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A DECISION SUPPORT SYSTEM FOR ALTERNATIVE PROJECT CHOICE BASED ON FUZZY NEURAL NETWORKS

Marcin Relich

University of Zielona Góra, Division of Controlling and Computer Applications in Economics

Corresponding author:
Marcin Relich
University of Zielona Góra
Division of Controlling and Computer Applications in Economics
Podgórna 50, 65-246 Zielona Góra, Poland
phone: +48 68 3282426
e-mail: m.relich@wez.uz.zgora.pl

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Abstract

The paper aims to present possibilities of management support by more precise estimates of critical tasks in projects through the use of intelligent techniques. In this paper a case is considered in which the client is forced to change the project specification after commencement of investment. To minimize the loss, the client may attempt to find other alternative solutions to complete the project. In view of expenditure and investment in progress, a group of alternative projects that fulfill the assumed constraints (e.g. financial and temporal) is sought. To support the choice of alternative projects, estimates of critical tasks within the project are calculated, using intelligent techniques as well as traditional statistical methods. The results are determined using the database of past projects that are found in the information systems of the enterprise.

Keywords

project evaluation, decision support, knowledge-based systems, fuzzy neural networks, investment salvage.

Introduction

In dynamic surroundings, the quality of decision-making in the enterprise has a great influence on profits. Particularly significant are decisions that relate to the considerable resources of the firm. This kind of decision may involve, for example, the choice of approach for parameters estimation of the project or the investment choice from alternative variants of the projects. When projects for client order are made, incorrect forecasting of expenses or time of project completion is usually connected with a financial penalty according to the contract or with cost payment from the enterprise's own means. An incorrect decision may worsen the liquidity of the enterprise, may decrease the number of future contracts or even lead towards bankruptcy. In this case, it seems very important to support the decision-maker with a decision-taking process.

In the activity of present organizations unique activities – projects are becoming more and more important. A project is a sequence of unique, complex, and connected activities having one goal or purpose and that must be completed by a specific time, within budget, and according to specification [1]. For this reason, the demand arises for new knowledge that enables the solution of problems occurring in the realisation of unique projects. In this case, particularly significant is knowledge of project management, which identifies factors which have an influence on the success or failure of the project, and that uses special methods and techniques.

Many cases of project failures, that were not completed or that overrun cost and schedule targets, occur in literature [2–5]. Reference [3] indicates that despite a belief that project management techniques have matured, the rate of failure of projects has never been higher [6]. There are various surveys on project failure; all agreed that failure is not uncommon. Reichelt and Lyneis reported the findings of various other authors, that projects which overrun are more common than projects which complete within original time scales, overruns likely to be between 40% and 200%; that fewer than half of projects examined in one survey met cost and schedule targets; and that only one third of World Bank projects met their aims, with typical delays of 50% [7]. Jorgensen and Sjoberg [8] reported another survey showing only 17% of projects meeting all three aspects of the project triangle (cost, time, and scope [9]), with typical cost overruns as high as 189%. Worse still are IT projects where it is reported just 3% are considered to be a success [10].

Project success or failure depends on many critical factors, such as factors related to the project (size, value, availability of resources, uniqueness of project activities, life cycle); project management (ability of the project manager/team members to coordinate, competence, commitment); and the external environment (political, economical, social, technological environment, clients, competitors, sub-contractors) [3, 11]. The reasons for project failure can be generally considered in terms of availability of resources (e.g. human, financial, raw materials) and changeability of the external environment. Failure implies difficulties in precision forecasts of project parameters. In this case, the building of tools that support managers by providing more precise forecasts for project parameters (e.g. resources), and finally the time and cost of projects seems to be justified. The improvement in project assessment can be carried out, for example, by increasing the number of variables that relate to project performance or by using methods that accept the imprecision of data.

The large number of project failures suggest a need for carrying out the approach that supports the decision-maker by the choice of alternative project completion. If a project time exceeded the fixed completion date or expenses overran the budget, the enterprise can be forced to modify the project. In this case, an alternative project set with new constraints (e.g. temporal, financial) is generated, and then the possibility of adaptation of completed project tasks for the alternative variant of project is tested. If the project is ordered by a client and his requirements are unacceptable, then the enterprise may develop a set of alternative project variants that fulfils the price and temporal constraints, but with a reduced functionality (the modification of project specification) or the variants set as required by client for functionality, but with larger price and/or project completion time. Project management literature lacks this type of approach, whereas salvage investment seems to be rather natural in critical circumstances.

Enterprises usually act in a changeable environment that causes some level of uncertainty for project parameters. In project management, it is common to refer to very high levels of uncertainty as sources of risk [12–13]. The two terms risk and uncertainty have different meanings, whereas they are often used interchangeably. The term risk is used to describe an investment project whose parameters (e.g. cash flow) are not known in advance with absolute certainty, but for which an array of alternative outcomes and their probabilities are known. If there is no way to assign any probabilities to future random events, pure uncertainty is addressed [12, 14]. Probability theory can be a powerful tool in the appropriate circumstances, but sometimes the type of uncertainty encountered in investment projects does not fit the axiomatic basis of this theory. It is simply that uncertainty in the projects is usually caused by the inherent fuzziness of the parameter estimate rather than randomness [15].

Risk magnitude is highly dependant on many involved factors, e.g. human, workplace, material and equipment factors, which are difficult to quantify and adequately measure in a traditional way [16]. For this reason, fuzzy logic was proposed as a tool which can describe imprecision. The difficulty of gaining knowledge from experts has led to automatic knowledge discovery from databases of enterprises. In this case, a fuzzy neural system may be used. Such a hybrid system aggregates the advantages of these techniques: the system's ability to learn and the processing of inaccurate data. The fuzzy neural system has been successfully applied in many investment projects, especially in the area of risk management [16–19].

The use of intelligent systems seems to be reasonable, taking into consideration the advantages of lessons learned from past similar projects. The importance of a knowledge-base for better project control has been recommended by many research works [20–22]. This paper not only contributes to the application of artificial intelligence techniques for resource estimation of tasks, but also introduces an original concept for salvaging investment projects that are at high risk of failure. The following sections of this paper concern the constraints of the model, the proposed method of procedure, numerical examples, the results of the study and suggestions for future studies.

Problem formulation

In this paper the enterprises that create the project for clients are taken into consideration. It is assumed that the enterprise has an information system that registers the data regarding the business processes, as well as past projects. The tool for project management supports the preparation and control of the project. Moreover it is assumed that enterprises act in changeable surroundings, which causes difficulty in the estimation of project parameters with the application of statistical techniques. The specification of each project contains preplanning, followed by versions of replanning and real performance. Each schedule contains data regarding, for example, the cost and time of investment tasks. In this way, variances between schedule and performance may be determined.

It is assumed that the client orders may be taken and commenced at any time (possibly adding the new projects to a set of projects already in progress). The expenses regarding an order are paid from the enterprise's own means or from a bank loan. The budget of the project is set with cash flow budget in the investment period. The client order is chosen by the profitability analysis and technical realizability. The enterprise receives the order specification with the client requirements, regarding among others the scope and price of project or time completion.

The enterprise model can be described by its resources. The project model is made from the requirements of the client. In both models, some parameters are determined, among which a set of constraints and decision variables may be distinguished. The constraints connect the variables that describe the capacity of the enterprise, as well as the variables that regard the conditions of project completion. It means that fulfilment of specified constraints enables project completion according to client requirements.

The considered project belongs to the class of investment project concerning a new shop floor. The enterprise according to the project specification fulfills in-house the project (without the help of subcontractors). The enterprise purchases from suppliers only materials that are required for completion some project activities.

The decisive variables contain the data concerning the enterprise, as well as the completed projects, e.g.:
- enterprise resources (financial, personal, logistic etc.),
- number and field of present and past projects,
- project tasks,
- project commencement,
- task time,
- task cost.

The use of an information system that supports enterprise management, e.g. the class of Enterprise Resource Planning, enables data collection or easy access to data. In this paper additional data is also distinguished, that does not usually occur in the information systems of enterprises. This includes data regarding external environment or project management.

The constraints contain, e.g.:
- available resources in the enterprise,
- task sequence in the project,
- fixed time of project completion.

The problem comes down to an answer to following double question:
1. which elements should be added to the data base of the enterprise to ensure the required accuracy of the project parameters?
2. is there an alternative project, and if yes, what is the schedule to ensure completion within the required time and new constraints?

The above questions may be complemented as followed:
- Is enterprise's database sufficient to achieve the required precision of project parameter identification?
- Is there a possibility to gather additional data, and if yes, what are the expenses connected with this?
- What is an optimal set of decision variables with regard to time and cost of gathered data?
- Is there a possibility to reallocate the resources from the basic project to the alternative one, and if yes, what is the cost?

The answers to the above questions support a decision-maker in two ways: more exact estimation of required resources values for project completion, and decision making concerning the alternative project choice.

The proposed approach

The proposed decision support system regards two fields: improved accuracy of estimation of required resources, and the proposal of an alternative project set. The stages of the proposed method are presented in Fig. 1.

In literature approaches for time estimation of task with the application of statistical techniques usually occur. These approaches are most often based on arithmetic average or program evaluation and review techniques. However, by significant variation of task time, the forecasts calculated with using these approaches are inaccurate.

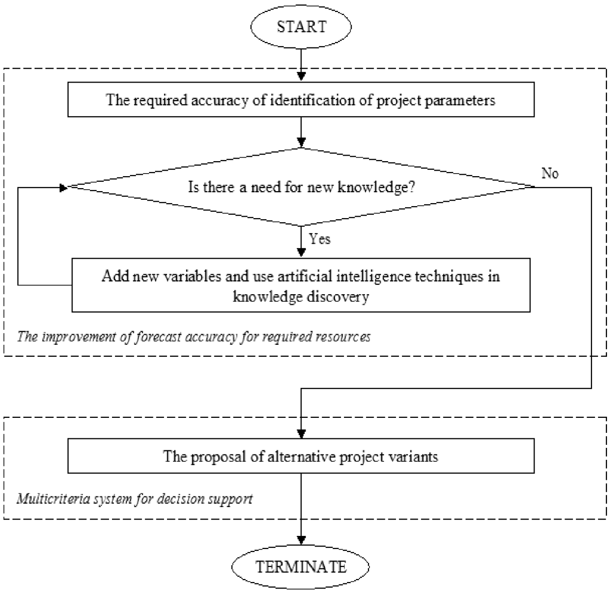

Fig. 1. The approach procedure.

If the decision-maker is not satisfied with forecast quality, new variables are successively added into the model, until the required value of forecasting improvement is exceeded. After the addition of a new variable, the relationship is tested between the new set of variables and the dependent variable. If the relationship is reduced, then a variable is not added into the model. The choice of potential variables may be made according to subjective criteria, with using e.g. the analysis of correlation coefficients, genetic algorithm or principal component analysis, which will be elaborated in further research. In this paper, the choice of potential variables is made according to subjective criteria concerning e.g. the logical relation between added variable and dependent variable or access to data. First, variables that are present in the information system of the enterprise are added into the model. If the required value of forecasting improvement is not achieved, then further variables are added into the model regarding, for example, project management (competence, commitment of the project manager) or the external environment of the enterprise (macroeconomics, branch ratios).

The second part of the presented approach concerns the set of alternative project variants (see Fig. 1). If the project is in progress and the client would like to change the project specification (because of e.g. financial difficulties or market changes), then the enterprise may elaborate the set of alternative project variants. The client declares the temporal and price constraints, and moreover the basic project functionality, i.e. the required tasks in order that the project does not miss its goals. In this stage the intelligent techniques can also be used to estimate e.g. task time of alternative variants.

For each project variant: time, cost of task, as well as other criteria are estimated. Moreover, the possibility of resource reallocation is tested, the reallocation from the original project to a modified one. The trade-off analysis is presented to the decision-maker (client), who also considers the functionality of the alternative project and makes a decision.

The difficulties in gaining knowledge from experts have led to the increase of interest in automatic knowledge discovery [23]. One of the successful techniques in this field is the hybrid fuzzy neural system. Both neural network and fuzzy systems are trainable dynamic systems that estimate input-output functions. They estimate a function without any mathematical model and learn from experience with sample data. A fuzzy system adaptively infers and modifies its fuzzy associations from representative numerical samples. Neural networks, on the other hand, can blindly generate and refine fuzzy rules from training data [24]. Fuzzy systems and neural networks are established as universal approximators. This implies that fuzzy systems and neural networks can approximate each other. This leads to a symbiotic relationship, in which fuzzy systems provide a powerful framework for knowledge representation, while neural networks provide learning capabilities and exceptional suitability for computationally efficient hardware implementations [25–27].

A forecasting procedure for task time has been constructed by adaptive network-based fuzzy inference systems (ANFIS). Basically, ANFIS encodes the fuzzy if-then rules into a neural network-like structure and then uses the appropriate learning algorithms to minimize the output error based on the training/validation data sets [18]. According to the past studies, there are a number of methods to develop adaptive neuro-fuzzy networks [28]. Mostly, the decision is made to use the ANFIS and its optimization process for the consideration of its accuracy [29].

The ANFIS approach adopts Gaussian functions (or other membership functions) for fuzzy sets, linear functions for the rule outputs, and Sugeno's inference mechanism [30]. The parameters of the network are the mean and standard deviation of the membership functions (antecedent parameters) and the coefficients of the output linear functions as well (consequent parameters). The ANFIS learning algorithm is then used to obtain these parameters [18].

In the next section a numerical example concerning the use of the above described approach is presented.

Example

The example regards a project that was ordered by the client and was divided into three parts:
– the description of the basic project,
– the estimation of the task time,
– the multicriteria system to support the alternative project choice.

The description of the basic project

It is assumed that the project contains 10 tasks, the sequence of which is presented in Fig. 2.

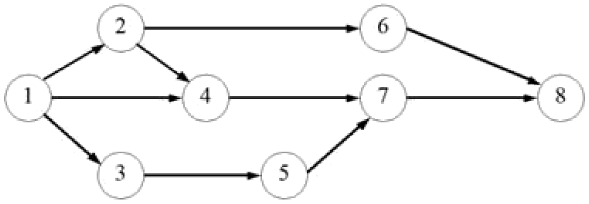

Fig. 2. The network diagram activities.

The task time, as well as earliest and latest finish, slack time and cost of task is presented in Table 1.

Table 1
The description of the project.

No task	Time (days)	Earliest finish (days)	Latest finish (days)	Slack time (days)	Cost (m.u.)
1–2	1	1	1	0	0.03
1–3	5	5	16	11	0.09
1–4	10	10	31	21	0.23
2–4	30	31	31	0	0.6
2–6	22	23	41	18	0.2
3–5	10	15	26	11	0.15
4–7	5	36	36	0	0.12
5–7	10	25	36	11	0.18
6–8	15	38	56	18	0.32
7–8	20	56	56	0	0.43

In the example it was assumed that the enterprise has enough personal and material resources to make the investment. The critical path regards tasks number 1-2-4-7-8. The planned finish time was estimated at 56 days, whilst the cost equals 2.35 monetary unit (m.u.).

Each project is unique, however, some projects may be included in the same class, for such reasons as the required resources or network of activities. In this case, the required resources can be estimated using the past experiences of the enterprise that made the projects. In this way, the enterprise might try to replace the subjective expert opinion concerning e.g. task time.

In the next subsection, the different approaches to estimate the activity time in the project are presented.

Estimation of the task time

This subsection presents the analysis of the sample data in ANFIS, artificial neural networks (ANN), and also statistical techniques. In proposed approaches, the relationships between project parameters are sought. There are taken particularly into consideration the activities that have a significant dispersion. In the example, as dependent variable, the activity time (Y) was chosen. In subjective way, as first independent variable, the activity cost (X_1) was assumed. From statistical techniques, the linear model was chosen. It was assumed that the accuracy of estimation should improve about 150% in comparison with estimates from linear models.

The procedure for the improvement of accuracy of task time identification was begun by the addition of a variable regarding the month of task commencement (X_2). In order to compare the forecasting quality, for each separate variable and for the combination of the variables, the error is determined. The number of combinations is calculated according to the formula $2^m - 1$, where m is the number of independent variables. The root mean square error is calculated as follows:

$$RMSE = \sqrt{\frac{1}{I}\sum_{i=1}^{I}(y_i - \widehat{y}_i)^2}, \tag{1}$$

where $\widehat{y}_i$ – forecast of task time in i project, y_i – real task time in i project, I – data set (past projects with considered task).

The increment of the forecasting quality is calculated as follows: $FQ_{j,k} = (RMSE_{LM,X1}/RMSE_{j,k})$ $^*100\%$, where $RMSE_{LM,X1}$ is root mean square error for linear model and variable X_1, and $RMSE_{j,k}$ is root mean square error for j approach and k combination.

In Table 2 is presented RMSE and FQ for task number 2–4, for all three combinations of independent variable ($\{X_1\}$,$\{X_2\}$,$\{X_1,X_2\}$) and different forecasting models. The realisation of task number 2–4 is especially significant, because it is connected with the considerable cost and time. In the case of fuzzy neural system, error was determined using the ANFIS tool that is MATLAB software. The estimation quality is usually made on learning and testing sets. In this way a function with a suitable approximation grade, that is not too adjusted to learning data, can be sought. The data set (55 samples) was divided into two sets: learning (L) – 44 samples and testing (T) – 11 samples.

Table 2
RMSE and FQ for additional variable X_2.

		X_1		X_2		X_1, X_2	
		L	T	L	T	L	T
Linear model	RMSE	4.52	4.42	5.99	7.20	4.49	4.16
	FQ	100	100	75	61	101	106
Neural network	RMSE	4.17	4.56	3.77	4.56	3.95	3.75
	FQ	108	97	120	97	114	118
ANFIS	RMSE	4.17	4.10	4.43	4.57	3.66	3.31
	FQ	108	108	102	97	123	134

Table 3
RMSE and FQ for additional variable X_3.

		X_3		X_1, X_3		X_2, X_3		X_1, X_2, X_3	
		L	T	L	T	L	T	L	T
Linear model	RMSE	5.65	8.08	4.56	6.32	3.62	5.71	3.56	5.76
	FQ	80	55	99	70	125	77	127	77
Neural network	RMSE	4.70	7.26	3.28	5.76	3.05	5.05	1.78	3.03
	FQ	96	61	138	77	148	88	254	146
ANFIS	RMSE	2.17	2.52	1.82	2.46	1.75	2.28	1.56	2.22
	FQ	208	175	248	180	258	194	290	199

The results indicate that the least error was generated in testing set by using ANFIS with two input variables. For comparison, RMSE for arithmetic average for learning and testing set equals 12.35 and 14.29. There is so the significant difference in the forecasts quality between arithmetic average and other models. However, the addition of variable regarding the month of task commencement (X_2) does not achieve the required improvement. In this case, to model is added the following variable: a number of the project team members (X_3). In Table 3 is presented RMSE and FQ for the additional combinations regarding the new independent variable ($\{X_3\}$,$\{X_1,X_3\}$,$\{X_2,X_3\}$,$\{X_1,X_2,X_3\}$) and different forecasting models.

The results indicate that the least error was generated in testing set also by using ANFIS, and the required improvement was achieved by $\{X_1,X_2,X_3\}$ combination.

In studies, a multilayer feedforward neural network was applied by use of the backpropagation algorithm, and optimisation weights according to Levenberg-Marquardt algorithm. The neural network structure was determined in experimental way, by comparison RMSE for the different number of layers and hidden neurons. In Fig. 3 is presented the RMSE for different number of hidden neurons by $\{X_1,X_2,X_3\}$ combination. The minimal value of RMSE was determined for a few hidden neurons in one hidden layer.

Also the use of fuzzy neural system requires the declaration of a few parameters concerning e.g. the system structure or type of membership function. Before learning the ANFIS usually takes place the identification of a class number. The identification of class (decisive rules) and the initial parameters of membership function (mf) of fuzzy sets can be made e.g. by grid partition or subtractive clustering [29]. In Table 4 is presented RMSE for different methods of fuzzy inference system (FIS), and different parameters defined for these methods.

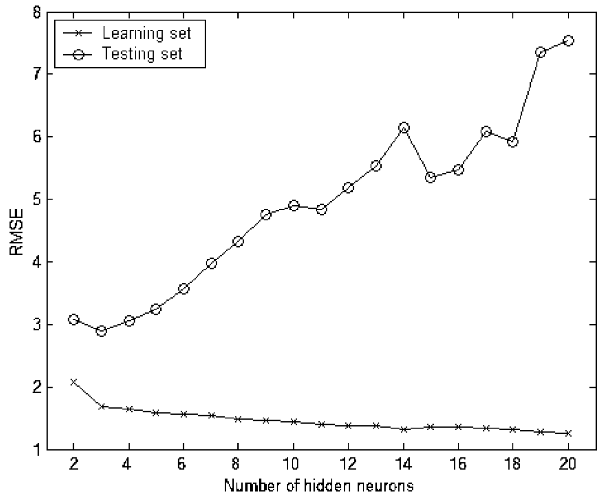

Fig. 3. A number of hidden neurons and forecasting quality.

The results indicate that grid partition method with 4 trapezoidal membership functions for each input generates the least error for testing set, and has better generalization characteristics for considered data set than subtractive clustering. This type of comparison should be made every time for other data set, and this is an example of a number and complexity of factors that influence on results obtained from fuzzy neural system.

Table 4
RMSE for different methods of FIS.

FIS method	Description	X_1, X_2, X_3	
		L	T
Subtractive clustering	Range of influence = 0.3	1.62	2.54
Subtractive clustering	Range of influence = 0.5	1.68	2.42
Subtractive clustering	Range of influence = 1	1.67	2.48
Grid partition	Gaussian mf	1.05	10.34
Grid partition	Triangular mf	1.30	5.57
Grid partition	Trapezoidal mf; 6 mfs to each input	1.15	8.67
Grid partition	Trapezoidal mf; 8 mfs to each input	1.16	9.35
Grid partition	Trapezoidal mf; 4 mfs to each input	1.56	2.22

The creation of fuzzy neural system requires the declaration of the input variables number or defuzzification method. Then for considered data set, the initial parameters of membership functions of fuzzy sets are estimated. In this way, the structure of fuzzy neural system is fitted. In next stage the fuzzy neural system is learnt according to e.g. backpropagation algorithm. In this way, the shape of membership function is determined. The rules can be presented for decision maker in descriptive form. In Fig. 4 are presented the example of fuzzy rules that were determined for combination $\{X_1,X_2\}$. The expression 'Cost is in2mf1', that occurs in first rule, regards first membership function for variable Cost, with two parameters that describe the function: the peak of the gaussian function (0.295 m.u.) and standard deviation (0.0617 m.u.).

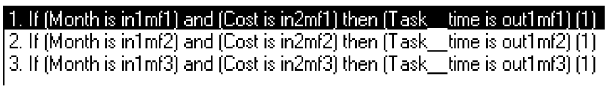
1. If (Month is in1mf1) and (Cost is in2mf1) then (Task__time is out1mf1) (1)
2. If (Month is in1mf2) and (Cost is in2mf2) then (Task__time is out1mf2) (1)
3. If (Month is in1mf3) and (Cost is in2mf3) then (Task__time is out1mf3) (1)

Fig. 4. The example of fuzzy rules.

The learning phase requires the declaration of method of weights optimisation, and stop criterion: error value or the number of iteration. After learning phase can be led the testing data to input of system to compare the forecasting error with learning data error. The estimates can be next used to support the alternative project choice. In next subsection is presented an example of multicriteria system to support the investment making decision.

The multicriteria system to support the alternative project choice

The set of alternative project variants is advantageous in many situations. For example, the client has the financial difficulties, and as a consequence the project should be changed. In this case, the client may expect that the enterprise presents the proposals of alternative variants of investment completion. Moreover, the enterprise can present the proposals of alternative variants in case of the temporal/cost client requirements are unrealistic. The client may be interested how many resources may be moved from rejected to new project, e.g. by least cost and according to the specification of new project. In the specification, the client should declare the basic functionality of new project, i.e. the required activities in order that the project does not miss its goals. In Fig. 5 is presented the example of alternative variants in comparison with the basic project (see Fig. 2).

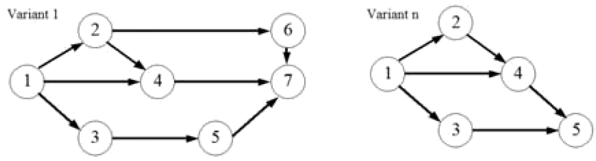

Fig. 5. The example of alternative project variants.

The set of alternatives variants can be presented in the form of multicriteria system that supports the decision-maker in the choice the most effective variant. The example of multicriteria system for considered project is presented in Table 5. The functionality level of project can be described by the rate of a task number of alternative variant to a task number of basic variant.

Table 5
The example of multicriteria system.

	Time (days)	Cost (m.u.)	Functionality level
Variant 1	40	1.6	0.9
...	...	...	...
Variant n	30	1.2	0.6

In the multicriteria system may be assigned the weights for each criterion that enable the choice the most effective variants. There can also be added the new criteria regarding, for example, required resources.

Conclusions

The possibility of using intelligent systems to supplement a knowledge base and to improve the precision of the estimates of requested resources was presented in this article. For models based on the fuzzy neural network, better results have been achieved than for neural network or statistical techniques. More exact identification of project parameters enables more precision of cash flow planning and finally, decreases the risk of lack of liquidity. In cases of significant variation of used resources, the traditional statistical techniques do not ensure satisfactory results. If in the enterprise is a database of past projects, then there is the possibility to gain additional information in the form of conditional rules. It enables more exact estimations e.g. for activity time. The additional advantages of a knowledge base may be using it to support a decision-making system concerning the choice of alternative project. In this case, the improvement of forecast quality for required resources may be interpreted as a risk reduction concerning the project completion. Moreover, more exact forecasts of project parameters ensure a significant advantage at the initial negotiation stage with the client. In this case the enterprise can be more precisely informed how cost-effective a client offer is.

The application of the proposed approach encounters some difficulties, among other things, by the gathering enough data of the past similar projects or the seeking of the similar project class. Moreover, the lack of uniform rules that regard the development of intelligent (e.g. fuzzy neural) systems may cause an acceptance problem for decision-makers. Also the difficulties of preprocessing, repeatability experiments and convergence appear in this type of system. The fuzzy neural system is like a 'black box' for users. The user cannot perceive the relationships and the influence of input data on results. This feature may lead to a lack of acceptance of intelligent techniques. It seems that the users acceptance may increase through the comparison of generated forecast errors for different approaches (in described case: traditional and proposed approaches based on intelligent systems). In the case of more accurate the forecasts, the user can accept the tool without its reasoning.

Further research contains, among other things, the development of a tool that seeks alternative variants of projects, and estimates the correctness of initial task sequences, required modifications and resources. Moreover, it seems to be important to give additional criteria to support a choice of alternative variant. The criterion may regard e.g. the description of required resources in the form of fuzzy sets. In addition to this, further research may concern a problem of data acquisition, a criterion of choice/removal variable to/from the model and analysis of the possibility of using data from outside the information systems of the enterprise.

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