A Knowledge-Based Approach to Product Concept Screening

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Abstract. This paper is concerned with developing a knowledge-based approach for selecting portfolio of product concepts for development. The critical success factors for new product development are identified on the basis of information acquired from an enterprise system, including the fields of sales and marketing, project management, and production. The model of new product screening consists of enterprise functional domains and business information systems. The model has been described in terms of a constraint satisfaction problem (CSP) that contains a set of decision variables, their domains, and the constraints. Knowledge base is specified according to CSP framework and it reflects the company's resources and relationships identified. The illustrative example presents the use of fuzzy neural network to estimating the success of new products and constraint programming to product concept screening in the context of the different search strategies.

Keywords: project management, new product development, concept selection, decision support system, constraint satisfaction problem, constraint programming.

1 Introduction

New product development (NPD) is the critical process that aims to maintain company's competitive position and continue business success. This process consists of the stages such as idea generation, evaluation and screening of product concepts (ideas), development of the selected concepts, testing and commercialization of new products [1]. In order to increase a chance of successful product, the project manager should select the most promising set of concepts according to company's constraints. One of the characteristics of many industrial companies concerns the management of several simultaneously developed new products using the same resources. The complexity of the NDP process results in developing a task-oriented tool to support the decision-makers, especially in the field of evaluation and screening of product concepts.

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As the success of the NPD projects is closely connected with the success of the entire company, the NPD projects play an important role in an organisation's growth and development [2]. To survive and succeed in the dynamic business environment, companies usually focus on several areas to improve their new product development, such as identifying customer needs for continuous new product development, improving product quality, and accelerating the process of commercialization [3].

The concept selection aims to identify the most promising products for development, and consequently, to reduce the potential expenses on the unsuccessful NPD projects. From this point of view, the concept selection is the crucial stage of the NPD process. Selection of new products for further development usually bases on metrics of the product success, and it should also take into account the company's resources. The success of a product is estimated in this study on the basis of the previous developed products which specification can be retrieved from an enterprise system. This system includes project management software, enterprise resource planning (ERP) system, customer relationship management (CRM) system, and computer aided design (CAD) system.

Knowledge creation and management through the new product development and management processes is of significant interest in the context of recent technology and infrastructure changes. Knowledge management is understood as the process of identification, sharing, and applying knowledge [4]. The advancement of information technology helps today's organisations in business management processes and collecting data that is potential source of information [5]. A main task faced by NPD projects is how to acquire knowledge and sustain success rate among the products. This paper aims to present the use of fuzzy neural network to estimating the success of new products and constraint programming to seeking the most promising set of potential products. The proposed approach takes into account data of the previous projects that is stored into an enterprise system. The next section presents the model of new product screening that is specified in term of a constraint satisfaction problem that in turn can be considered as a knowledge base enabling the design of a decision support system.

2 Model of New Product Screening

The development of new product projects depends on the external and internal factors. The external factors include customer demand, changes in regulations, technology or financial limitations. In turn, internal factors concern the resources and processes that appear in the different fields of an organization. Specifications of the previous products, customer requirements, design parameters, and product portfolios are registered and stored in an enterprise system that mainly includes ERP, CRM or CAD. The selected attributes of an enterprise system, resources, and the identified relationships are stored in knowledge base that aims to facilitate the project manager to evaluate the success of a new product, and finally, select a set of the most promising products for further development. Figure 1 illustrates new product screening in the context of the NPD process and enterprise system.

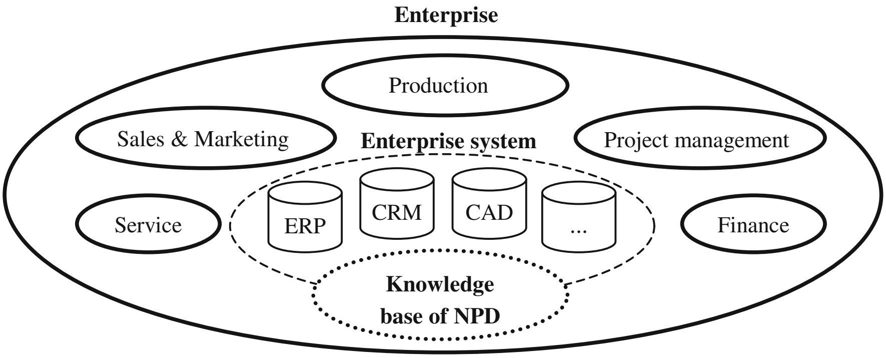

Fig. 1. Reference model of knowledge acquisition for new product screening

The proposed model consists of variables that describe the product success (output variable), and that are suspected of significant impact on this success (input variables). Taking into account the product lifetime and return on product development expense, as the output variable and the measure of the product success, the average net profit from a product per month is chosen. The model contains a set of decision variables, their domains, and the constraints that can be referred to the performance indicators and company's resources. The decision problem concerning the selection of the most promising set of products for further development has been described in terms of a constraint satisfaction problem (CSP). The model description encompasses the limitations of a company, parameters of new products that are considered for development, and a set of routine queries (the instances of decision problems) that are formulated in the framework of CSP. The structure of the constraint satisfaction problem may be described as follows [6]:

$$\mathrm{CSP} = ((\mathrm{V}, \mathrm{D}), \mathrm{C})$$

where: $\mathrm{V} = \{v_1, v_2, ..., v_n\}$ – a finite set of n variables, $\mathrm{D} = \{d_1, d_2, ..., d_n\}$ – a finite set of n discrete domains of variables, and $\mathrm{C} = \{c_1, c_2, ..., c_k\}$ – a finite set of k constraints limiting and linking variables.

Consider a set of new products for development $\mathrm{P} = \{P_1, ..., P_i, \ldots, P_I\}$, where P_i consists of J activities. The following variables have been chosen: duration of new product development ($\mathrm{PD_i}$) and its cost ($\mathrm{PC_i}$), number of project team members ($\mathrm{PTM_i}$), percentage of existing parts used in a new product ($\mathrm{PEP_i}$), production cost of the product ($\mathrm{PPC_i}$), duration of marketing campaign of the product ($\mathrm{PMD_i}$) and its cost ($\mathrm{PMC_i}$), number of customer requirements for a new product ($\mathrm{PCR_i}$), percentage of customer requirements translated into technical specification ($\mathrm{PTS_i}$), and net profit of the product ($\mathrm{PNP_i}$). The company's limitations include the total number of R&D employees (project team members) $C_{1,t}$ and financial means $C_{2,t}$ in the t-th time unit. Variables are limited and linked through constraints, e.g. $\sum \mathrm{PC_i} + \sum \mathrm{PMC_i} \leq C_2$. The problem solution can be stated as seeking the answers to the following two types of questions: what products should be selected to the product portfolio by a fixed amount of resources to ensure the maximal total net profit from the products, and what resources in which quantities are minimally necessary to complete the product portfolio by the desired net profit from the products?

The model description in terms of constraint satisfaction problem enables the design of a decision support system taking into account the available specifications, routine queries, and expert knowledge. Consequently, the model integrates technical parameters, available resources, expert experience, identified relationships (rules), and user requirements in the form of knowledge base. Knowledge base is a platform for query formulation and for obtaining answers, and it comprises of facts and rules that are relevant to the system's properties and the relations between its different parts [7]. The proposed method of developing a decision support system for evaluating the net profit from a new product and selecting product concept portfolio is presented in the next section.

3 Decision Support System for Product Concept Screening

As the amount of available data in companies becomes greater and greater, companies have become aware of an opportunity to derive valuable information from their databases, which can be further used to improve their business [8]. The process of identifying novel and potentially useful patterns in data is known as knowledge discovery, and it consists of the stages such as data selection, data preprocessing, data transformation, data mining, and evaluation of the identified patterns [9]. Figure 2 illustrates the framework of the knowledge discovery in the context of developing a decision support system for product concept screening.

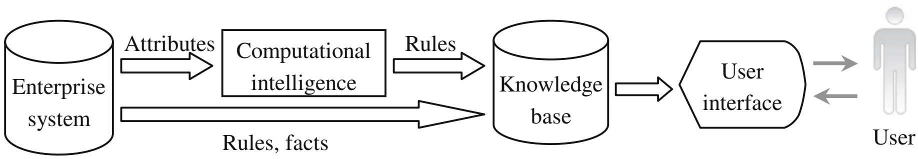

Fig. 2. Framework of decision support system for product concept screening

The selected attributes from an enterprise system are led to a fuzzy neural network (FNN) as input and output variables. The identified relationships are stored in the form of rules in knowledge base that also includes rules and facts acquired by an expert from an enterprise system (e.g. financial, temporal, personal constraints). Knowledge base is used to estimate the success of product concepts, to select the most promising concepts for further development, and to identify amount of resources that ensure the desired value of total net profit for the selected product concepts. Knowledge base is specified in term of CSP that in turn can be implemented in constraint programming environment providing the solution in the effective way. The user interface presents the project manager a set of products that are selected according to user's preferences, and the evaluation of these products in the context of their estimated profits. Moreover, the project manager can check which amount of resources is needed to obtain the desire total net profit from the selected products.

The use of computational intelligence techniques (FNN) aims to identify the hidden relationships between the success of a product and the variables that are suspected of impact on the project success. FNN is able to identify these nonlinear and complex relationships (if there are any), and consequently, develop the knowledge base. The fuzzy neural network has the advantages of both neural networks (e.g. learning abilities, optimization abilities and connectionist structures) and fuzzy systems (e.g. if-then reasoning, simplicity of incorporating expert knowledge). FNN can learn from training samples, and after learning it is possible to obtain fuzzy if-then rules that can be further used to perform nonlinear predictive modelling, simulation, and forecasting. Taking into account good forecasting properties and the possibility of obtaining if-then rules that can be saved in knowledge base, among computational intelligence techniques, fuzzy neural network has been chosen in this study.

The constraint programming (CP) is an emergent software technology for a declarative constraints satisfaction problem (CSP) description and can be considered as a pertinent framework for the development of decision support system software [10]. In the case of extensive search space, the processing time of calculations can be significantly reduced with the use of constraints programming techniques [11-12].

CP consists of a set of techniques for solving a CSP that is specified as a set of constraints on a set of variables. CP approach tackles with CSPs with the use of paradigms such as propagate-and-search or propagate-and-distribute. CP has embedded ways to solve constraints satisfaction problems with greatly reduction of the amount of search needed [13]. This is sufficient to solve many practical problems such as supply chain problem [14-16] or scheduling problem [11], [17-18]. The next section presents an example of using the proposed decision support system to product concept screening.

4 Illustrative Example

The success of a new product is estimated on the basis of information about the previous NPD projects. With the use of fuzzy neural networks, there are sought the relationships between the input variables and net profit from a product (PNP). The following input variables have been chosen from an enterprise database: number of activities in the NPD project (J), duration of the NPD project (PD), cost of the NPD project (PC), number of project team members (PTM), percentage of existing parts used in a new product (PEP), unit cost of production for the product (PPC), duration of marketing campaign of the product (PMD), cost of marketing campaign of the product (PMC), number of customer requirements for a new product (PCR), and percentage of customer requirements translated into technical specification (PTS).

The relationships between the input variables and net profit from a product has been sought with the use of the adaptive neuro-fuzzy inference system (ANFIS). In order to eliminate the overtraining of ANFIS and increase the estimation quality, the data set concerning the past NPD projects has been divided into learning and testing sets. In studies, the ANFIS has been trained according to subtractive clustering method that was implemented in the Matlab® software. The identified relationships can be described as if-then rules and used to estimating net profit from a new product. Figure 3 presents the membership functions for 11 rules that are used to estimating net profit for P_1.

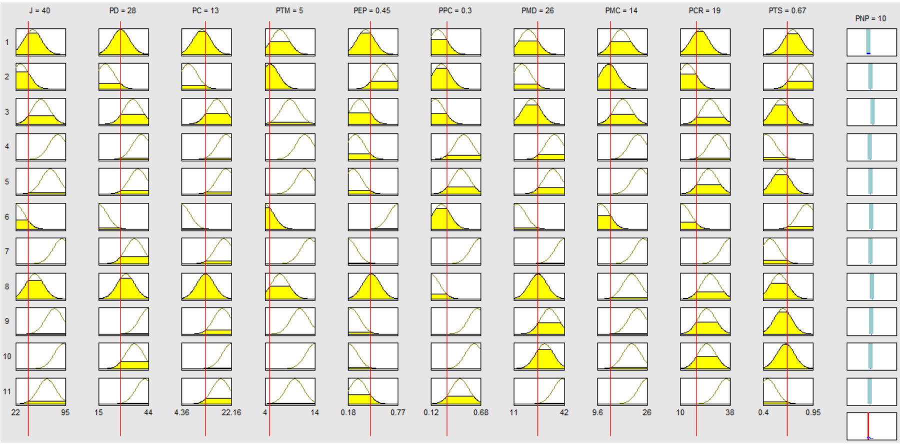

Fig. 3. Estimation of net profit for product P_1

The estimated net profits of the products are further used to seeking the NPD project portfolio that ensures the maximal total net profit from all products, and selecting the NPD project portfolios that ensure the desired level of total net profit according to the user's preferences. The R&D department generated 28 concepts for new products that are evaluated according to net profit, cost of development, and the number of people in a NPD project. In the NDP projects can participate 19 employees (C_1) and the total budget for NDP projects (C_2), including the R&D and marketing campaign budget, equals 225,000 €. The number of possible solutions, i.e. combinations of new product portfolio, is very large. This imposes the use of techniques that enable the reduction of the amount of search needed, such as constraint programming.

The considered problem has been implemented in the Oz Mozart programming environment that includes CP paradigms, and tested on an AMD Turion(tm) II Dual-Core M600 2.40GHz, RAM 2 GB platform. The number of the admissible solutions equals 5,660 instances. The set of the NPD projects that ensures the maximal total net profit (78,000 € per month) consists of product P_3, P_6, P_{20}, and P_{21}. Let us assume that the project manager wants to check what amount of resources is needed to obtain the total net profit equals 90,000 € per month. In order to compare the time consumption, among the distribution strategies, naïve and first-fail distribution has been chosen. The naïve distribution strategy chooses the first not yet determined variable from a list, i.e. it simply checks variables in their order. In turn, the first fail distribution checks next a variable with smallest domain. The selection of a suitable distribution strategy is crucial for the performance of the search process. Table 1 presents the results of finding solution for the different distribution strategies.

Table 1. Comparison of distribution strategies

Case	Product portfolio	Net profit	Distribution strategy	Time [sec]	Number of solutions	Number of nodes
$C_1 \bullet 22$; $C_2 \bullet 225{,}000$	$P_3, P_{20}, P_{21}, P_{23}$	90,000	Naïve	0.78	1	8877
			First-fail	0.72		
$C_1 \bullet 25$; $C_2 \bullet 225{,}000$	$P_{19}, P_{21}, P_{25}, P_{27}$	92,000	Naïve	1.54	577	18041
			First-fail	1.50		
$C_1 \bullet 25$; $C_2 \bullet 235{,}000$	$P_{10}, P_{20}, P_{21}, P_{23}$	98,000	Naïve	6.84	2509	22963
			First-fail	5.22		
$C_1 \bullet 25$; $C_2 \bullet 245{,}000$	$P_{10}, P_{15}, P_{16}, P_{20}$	109,000	Naïve	31.4	23241	40772
			First-fail	25.4		

The presented comparison consists of four cases for the additional resources (employees and budget increase) to illustrate the impact of the different distribution strategies on time of searching solution, the number of solutions and nodes. The product portfolio presented in Table 1 concerns the optimal solution, in which the selection criterion is portfolio with the maximal total net profit. The results indicate that the first-fail distribution strategy outperforms the naïve strategy, especially in the case of the large number of admissible solutions. The proper choice of distribution strategy can shorten time taken in searching solution and facilitate development of an interactive decision support system.

5 Conclusions

The characteristics of the presented approach includes the use of an enterprise system database to knowledge creation, fuzzy neural network to seek the relationships and their description in the form of if-then rules, and framework of constraint satisfaction problem to specify a knowledge base. This knowledge base includes the rules identified by fuzzy neural network or/and an expert, facts (including company's resources), and it allows the project managers to obtain an answer to the routine questions such as what is the most promising set of products for development? The use of constraint programming to implementing the constraint satisfaction problem allows developing a decision support system in a pertinent framework.

The proposed approach has several advantages such as the problem description in terms of CSP that can be solved effectively in constraint programming environment, the low effort of data retrieval from an enterprise system, the possibility of what-if analysis, and the identification of resource amounts that are needed to obtain the desired value of net profit from new products. Moreover, the identified relationships are used in the decision support system to help the managers in conducting simulation of the NPD projects, selecting the most promising product portfolio, and reducing the risk of unsuccessful product development. On the other hand, the application of the proposed approach encounters some difficulties, for instance, by collecting enough amount of data of the past similar NPD projects and ambiguous principles to build structure of fuzzy neural network. Nevertheless, the presented approach seems to have the promising properties for acquiring information from an enterprise system and improving the decision making process in the context of product concept screening.

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