIS

We have taken into consideration 808 new product ideas examined by the company in the last three years. 311 of them were found to be acceptable at some extent, while the remaining 497 ideas were found not satisfactory at all or not correlating with the company goals and policies. We have divided this data into two training and test sets so as to train the neuro-fuzzy inference system. As there is no common understanding on how to separate the data in the literature, we have used the following rule of thumb. First, we considered only accepted ideas one by one. A uniform number is generated between 0 and 1, and if it shows to be less than 3/4, the chosen instance is added to the training set; otherwise it is added to the test set. Then, we applied the same rule for rejected ideas to complete the sets.

At first, we have used Matlab Fuzzy Logic Toolbox [18] fuzzy inference engine to better benefit from a reliable code. To construct a fuzzy inference process for the idea evaluation, the selection of a method to partition the input space to reflect the premise part of the fuzzy inference is an important consideration. As there are no preferable membership functions, we created an initial set of membership functions using grid-partitioning method [19]. Grid partitioning covers the whole input space with membership functions that have uniform distribution. We considered different number and type of membership functions. Finally, with the Gaussian membership functions corresponding to each input variable, we obtained the least training and test errors.

The results were convincing with small (<%10) and close training and test errors. This implicitly implies that the past evaluations are very representative and robust, since usually test error is expected to be much higher than the training error. Then, it can be argued that the constructed FIS imitated properly the company attitude towards new ideas. The final point is that there are also some misaccepted and misrejected ideas. A close investigation shows that these ideas correspond to ones with almost equal membership function values for a given index. Since these cases are the hardest to classify, it is quite natural to expect this type of error.

The obtained FIS together with its adjusted parameters were implemented as a decision support software by the authors to integrate the approach with the actual company's system. Then, eighteen actual new product ideas covering one month were presented to the trained FIS. The outcome shows that only five of them were acceptable for further analysis. As the company's managers agreed on the results, we proceed to the second phase of our approach.

To determine project prioritization for resource allocation, our approach calls for a detailed analysis on the projects corresponding to the previously selected product ideas by means of Choquet integral aggregation method. In our case, the hierarchical structure of criteria in new product project evaluation is shown in Fig. 4. The factors were identified from the review of the related literature [20], [21], [22], [23], [24] and interviews of the managers of company under study.
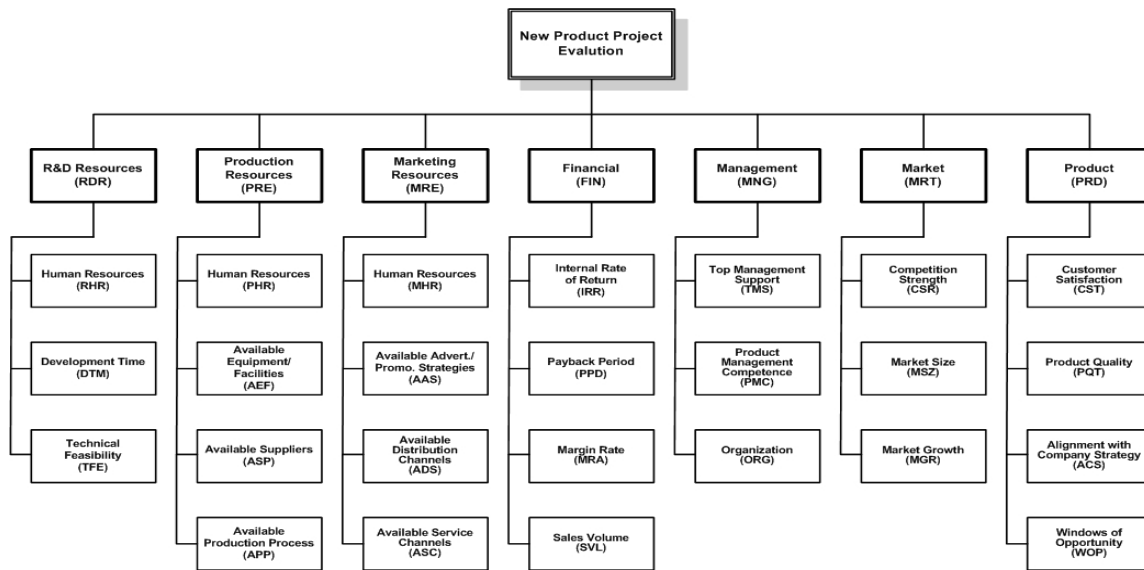
Fig. 4 Decision criteria hierarchy in new product project evaluation

TABLE I
WEIGHTS OF EVALUATION CRITERIA

c_i	w_i	c_i	w_i	c_i	w_i	c_i	w_i	c_i	w_i	c_i	w_i
RDR	**0.14**	AEF	0.30	ORG	0.35	**FIN**	**0.15**	CSR	0.35	ACS	0.30
RHR	0.25	ASP	0.25	**MRE**	**0.10**	IRR	0.25	MSZ	0.35	WOP	0.20
DTM	0.30	APP	0.30	MHR	0.20	PPD	0.25	MGR	0.30		
TFE	0.45	**MNG**	**0.18**	AAS	0.25	MRA	0.20	**PRD**	**0.18**		
PRE	**0.10**	TMS	0.40	ADS	0.35	SVL	0.30	CST	0.30		
PHR	0.15	PMC	0.25	ASC	0.20	**MRT**	**0.15**	PQT	0.20		

TABLE II
INTERACTIONS AMONG EVALUATION CRITERIA

c_i	c_j	I_{ij}	c_i	c_j	I_{ij}	c_i	c_j	I_{ij}	c_i	c_j	I_{ij}
RDR	PRE	-0.03	FIN	MRT	0.03	IIR	PPD	-0.10	CSR	MGR	-0.10
RDR	MRE	0.01	FIN	PRD	0.07	IIR	MRA	0.10	MSZ	MGR	0.15
RDR	FIN	0.04	MRT	PRD	0.07	IIR	SVL	0.15	CST	PQT	0.05
RDR	MNG	0.03	DTM	TFE	0.10	PPD	MRA	0.10	CST	ACS	0.20
RDR	MRT	0.03	PHR	AEF	-0.10	PPD	SVL	0.15	CST	WOP	0.10
PRE	FIN	0.02	PHR	APP	-0.05	MRA	SVL	-0.15	ACS	WOP	-0.10
PRE	PRD	0.07	AEF	APP	0.15	TMS	ORG	-0.10			
MRE	FIN	0.03	AAS	ADS	0.15	PMC	ORG	0.05			
MRE	MRT	0.05	AAS	ASC	0.10	CSR	MSZ	-0.10			

TABLE III
RATING OF ALTERNATIVES

| | Alternatives | | | | | | Alternatives | | | | |
Criteria	1	2	3	4	5	Criteria	1	2	3	4	5
RHR	95	95	55	95	75	MRA	100	60	55	80	75
DTM	100	100	65	75	100	SVL	70	70	60	65	85
TFE	95	55	60	85	95	TMS	55	65	65	80	85
PHR	75	65	55	70	75	PMC	85	60	100	90	95
AEF	80	100	60	60	65	ORG	95	60	55	90	65
ASP	75	55	70	80	80	CSR	70	55	60	85	90
APP	80	70	55	95	65	MSZ	80	85	95	60	100
MHR	85	70	65	100	65	MGR	70	55	55	70	90
AAS	95	60	90	65	90	CST	80	60	95	60	100
ADS	85	80	75	100	90	PQT	80	65	65	90	65
ASC	85	95	75	55	100	ACS	85	85	85	70	85
IIR	90	95	90	70	90	WOP	90	100	75	75	100
PPD	60	65	55	65	60						

The weight of the criteria and their possible interactions were again determined by an interdisciplinary board of the company with a Delphi type method. The final evaluations are shown in below Tables I-II. We assumed that there is no direct interaction between two second level criteria belonging to two different primary criteria. However, synergy may exist either between primary criteria or between secondary criteria that belong to the same primary criteria (see also [25]).

Finally, concurring five projects were rated for secondary criteria as shown in Table III. Given the ratings, the score of each primary criterion is computed using Eq.7. As for example, the fifth project scores are RDR 91.25, PRE 71.00, MRE 86.50, FIN 76.50, MNG 80.75, MRT 93.25, PRD 86.875. Then, again using Eq.7, the final scores of the projects are computed such that 79.56, 68.79, 66.21, 75.01, 82.19. As the highest scored projects are preferable, the implementation order is determined as 5 > 1 > 4 > 2 > 3 for this case.

IV. FINAL REMARKS AND PERSPECTIVES

In this study, we aim to improve the quality of the decision-making and to increase the probability of success in NPD under uncertainty by introducing a new iterative methodology. First, we give the motivation behind our approach, which incorporates fuzzy logic and artificial intelligence for the new product project evaluation. Then, we detailed our proposed approach. Finally, an industrial application is given to demonstrate the potential of the proposed framework. The approach is general 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:

- 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.

- There is a need for intellectual capital evaluation for highly innovative and creative, very few new product developing or highly R&D oriented companies.

We can easily articulate that our approach has offered significant savings by shortening the time and decreasing the steps necessary for the evaluation process while deviated in the totality from the traditional system results with almost 15%. Moreover, the company authorities were very pleased with the results and strongly supported the project. However, a long period of time is always necessary to observe the results of such a strategic level decision. Additionally, the product success is not only depending on catching the best idea but also on how to manage subsequent development stages. We keep trying to understand the sources of conflict and possible improvements on the approach.

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

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