Chapter 8
A Knowledge-Based System for New Product Portfolio Selection

Marcin Relich

Abstract This chapter is concerned with designing and developing a knowledge-based system for evaluating concepts of new products and selecting product portfolio. The model of measuring the product success includes metrics identified by an expert, such as duration and cost of product development or net profit from a product. The model contains a set of decision variables, their domains, and the constraints that can be described in terms of a constraint satisfaction problem (CSP). Knowledge base is specified according to CSP framework and it reflects the company's resources, performance metrics, and relationships identified. The presented knowledge discovery process consists of the stages such as data selection, data preprocessing, and data mining in the context of an enterprise system database. In order to identify the patterns, fuzzy neural networks have been used and compared with the results from artificial neural networks and linear regression. The illustrative example presents the use of fuzzy neural networks to the identification of patterns that are translated into rules understandable by users. The proposed knowledge-based system helps the managers in selecting the most promising product portfolio and reducing the risk of unsuccessful product development.

Keywords Knowledge acquisition · Data mining · Fuzzy neural networks · Constraint satisfaction problem · Project management · New product development

8.1 Introduction

A dynamic and turbulent environment imposes organizations to be smart, agile, and responsive to fast changes of business needs. Faced with uncertain environment, companies are seeking new ways to improve their performance and flexibility for

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the changing business requirements. In order to maintain survival and development, organizations have paid attention towards expert systems to develop knowledge management systems that can provide the basis for future sustainability and competence (Malhota 2001).

In recent years, the knowledge-based economy has become the major trend in international society (Hsu et al. 2008; Ullman 2009; Li et al. 2011). Knowledge is a combination of information and experience, context, interpretation and reflection (Davenport 1998). Product knowledge, as a type of knowledge, is important to support manufacturing activities (Kulon 2006). Product knowledge has played increasingly significant roles in the new product development process especially in the development of one-of-a-kind products (Li et al. 2011).

New product development (NPD) is one of the most important processes in maintaining company's competitive position and continuing business success. New products and innovations impact on sales volume, employment, technological process, and economic progress. Contribution of NPD to the growth of the companies, its influence on profit performance, and its role as a key factor in business planning has been widely considered (e.g. Benedetto 1999; Cooper and Edgett 2008; Ulrich and Eppinger 2011). Nevertheless, it is still reported that the success rate of product development projects is unsatisfactory, with more cost and time than expected having been consumed to achieve the project goals. A key challenge faced by new product development projects is how to acquire knowledge, sustain success rate among the products, and manage the project in order to reduce the risk of failure of the product (Cooper 2003).

The main reasons of failures concerning new product development derive from extrinsic and intrinsic problems. Extrinsic problems include flops in the market, changes in regulations or simply competition develops product first (Cooper 2003). Intrinsic problems concern the limited resources (e.g. money, highly qualified employees) and result in the difficulties to meet the project goals, including product innovativeness. Unsatisfactory success rate of product development projects can also be considered from the perspective of inherent feature of NPD, i.e. it is a relatively risky activity (Kahraman et al. 2007), as market competition and product technology advancement are often intense (McCarthy et al. 2006).

Although the success of a new product depends on the environmental uncertainties that are beyond a firm's control, companies should take into account both external and internal indices and try to improve the NPD process. Internal indices can be acquired from company's databases, including enterprise resource planning (ERP) system, project management software, customer relationship management (CRM) system, and computer aided design (CAD) system. The advancement of information technology helps today's organisations in business management processes and collecting data. As a result, enterprise systems generate and store a huge amount of data that is potential source of information (Doskočil 2013; Relich 2013). 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. Data mining applications have vastly increased the amount of information available and the ease of manipulating and using it (Zahay et al. 2004).

The effective management of NPD projects is a challenging goal, due to factors such as intensive research and development investment, long and uncertain development times, low probability of technical success, and uncertain market impact and competition (Zapata 2008). One of the most important decisions that impact on business success is the selection of concepts for further development. Companies usually develop a set of new products simultaneously, what requires a task-oriented tool to support the decision-makers. Although knowledge-based systems have been proposed to support product development activities and new knowledge modelling methodologies have been developed, there is a scarcity in the context of new product portfolio selection.

This chapter aims to develop an approach that identifies the relationships between the success of a product and the key factors that are stored in an enterprise system and that influence on this success. The proposed approach takes into account data of the previous projects that can be retrieved from an enterprise system, including the fields such as marketing and sales, production, project management and the customers' complains. The relationships between the product success and metrics of the NPD process are sought with the use of a fuzzy neural network that enables the description of the identified relationships in form of if-then rules. The proposed knowledge-based system uses these rules to estimating net profit for the products that are considered for development, and proposing a set of the most promising products according to the decision-maker's preferences. The knowledge-based system can also be used to generating and evaluating the alternative NPD portfolios, and identifying such changes in project environment that can increase the chance to develop a successful product. The set of potential products for development is determined with the use of constraint programming taking into account the company's constraints.

The novelty of this research includes the model of measuring product success that is specified in term of a constraint satisfaction problem as a set of variables, domains, and constraints. The constraint satisfaction problem can be considered as a knowledge base enabling the design of a knowledge-based system that includes the identified patterns, expert knowledge, and routine queries, for example, what is the most promising set of products for development, or what resources are required to implement the NPD project portfolio and to ensure the desired success rate of new products? Knowledge base and inference engine of the proposed knowledge-based system has been developed with the use of constraint programming environment.

The remaining sections of this chapter are organised as follows: Sect. 8.2 presents the literature review regarding new product development, performance metrics in the NPD process and the use of knowledge-based systems in new product development. A model of measuring product success in terms of constraint satisfaction problem is presented in Sect. 8.3. The proposed method of product portfolio selection is shown in Sect. 8.4. An illustrative example of the proposed approach is illustrated in Sect. 8.5. Finally, some concluding remarks are contained in Sect. 8.6.

8.2 Literature Review

8.2.1 New Product Development

The new product development literature emphasizes the importance of introducing new products on the market for continuing business success. New products influence on employment, economic growth, technological progress, and high standards of living (Bhuiyan 2011; Spalek 2014). As new product development helps firms to survive and succeed in dynamic markets, it is a crucial process in maintaining a company's competitive position (Chin et al. 2009). However, market competition and product technology advancement is often intense (McCarty et al. 2006), resulting that NPD is a relatively risky activity (Kahraman et al. 2007). Consequently, companies try to meet customer requirements by improving product attributes and processes. To survive and succeed in the current 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 (Chan and Ip 2011).

New product development is a complicated and time-consuming process in which several different activities are involved. The NPD process consists of the stages, in which an initial product concept is evaluated, developed, tested, and launched on the market. Many NPD models have been developed over the years taking into account the above-mentioned stages of the NPD process. Sun and Wing (2005) presented the NPD process in the context of the following phases: ideas generation and conceptual design, definition and specification, prototype and development, and commercialization. According to Ulrich and Eppinger (2011), overall concept development process includes identify customer needs, establish target specification, concept generation, concept selection, test the concept, set final specification and develop product development plan.

The concept selection aims to choose the most promising set of products for further development. As the stage of concept selection precedes the more expensive and long-term development of the selected products, it is the critical stage of the NPD process and one of the most important decisions that impact on business success. In this stage, the proposed concepts are evaluated and optimized with the use of relevant performance metrics. This study considers the performance metrics for selecting a set of concepts for further development in the context of the predicted success of a product, and the factors that impact on the successful NPD. These factors derive from the fields of research and development (R&D), marketing and sales, production, and they can be retrieved from an enterprise system database.

8.2.2 Performance Metrics in the NDP Process

Performance metrics allow companies to measure the impact of process improvement over time resulting enhancement their NPD efforts. A successful NPD project is usually considered in the literature as the fulfilment of a fixed goal, the compliance with budget progress, or achieving an acceptable level of performance (Chang and Chen 2004). Cooper and Kleinschmidt (1995) presented the NPD performance with 10 measures: success rate, percent of sales, profitability relative to spending, technical success rating, sales impact, profit impact, success in meeting sales objectives, success in meeting profit objectives, profitability relative to competitors, and overall success. In turn, Sounder and Song (1997) proposed seven criteria in making overall judgments about the new product development in the context of actual performance versus the original expectations: sales, market share, return on investment, profit, customer satisfaction, contribution to technology leadership, and contribution to market leadership.

Metrics and critical success factors can refer to the entire NPD process or to its stages such as idea generation, concept selection, development, and testing. Metrics for idea generation include number of ideas generated from the customer, number of ideas retrieved and enhanced from an idea portfolio, number of ideas generated over a period of time, and the value of ideas in idea collection. Among all of these metrics, the number of ideas generated from the customers seems to be especially important due to identification of customer needs, and finally, customer satisfaction with a new product. Metrics for concept selection can be based on the expected return of investment (commercial value, net present value, internal rate of return), export rate, market share, or sales growth. Taking into account the product lifetime and return on product development expense, the net profit from a product in the first year after launch is further considered as a metric of the product success.

Metrics for development include mainly time and resources that impact on time frame. Reduction of development time is critical for business sustainability because companies that develop products quickly gain many advantages over their competitors (e.g. premium prices, valuable market information, leadership reputation, lower development costs, accelerated learning). In the stage of product testing, metrics can refer to product functionality (e.g. testing physical features, perceptual features, functional modes) and customer acceptance (e.g. customer-perceived value).

8.2.3 Knowledge-Based Systems in New Product Development

A knowledge-based system is a computer-based information system that represents knowledge of experts and manipulates the expertise to solve problems at an expert's level of performance (Jadhav and Sonar 2011). Such a system has three main components: knowledge base, inference engine, and user interface. The knowledge base consists of highly specialized knowledge of problem areas as provided by experts or/and data mining techniques. It includes facts, rules, concepts, and relationships that describe a given problem (Leung and Chuah 1998). The inference engine is the knowledge processor that works with the available information of the problem, coupled with the knowledge stored in the knowledge base, to draw conclusions or provide recommendations (Durkin 1994).

Development of a knowledge-based system involves capturing domain knowledge and knowledge about problem adjusting methodology to real world problems associated with the particular domain of application. Rule based reasoning and case based reasoning are two fundamental and complementary reasoning methods of knowledge-based systems (Pal and Campbell 1997). Knowledge-based systems have widely been adopted to solve decision-making problems in many domains, such as manufacturing (Kathuria et al. 1999), help desk operations (Chan et al. 2000), make or buy decision (McIvor and Humphreys 2000), technology investments (Tan et al. 2005), software effort estimation (Park and Baek 2008), resource allocation in project portfolio (Bocewicz et al. 2009), product safety and recalls (Kumar 2014).

The application of knowledge-based systems in the field of new product development can be considered from the perspective of stages in the NPD process including generation and selection of new product idea. In creating new ideas for products, designers often use creative problem solving techniques (Wu et al. 2006), where the brainstorming method is one of the most widely used. However, the use of the brainstorming method for generating new product ideas encounters some difficulties. Namely, this method has been developed for a team and its performance highly depends on the capacities of team members. Moreover, the brainstorming method facilitates team members to generate new ideas through a free-association mechanism that is not always customer-oriented or user-centered. As a result, some ideas good for users might be ignored in the brainstorming method (Wu et al. 2006). Therefore, to overcome these drawbacks the computer-aided techniques to create new product ideas have been developed. For instance, in the process of generating new product idea and product design can be used case-based reasoning (Tseng et al. 2005; Wu et al. 2006), TRIZ method (Yang and Chen 2011), and design structure matrix (Tang et al. 2010).

A number of new product ideas is usually larger than the financial and production capacity in an enterprise to develop all new products. Therefore, a set of product concepts should be reduced towards selecting the most promising product portfolio. Among approaches to selecting product portfolio can meet association rule mining (Jiao and Zhang 2005), multi-objective genetic algorithm (Yu and Wang 2010), integrating technology roadmapping (Oliveira and Rozenfeld 2010), fuzzy multi-criteria group decision (Wei and Chang 2011), or visual product architecture modeling (Ulonska and Welo 2014). Recent development of knowledge-based systems in the context of one-of-a kind production includes web-based, ontology-based, STEP-based, and case-based approaches (Li et al. 2011). STandard Exchange of Product model data (STEP) is an international standard defined to provide a complete, unambiguous and computer readable definition. With the use of a set of standards, STEP can improve the level of knowledge exchange and sharing in different formats appearing in CAD, CAE, CAM, PDM/EDM and other CAx systems.

The NPD process includes tasks such as scheduling, estimating and monitoring, which involve considerable skills and experience to plan the activities, time, people, equipment, material and the money required. A task-oriented knowledge-based system may assist project managers in indicating what is likely to happen in future, presenting facts in a manner that makes judgment easier, retaining project managers' expertise for future uses, and showing what has happened and why. This system is an aid to decision-making and problem solving, as well as it may be useful in training inexperienced project managers (Leung and Chuah 1998).

8.3 Model of Measuring Product Success

The product design process can be divided into the customer, functional, physical and process domains (Yu and Wang 2010). These domains concern the customer satisfaction, functionality, technical feasibility, and manufacturability/cost issues connected with the products. In general, new product development encompasses three successive stages (Jiao and Zhang 2005): (1) product definition connected with mapping of customer needs in the customer domain to functional requirements in the functional domain; (2) product design connected with mapping of functional requirements to design parameters in the physical domain; (3) process design connected with mapping of design parameters in the physical domain to process variables in the process domain.

Within the context of mass customization, product design and process design are embodied in the respective product lines and process platforms. Product portfolio represents the functional specification of product families, i.e. the functional view of product lines and process platforms (Jiao and Zhang 2005). The specification of the previous product lines, customer requirements, design parameters, and product portfolios is stored in an enterprise system that can include ERP, CRM and CAD system. Figure 8.1 illustrates the principles of model of measuring product success on the basis of an enterprise system.

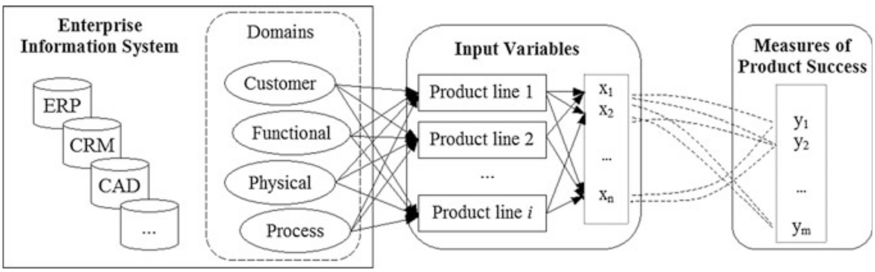

Fig. 8.1 Model of measuring product success

The proposed model consists of output variables that describe the product success and input variables that are suspected of significant impact on this success. The set of variables can be selected from an enterprise database with the use of variable reduction methods or specified by an expert. It is noteworthy that a variable selection method should take into account the nature of the problem because automatic variable selection is not guaranteed to be consistent with the assumed goals (Relich and Muszyński 2014). In this study, an expert approach is applied for selecting a set of variables for each product line. As a result, an expert experience is used to developing a knowledge-based system.

The success of a product can be evaluated according to the measures such as sales growth, export rate, market share, return of investment, and customer satisfaction (Sounder and Song 1997). Taking into account the product lifetime and return on product development expense, as the output variable and the measure of the product success, the net profit from a product in the first year after launch is chosen. In turn, the input variables derive from the fields such as marketing, customer, project management and production, and they are as follows: duration of marketing campaign of the product and cost of marketing campaign of the product, number of customer's complains (requirements, comments) for the previous products that have been used to developing a new product, number of project team members, number of activities in the project, percentage of existing parts used in new products, production cost of the product. These variables can be easily retrieved from an enterprise system database.

The presented model contains a set of decision variables, their domains, and the constraints that can be referred to the company's resources and performance indicators. The decision problem concerning the selection of the most promising set of products for 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 (Rossi et al. 2006):

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

where:

$V = \{v_1, v_2, \ldots, v_n\}$—a finite set of n variables,

$D = \{d_1, d_2, \ldots, d_n\}$—a finite set of n discrete domains of variables,

$C = \{c_1, c_2, \ldots, c_k\}$—a finite set of k constraints limiting and linking variables.

Consider a set of new products for development $P = \{P_1 \ldots, P_i, \ldots, P_I\}$, where P_i consists of J activities. Moreover, the following variables are considered: duration of new product development (PD_i) and its cost (PC_i), number of project team members (PTM_i), technical innovativeness (percentage of existing parts used in a new product) (PEP_i), production cost of the product (PPC_i), duration of marketing campaign of the product (PMD_i) and its cost (PMC_i), number of customer requirements for a new product (PCR_i), percentage of customer requirements translated into technical specification (PTS_i), and net profit of the product (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 tth time unit.

The constraint satisfaction problem can be considered in the context of a knowledge base. The knowledge base is a platform for query formulation as well as 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. As a knowledge base can be considered in terms of a system, at the input of the system are led the variables concerning basic characteristics of an object that are known and given by user (Bocewicz et al. 2009). For instance, the available resources in the enterprise and parameters of new products occur in the knowledge base describing the enterprise-product portfolio model. The output of the system is described by the characteristics of the object that are unknown or are only partially known. For example, there is a value of the product success or a set of the most promising products for development.

The model description in terms of constraint satisfaction problem enables the design of a knowledge-based 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. Interpretation of such a model allows for using the logic-algebraic method as a reference engine (Bocewicz et al. 2009).

A distinction of decision variables that are embedded in the knowledge base as an input-output variable permits the formulation of two classes of standard routine queries that concern two different problems with respect to resources (Bocewicz et al. 2009; Relich et al. 2015):

- what products should be chosen to the product portfolio by a fixed amount of resources to ensure the optimal value of criterion of the purpose (e.g. the minimal cost and time of the product portfolio, the maximal net profit from the product portfolio)?
- what resources in which quantities are minimally necessary to be able to complete the product portfolio before a certain deadline, by a desired cost, or by a desired net profit from new products?

The method of finding admissible solutions (variants of product portfolio) for the above-described problem is presented in the next section.

8.4 Method of Product Portfolio Selection

The enterprise system generates routinely an enormous amount of data according to the business processes in a company. 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

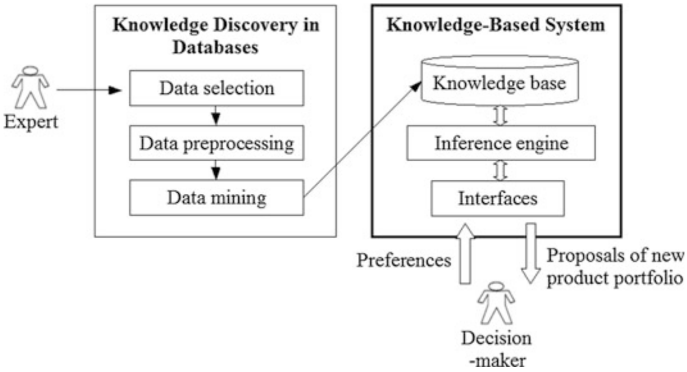

Fig. 8.2 Framework of a knowledge-based system for product portfolio selection

improve their business (Li and Ruan 2007). The process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data is known as knowledge discovery (Fayyad et al. 1996). The knowledge discovery process includes the stages such as data selection, data preprocessing, data transformation, data mining, and interpretation (evaluation) of the patterns identified (Fayyad et al. 1996; Jiao and Zhang 2005). Figure 8.2 illustrates the framework of the knowledge discovery in the context of developing a knowledge-based system for product portfolio selection.

Initially, an expert selects a set of variables from the enterprise databases, variables that are suspected of significant impact on the success of previous products. In the next step, data is preprocessed to the form that is suitable for a chosen data mining technique. As analysis of huge amount of data and knowledge acquisition with the use of manual methods is slow, expensive, subjective, and prone to errors, there is a need to automate the process through using data mining techniques (Han and Kamber 2006; Cios et al. 2007).

Pattern discovery from databases requires some data mining techniques that cope with the description of relationships among data and that solve the problems connected with e.g. classification, regression, clustering, and estimation that is further considered. These techniques include neural networks, fuzzy sets, rough sets, time series analysis, Bayesian networks, evolutionary programming and genetic algorithms, decision trees, etc. The artificial neural networks and fuzzy logic are complementary technologies and powerful design techniques that can be used in the identification of patterns from a large database and noisy data that is common for an enterprise system.

The fuzzy neural system 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). One of the possibilities to combine neural networks and fuzzy logic is to use a neural network as an inference engine to develop a classification system. In this case, the network can learn from training samples, and after learning it is possible to decode the network to extract fuzzy if-then rules. The outcome of a fuzzy neural system is a set of humanly understandable rules that can be used to perform nonlinear predictive modelling, simulation, and forecasting. One well-known structure of fuzzy neural networks is the adaptive neuro-fuzzy inference system (ANFIS).

The use of ANFIS requires preprocessing the data that is retrieved from enterprise systems (Relich 2015). One of the feature reduction methods is principal component analysis (PCA) that reduces the dimension for linearly mapping high dimensional data onto a lower dimension with minimal loss of information. Data preprocessing has been performed with the use of PCA that is the best, in the mean-square error sense, linear dimension reduction technique (Chizi and Maimon 2010).

The identified relationships between input and output variables are stored in a knowledge base and used to estimate the success of a potential product and further used to select the most promising products for development. The knowledge base stores the identified relationships as well as the resource constraints (financial, temporal, personal, etc.) that determine product portfolio.

The output of a knowledge-based system is the proposal of project portfolio that is adjusted to the decision-maker's preferences (e.g. the desired value of the total net profit from new products). The decision-maker can also carry out what-if analysis and check whether the product portfolio will be changed in the case of others values of the input variables. Moreover, the decision-maker should be able to check what resources and in which amount are needed to obtain the desired value of the total net profit from products.

A growing number of admissible solutions resulting from increase of the changed parameters requires taking into consideration more efficient algorithms in order to shorten time taken in the searching process of solution. Moreover, the impact of real-life constraints on decision-making is of significant importance, especially for designing an interactive knowledge-based system. In the case of extensive search space, the processing time of calculations can be significantly reduced with the use of constraints programming techniques (Banaszak et al. 2009; Sitek and Wikarek 2014).

The constraint programming (CP) environment seems to be particularly well suited to modelling real-life and day-to-day decision-making processes at an enterprise. CP is qualitatively different from the other programming paradigms, in terms of declarative, object-oriented and concurrent programming. Compared to these paradigms, constraint programming is much closer to the ideal of declarative programming: to state what we want without stating how to achieve it (Van Roy and Haridi 2004). CP is an emergent software technology for a declarative constraints satisfaction problem description and can be considered as a pertinent framework for the development of decision support and knowledge-based system software.

To sum up, the proposed method bases on a fuzzy-neural system that identifies the relationships between the input variables chosen by an expert from an enterprise system and the net profit from the previous products. These relationships are used to estimate the net profit for product concepts that are considered for development. In the next step taking into account the decision-maker preferences, the portfolio of the most promising NPD projects is selected with the use of constraint programming. The next section presents an illustrative example of the use of ANFIS and CP techniques that enable the development of a knowledge-based system in the context of knowledge base, inference engine and interfaces.

8.5 Illustrative Example

An illustrative example includes two parts: determination of the optimal product portfolio by the limited (fixed) resources and seeking the feasible set of product portfolio that ensures the desired value of total net profit from new products. These tasks refer to two types of questions presented in the model formulation section.

The output variable is net profit from a product (PNP) that is considered as a measure of product success. The input variables concern the fields of marketing, project management, research and development (R&D), and production. Among an enterprise database, the following input variables have been chosen:

- 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),
- percentage of customer requirements translated into technical specification (PTS).

The success of new product is estimated on the basis of information about the previous NPD projects. There are sought the relationships between the above-described input variables and net profit from a product. Moreover, some input variables can be used to estimate the duration of product development {J, PTM, PEP, PCR}, and the cost of product development {J, PD, PTM, PEP, PCR}. The R&D department considers five possible products {P1, P2, P3, P4, P5} for the development. The number of employees that can participate in the NDP projects equals 25 people. Other constraints concern the R&D budget (200 thousand Euros) and the budget of marketing campaign (250 thousand Euros).

The identification of 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) and compared with the artificial neural networks (ANN), linear regression model, and the average. In order to eliminate the overtraining (i.e. too strict function adjustment to data) of ANFIS and ANN and to increase the estimation quality, the data set has been divided into learning (27 past products) and testing sets (7 past

Table 8.1 RMSE for different models

Model	Learning set	Testing set
ANN—GDX	30.28	25.24
ANN—LM	1e–12	23.42
ANFIS—hybrid (RI = 0.9)	0.0032	24.32
ANFIS—hybrid (RI = 0.7)	9e-5	26.37
ANFIS—hybrid (RI = 0.5)	0.0004	17.19
ANFIS—hybrid (RI = 0.4)	0.0006	16.76
ANFIS—hybrid (RI = 0.3)	0.0014	12.54
ANFIS—hybrid (RI = 0.2)	0.0009	16.28
ANFIS—hybrid (RI = 0.1)	0.0005	21.19
ANFIS—back-propagation	1.10	49.13
Linear regression	11.08	30.47
Average	72.04	78.45

products). The data has been preprocessed before the learning stage with the use of principal component analysis.

In studies, the ANFIS has been trained according to subtractive clustering method by the use of the back-propagation (for 5000 iterations) and hybrid algorithm for the different values for range of influence (RI). In turn, a multilayer feed-forward neural network has been trained according to the back-propagation algorithm. Weights have been optimised according to the Levenberg-Marquardt algorithm (LM) and gradient descent momentum with adaptive learning rate algorithm (GDX). The neural network structure has been determined in an experimental way, by the comparison of learning and testing sets for the different number of layers and hidden neurons. The root mean square errors (RMSE) have been calculated as the average of 20 simulations for each structure of neural network with a number to the extent of 20 hidden neurons. After learning phase, the testing data has been led to input of the ANFIS, ANN and other models. The results have been calculated in the Matlab® software and presented in Table 8.1 as the root mean square errors for the learning and testing set.

The presented in Table 8.1 results indicate that the least error in the testing set has been generated with the use of the ANFIS trained according to the hybrid method and with the parameter of RI equals 0.3. The ANFIS obtained better results for the testing set (by RI between 0.1 and 0.5) than the artificial neural networks. The ANN trained according to the Levenberg-Marquardt algorithm generated the least RMSE for the learning set, but the results for the testing set are worse than for the majority of ANFIS models. This can result from the overtraining of the ANN in the learning phase and the lack of its ability to generalization. It is noteworthy that RMSE generated with the use of the ANFIS and ANN is smaller than RMSE for the average and the linear regression model (the exception is the ANFIS trained according to back-propagation method). The comparison of different forecasting models is especially recommended in the case of significant variance of an output variable.

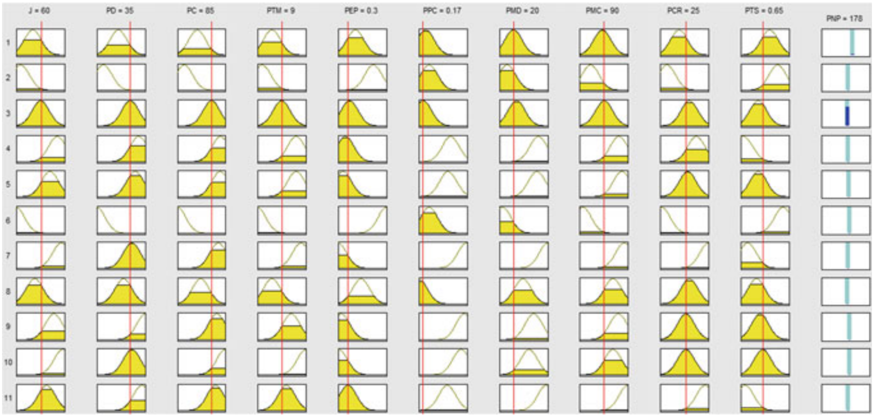

Fig. 8.3 Estimating net profit from product P1

The identified relationships between input and output data are stored in the structure of ANN and ANFIS. The fuzzy neural system identified 11 rules that have been used to compute the estimation of net profit for five products. In order to calculate the forecasts of net profit for the considered products, the planned values of ten input variables have been led to the trained ANFIS structure. Figure 8.3 illustrates the membership functions for the rules that are used for estimating net profit from product P1.

The estimated net profit for products P1, P2, P3, P4 and P5 equals 178, 115, 81, 251, and 154, respectively. The presented example include the following constraints: 35 weeks for duration of the NPD projects (all projects are developed simultaneously), 25 people involve directly in the NPD projects, 200 thousand Euros for the R&D budget, and 250 thousand Euros for the budget of marketing campaign. The maximal total net profit from new product is the criterion of project portfolio selection. From this point of view, the optimal product portfolio includes product P3, P4 and P5 with the total net profit equals 486. Figure 8.4 presents a user interface of the proposed knowledge-based system for product portfolio selection. Interface allows the decision-maker to assign the values of input variables for each product, the limits for resources, and consequently, to obtain the optimal product portfolio and the estimated values for the resources and total net profit for all products.

The presented knowledge-based system enables what-if analysis for the different values of input variables and constraints. This analysis can be extended towards a reverse approach, i.e. the determination such values of the input variables or/and resources to obtain the desired value of net profit from new product. Figure 8.5 presents a user interface of the proposed knowledge-based system for seeking the feasible product portfolios for the desired value of total net profit and the changes in the field of resources.

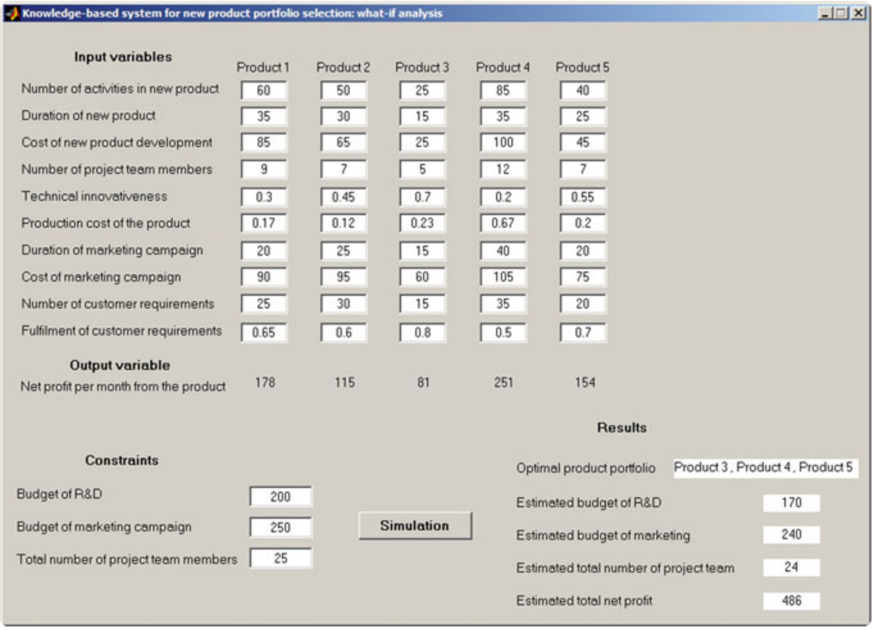

Fig. 8.4 User interface for product portfolio selection

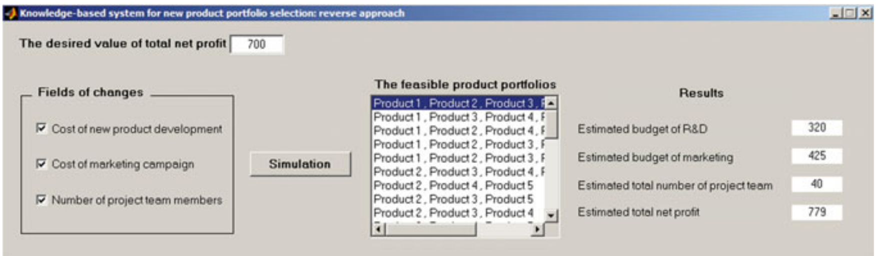

Fig. 8.5 User interface for product portfolio selection: a reverse approach

The reverse approach is connected with seeking an answer to the question what values should have the input variables or/and resources to reach the desired value of net profit from new product. In order to obtain a set of the feasible solutions, the constraint programming framework is used. This framework integrates the relationships identified by the ANFIS, technical parameters, expert experience, and user requirements into a knowledge base. Moreover, the constraint programming facilitates the implementation of model in terms of constraint satisfaction problem and the inference engine of the proposed knowledge-based system. In studies, the constraint programming framework has been implemented in Oz Mozart programming environment.

8.6 Conclusions

The continuous development and launching of new products is an important determinant of maintaining the company's success. However, due to its inherent features, new product development is a relatively risky activity. Failed NPD projects can decrease market share, profitability, and finally, lead to bankruptcy. The rapid evolving technology, the fast changing markets and the more demanding customers, require developing high quality new products more efficiently and effectively. To ensure these requirements, the identification of the key success factors of product is needed. As an enterprise system stores the data connected with the various areas of business, including customers' demand and NPD projects, its database can be used to seeking the relationships between these areas and the success of a product. These relationships can be further used to evaluating concepts for new products and selecting product portfolio for development.

The characteristics of the presented knowledge-based system includes the use of expert knowledge to select variables used in the knowledge discovery process, fuzzy neural networks 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 managers to obtain an answer to the routine questions such as what is the most promising set of products for development, or what parameters should have the NPD projects to increase their chances for the success? The use of constraint programming to describe the constraint satisfaction problem allows the development of a knowledge-based system in a pertinent framework.

This study presents the possibility of using an enterprise system database to the identification of relationships between the success of a product and the factors in the field of marketing, customer complaints, production, and project management. These relationships are sought with the use of fuzzy neural networks that have been compared with the results from artificial neural networks and linear regression. The results indicate that the least error in the testing set has been generated with the use of fuzzy neural network trained according to the hybrid method. Nevertheless, the learning of fuzzy neural network requires declaration of several parameters that are chosen in an experimental way, what can be considered as a drawback of the proposed approach.

The proposed approach has several advantages such as the low effort of data retrieval (the data are accessible in an enterprise system), the possibility of parameter change and what-if analysis, as well as the determination such values of resources to obtain the desired value of net profit from new products. Moreover, the recognized patterns are used in the knowledge-based 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.

The proposed approach gives new insights to the literature of pattern identification with the use of an enterprise system database that aims to improve development of new products, and finally, the success rate of products. On the other hand, the application of the proposed approach encounters some difficulties, for instance, by collecting enough amounts 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 selecting new product portfolio.

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