2011 International Conference on Financial Management and Economics
IPEDR vol.11 (2011) © (2011) IACSIT Press, Singapore

An RBF-Based Neuro-fuzzy System for Scenario Planning in Project Management

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Abstract. Uncertainties in the project management due to the sources of external factors, shifting business objectives and poorly defined methods for project realization are indispensable aspects of this domain. For handling these uncertainties, we proposed a neuro-fuzzy system for scenario planning in project management in this paper. The proposed system uses fuzzy inference engine with fuzzy rules for modeling the project uncertainties which is enhanced through learning the various situations with a radial basis function neural network. We applied the proposed system for recommendation of the best scenario for the project management depending on its relative risks.

Keywords: Neuro-fuzzy system, Radial basis function neural network, Project management, Scenario planning, Business intelligence.

1. Introduction

A project is a transitory venture undertaken to generate an exclusive outcome or service, so as transitory means that the project has an end date, and exclusive is equivalent with that the project's end results are different than the results of other functions of the organization [1]. Project management can be defined as the process of controlling the achievement of the project objectives. Utilising the existing organizational structures and resources, it seeks to manage the project by applying a collection of tools and techniques, without adversely disturbing the routine operation of a company. The functions of project management include defining the requirement of work, establishing the extent of work, allocating the resources required, planning the execution of the work, monitoring the progress of the work, and adjusting the derivations of the plan [2].

On the other hand, today's projects are subject to uncertainties due to the three principal sources: external factors, shifting business objectives and poorly defined methods for project realization. The latter is not only due to poor knowledge and experience of the project team but also due to project complexity and absence of repetition (most projects are unique undertakings). Examples of external factors include commercial and competitive pressures, collision of social, political and institutional norms and rules with project financial and technical goals, shifting requirements of project stakeholders etc.[3].

Scenario planning has been defined as ‘‘a process of positioning several informed, plausible and imaginative alternative future environment in which decisions about the future may be played out for the purpose of changing current thinking, improving decision making, enhancing human and organizational learning and improving performance”[4]. Various scenario planning approaches from literature are classified into two major categories: qualitative and quantitative [5]. Also, the business intelligence (BI) consists of a collection of techniques and tools, aiming at providing businesses with the necessary support for decision making [6].

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The future events play a key role in project management, and managers need a mental model of the future to make better decisions. There are some differences among uncertainties pertaining to future occurrence probability. When there is the low level of uncertainties in environment, quantitative approaches such as probability distribution and forecasting techniques are very useful for managing the existing risk and uncertainty. In the high level of uncertainty, qualitative approaches such as scenario planning may be useful to employ [7]. Scenario planning is not aimed at obtaining a forecast but instead produces alternative images of the future which can avoid the pitfalls of more traditional methods [8, 9]. Managers are able to have much better positioning with regard to unexpected events by using scenario planning methods. Scenario planning attempts to capture the richness and range of possibilities, and considers changes that decision makers would otherwise ignore [10]. In this paper, we proposed a neuro-fuzzy system for scenario planning in project management to encounter and model the uncertainties of the risks in the project management.

2. Preliminaries

In this section, the preliminaries needed to understand the proposed system are represented. For this purpose, the fundamentals of the fuzzy systems and radial basis function neural networks are described in following.

2.1. Fuzzy Systems

Fuzzy rules have been s far two major approaches: manual rule generation and automatic rule generation.

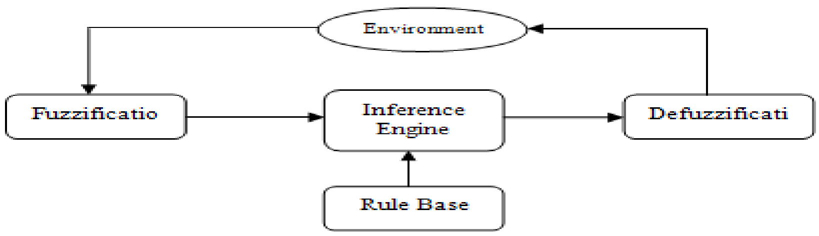

Fig. 1: A General Schema of a Fuzzy System [11]

As shown in Fig. 1, a fuzzy system is a class of expert systems that make decisions using built-in fuzzy rules. Fuzzification and defuzzification are the essential interfaces from a fuzzy system to an environment. The fuzzy system maps an input fuzzy set X into an output fuzzy set Y:

$$Y = X \circ R \tag{1}$$

where denotes the compositional rule of inference. The fuzzy rule base denoted by a fuzzy relation R governs the characteristics of the mapping given in (1). One way to look at automatic rule generation is to find a proper fuzzy relation from a set of numerical data. Fuzzy associative memory (FAM) developed by Kosko [12] provides a natural structure to store a fuzzy relation and to process fuzzy inference in parallel. Learning an FAM involves clustering of a set of given numerical data in the product space. Using the centres of the resultant clusters the weight matrix of the FAM which is equivalent to the elements of the fuzzy relation in Eq. 1 is computed as

$$\mu_R(x, y) = \overset{m}{\underset{i=1}{T^*}} \left\{ T(\mu_{X_i}(x), \mu_{Y_i}(y)) \right\} \tag{2}$$

where m is the number of clusters, X_i is the centre of the ith cluster, and Y_i is its corresponding output. T and T* are the *t*-norm and *t*-conorm, respectively.

2.2. Radial Basis Function Neural Network

A radial basis function (RBF) neural network consists of an input layer, hidden layer and output layer with the activation function of the hidden units being radial basis functions. Normally, an RBF consists of one hidden layer, and a linear output layer. One of the most common kinds of radial basis function is the Gaussian bell-shaped distribution [11, 13]. The response of the hidden layer unit is dependent on the distance an input is from the centre represented by the radial basis function (Euclidean Distance). Each radial function has two parameters: a centre and a width. The width of the basis function determines the spread of the function and how quickly the activation of the hidden node decreases with the input being an increased distance from the centre [14]. The output layer neurons are weighted linear combination of the RBF in the hidden layer. RBF network can be modeled by the following equations:

$$y_j(\mathrm{x}) = \sum_{i=1}^{n} w_{ji}\psi_i(\mathrm{x}) + b_j \tag{3}$$

where $y_j(\mathrm{x})$ is the output at the jth node in the output layer, n is the number of hidden nodes, w_{ji} is the weight factor from the ith hidden node to the jth output node, $\Psi_i(\mathrm{x})$ is the radial basis activation function of the hidden layer and b_j is the bias parameter of the jth output node. Some of the common types of RBF are linear function, Duchon radial cubic, radial quadratic plus cubic and Gaussian activation function [13]. The last function has the form:

$$\psi_i(\mathrm{x}) = \exp\left(\frac{-||\mathrm{X} - \mathrm{u}_i||^2}{2\sigma_i^2}\right) \tag{4}$$

where X is the input vector, u_i is the center vector of ith hidden node and σ is the width of the basis function. There are two distinct types of Gaussian RBF architectures. The first type uses the exponential activation function, so the activation of the unit is a Gaussian bump as a function of the inputs. The second type of Gaussian RBF architecture uses the softmax activation function, so the activations of all the hidden units are normalized to sum to one. This type of network is often called a "normalized RBF" or NRBF network. An NRBF network with unequal widths and equal heights can be written in the following form:

$$\psi_i(\mathrm{x})(\mathrm{softmax}) = \frac{\exp(h_i)}{\sum_{i=1}^{n}\exp(h_i)} \tag{5}$$

$$h_i = \left(-\sum_{l=1}^{2}\frac{(\mathrm{X}_l - \mathrm{u}_{il})^2}{2\sigma_i^2}\right) \tag{6}$$

Again, X is the input vector, u_{il} is the centre of the ith hidden node (i=1,. . .,12) that is associated with the lth (l = 1,2) input vector, σ_i is a common width of the ith hidden node in the layer and softmax (h_i) is the output vector of the ith hidden node. The radial basis activation function used in this study is the softmax activation function [15]. The NRBF neural network developed during this study consists of an input layer, a hidden layer and an output layer, which include 2, 12 and 1 node, respectively. At first, the input data is used to determine the centers and the widths of the basis functions for each hidden node. The second step includes the procedure, which is used to find the output layer weights that minimize the quadratic error between the predicted values and the target values. Mean square error (the average sum of squares error) is defined as:

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N}\left((\mathrm{TE})_k^{\mathrm{exp}} - (\mathrm{TE})_k^{\mathrm{cal}}\right)^2 \tag{7}$$

3. RBF Based Neuro-fuzzy System for Scenario Planning

In this section, we proposed a neuro-fuzzy system for scenario planning in project management. The proposed system uses fuzzy inference engine with fuzzy rules for modelling the project uncertainties which is enhanced through learning the various situations with a radial basis function neural network.

We focused on the risks in the project management to propose the appropriate scenarios. For this purpose, the various risks involved in the project management were obtained from Jaafari study [3]. In his study, thirteen categories of project management risks were determined, as shown in Table 1. We used these findings as the reference for our rule base. Also, we enhanced the capability of these rules using the fuzzy sets theory to encounter the uncertain and vague situations and information, so as we determined fuzzy membership functions for the rules' antecedents and consequents based on the field experts opinions. Then, we mixed up various rules with each other to construct appropriate scenarios for project management because usually several of these risks are present in practice, and we need to apply several corresponding strategies to encounter with them. Therefore, our rules include several risks with fuzzy degrees as antecedents and several strategies with fuzzy degrees as consequents. In this way, we constructed our fuzzy rule base to cover all the possible situations for the project management risks.

In the next step, we used a radial basis function neural network to augment the proposed inference system with learning from previous processed data. This RBF-based neural network learns the appropriate scenario for different risks, so as it has the ability to recognize and recommend the best scenario for our project management risks. The methodology of the proposed system has been represented in Fig. 3.

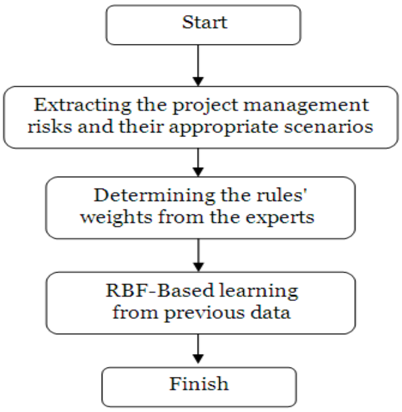

Fig. 3: The Proposed Methodology for the Neuro-fuzzy System.

In the following, the training and test data set were determined, so as 60% of the data set was used for the network training and the remained 40% was used for checking the network. Also, the learning rate and acceptance error were set 0.02 and 0.005, respectively. At the end of 300 training epochs, the network error convergence curve can be derived as shown in Fig. 4. Therefore, the architecture of the proposed system includes a fuzzy system comprising of fuzzy input, inference engine and fuzzy output which is enhanced with the RBF-based learning in the rule base, as shown in Fig. 5. Also, some of the proposed system outcomes are represented in Table 2.

Table 1: Risks in Project Management and their Appropriate Strategies.

Risk	Appropriate Strategy
Promotion risk	Form strategic partnerships with customers or suppliers, lock in deals
Market risk, volume	Use strategic planning and supply curve and base forecasts on competitiveness. Then form strategic partnerships as above
Market risk, price	Generate probability distribution for unit price and test against potential price variations. Then form strategic alliances
Political risks	Secure insurance from Export Finance, Overseas Investment Corporation or World Bank's Multilateral Investment Guarantee. Also form local strategic alliances and risk assessment criteria
Technical risks	This risk is managed via integration of downstream/upstream data & pooling of team expertise within a strategy based evaluation system and holistic approach
Financing risks	Project is conceptualized & developed as a business market-driven entity
Environmental risks	Environmental decisions are integrated into mainstream decisions and proactively managed to maximize benefits
Cost estimate risk (Completion risk)	Estimate accurately and to deliver below targets set
Schedule risk (Delay risk)	Plan and deliver vs. targets set
Operating risk	Integrated data and teams, real time evaluations versus simulation of project will ensure high operability
Organizational risk	Project alliance board & single agreement will ensure synergistic behavior
Integration risk	Less likely to arise due to the whole of life focus and early integration of data
Force majeure (Superior force)	Reduced due to both insurance coverage and intelligent proactive risk management

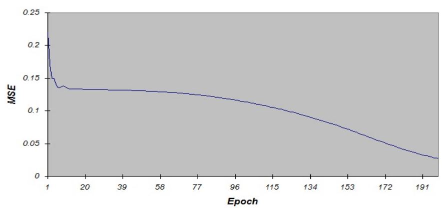

Fig. 4: The Curve of the Network Error Convergence.

Table 2: Some of the Proposed System Outcomes.

Risks/Scenario No.	Promotion risk	Market risk, volume	Market risk, price	Political risks	Technical risks	Financing risks	Environmental risks	Cost estimate risk (Completion risk)	Schedule risk (Delay risk)	Operating risk	Organizational risk	Integration risk	Force majeure (Superior force)	Scenario
1	0.1	0.5	0.7	0.6	0.5	0.4	0.3	0.2	0.7	0.8	0.1	0.6	0.8	*5*
2	0.2	0.7	0.4	0.6	0.2	0.8	0.7	0.4	0.6	0.9	0.5	0.2	0.7	*3*
3	0.6	0.7	0.2	0.5	0.4	0.7	0.8	0.9	0.3	0.4	0.5	0.4	0.1	*7*

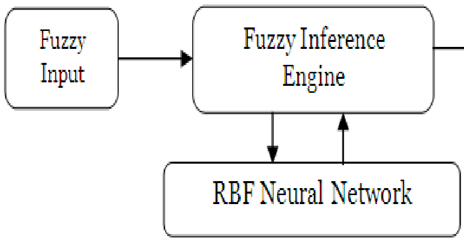

Fig. 5: The Architecture of the Proposed Neuro-fuzzy System.

4. Conclusions

Because of various risks in the project management, it is necessary to handle the turbulence of the situations in the future through appropriate scenarios. In this paper, we proposed a neuro-fuzzy system for scenario planning in project management which is capable to use fuzzy inference engine with fuzzy rules for modelling the project uncertainties. Also, the rule base is enhanced through learning the various situations with a radial basis function neural network. For applicability study of the proposed system, it was applied for recommendation of the best scenario for the project management depending on its relative risks.

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