An Intelligent Management System for Evaluating Science Research Projects

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Abstract. Proposed in this paper is an intelligent management system for evaluating science research projects based on fuzzy neural networks with genetic algorithms. This system was planned, designed and tested employing theories and approaches of software engineering. This system was then applied to evaluate science research projects of the Natural Science Foundation of Guangdong Province, People's Republic of China. The outcome / results shows the feasibility and validity of the system and its possible application to other intelligent management systems.

Keywords: science research projects, evaluation, intelligent management, software engineering

1. INTRODUCTION

Evaluating science research projects plays a key role in science research management, and induction inference and summarization of experts' evaluation opinions are always the most important content in the evaluation task. Along with in-depth research and development of computer sciences and artificial intelligence technologies, the construction of intelligent management systems for science research projects has become a trend of developing science research management. (Tu et al. 1995)

At present, the main information processing techniques used to build intelligent expert systems are fuzzy systems, artificial neural networks and genetic algorithms, which are three significant information processing tools in the field of soft computing. The synergies of information processing based on soft computing are followed with interest by many scholars.

An intelligent management system for the evaluation of science research projects (IMSESRP) based on fuzzy neural networks with genetic algorithms is proposed in this paper. The characteristics of experts' evaluations and conclusions, which were obtained from historical evaluation scoring data, are simulated and optimized. The intelligent system is applied to evaluate science research projects of the Natural Science Foundation of Guangdong Province, People's Republic of China. The performance of the system not only shows its feasibility and validity in application but also implies that the system could be broadly applied to other intelligent management systems.

2. SYNERGETICS OF FUZZY SYSTEMS, ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHMS

Nowadays, soft compution tools such as fuzzy systems, artificial neural networks and genetic algorithms are significant techniques for processing information in advanced artificial intelligent systems adopted for intelligent expert systems. A brief introduction to them is given below.

2.1 Fuzzy Systems (FSs)

The American scholar L. A. Zadeh proposed fuzzy sets (Zadeh, 1965) and introduced a numerical way to study and process fuzzy phenomena. Fuzzy system approaches

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deal with a large amount of uncertain and fuzzy information in the objective world, and utilize the human brain's abilities to process fuzzy problems. The approaches seek to program fuzzy information represented by natural language into computers so that computers can complete more complex tasks. Fuzzy system approaches are based on fuzzy sets, fuzzy language and fuzzy logics, and try to simulate the fuzzy modes of the human brain's higher-order thinking. Fuzzy sets are now widely and successfully applied, such as to management sciences. (Chen, 1990; 1994)

2.2 Artificial Neural Networks (ANNs)

Artificial neural networks are mathematical representations inspired by the functioning of the human brain. They possess characteristics such as parallel processing, non-linearity and high fault tolerance, and have the capabilities of adaptation self-learning and generalization. ANNs are trained using training samples and can be employed to output the results of self-adaptation, which is applicable in the modeling of complicated phenomena and in dealing with practical problems.

Acquiring knowledge and improving self-performance by learning from the environment are important characteristics of the learning mechanisms of ANNs Normally, the improvement of performance is achieved by gradually modulating an ANN's own parameters (e.g. weights) under certain predefined measurements. There are two main methods of learning: (1) supervised learning (learning with a teacher), in which the learning system optimizes parameters (or weights) by receiving feedback about any errors between the ANN's actual output and the desired output; (2) unsupervised learning (learning without a teacher), in which the learning system adjusts its own parameters or structures (self-organization) by virtue of local interaction sufficient to achieve a global organization, representing certain inherent characteristics of inputs. (Rojas, Feldman, 1996; Yu. 1999)

2.3 Genetic Algorithms (GAs)

Genetic algorithms provide an approach to iterative search algorithms of adaptation probability. This is based on principles of evolution and hereditary and uses the stochastic search algorithms of biologic natural selection and natural genetic mechanisms for reference proposed by Holland (Holland, 1984). The main peculiarity of GA is random search, a typical example of a strategy, which explores the search space and exploits the best solutions. This kind of search does not depend on the gradient of information.

During iterations, GA maintains a population of potential solutions (individuals or chromosomes). Some members of this new population undergo alterations by means of crossover and mutation to form new solutions. Each solution is evaluated to give some measure of its "fitness": at each generation the relatively "good" solutions reproduce, while the relatively "bad" solutions die. Then, a new population is formed by selecting the more fit individuals. Genetic algorithms, as a good global optimization search tool, have been quite successfully applied to optimization problems. (Michalewicz, 1999; Yun, 2000)

2.4 Fuzzy Neural Networks (FNNs)

Standard FNNs use the synergies of the structures of ANNs and inference rules of FSs; that is, FSs are constituted logically by ANNs, which take advantage of the capability of mapping learning into laws from the pairs of learning sets to establish rules about what FSs need. Most FNN models are multi-layer feed-forward ANNs attributed to the unidirectional character of fuzzy logic. A variety of FNNs are distinguished by their mem-bership functions, fuzzy weighted operators, fuzzy acti-vation functions, forms of input-output, and settings and adjustment of their structures and parameters.

The fundamental structure of multi-layer feedforward FNNs consists of the input layer, the hidden layers (one or more layers) and the output layer. In this kind of structure, the input layer does not deal with the input fuzzy data in general, or makes simple scaling changing at most. The input or output layer can receive or produce fuzzy outputs, and those fuzzy outputs can be represented by continuous membership functions or their forms of discretization. The connected strength $\tilde{\omega}_{ii}$ representing the efficiency with which the output signal of unit j is transmitted to unit i can also be fuzzy numbers. The outputs of hidden neuron units and the output units are the new states produced by combining the network input signals with the current states of the neuron units. The fundamental structure above is the 'fuzzification' of the ordinary back-propagation (BP) neural networks, whose learning rule is also based on the BP algorithm.

To meet performance demands, networks' computing and learning, input-output representation, the form of connected fuzzy weights and the output computing of each node should be redefined according the specific problem requirement. Therefore, many deformational FNN structures, based on a fundamental structure, are proposed. (Zadeh, 1994; Pal, 1999; Ostermark, 1999; Hoffmann, 2000).

2.5 Fuzzy Neural Networks with Genetic Algorithms (FNGs)

The integration of GAs and ANNs can extend the searching space of ANN systems, increase the efficiency of computing and enhance the automatic level of modeling of ANNs. Currently, the goals of integrating GAs and ANNs are concentrated on improving the performance of ANNs so as to create efficient ANN systems that can solve problems, for instance lightening the burden of manually modulating ANNs. There are several methods of combining GAs and ANNs. According to actual needs, efficient ways of integrating GAs and ANNs should be proposed from known specific problems. (Whiteley, 1995)

The integration of GAs and FSs, which combines knowledge acquisition and its representation, has been adapted to deal with non-linear systems and complex data. Therefore, the efficiency of processing and the velocity of systems have clearly been improved. The goal of applying GAs to FSs is to improve the procedure of design and the performance of systems. GAs can find the optimal values of membership functions or the optimal rules of fuzzy logics; artificial selection, however, is too difficult.

2.6 Intelligent Management Systems Based on FNGs

By virtue of theories above, FSs, ANNs, GAs and their combinations can be applied to management sciences to build different kinds of intelligent management systems with their own specialities. Thereinto, the synergies of FSs and ANNs were firstly applied to management sciences to build intelligent management systems based on FNNs (Xiao et al., 1999; Chen et al., 2000; Sun et al., 2001). After meeting certainly remarkable achievements, the global optimization approaches of GAs were added to improve the performance of those systems to propose intelligent management systems based on FNGs.

3. INTELLIGENT MANAGEMENT SYSTEM FOR EVALUATING SCIENCE RESEARCH PROJECTS (IMSESRP) BASED ON FNGs

Aimed at the processing of science research projects, an intelligent management system for evaluating science research projects (IMSESRP) based on FNG is proposed and developed in this paper. It is introduced using some theories and approaches to software engineering.

3.1 System Planning

3.1.1 Problem Proposal

In the current application processing for scientific research funding, some valuable research projects may not be subsidized or even further developing, due not only to lack of funds for research but also especially to delays in evaluating projects. Moreover, some projects without satisfying with the subsidized qualities may be given the financial support. How to distribute limited funds to the most promising projects in order to achieve the best outcomes has become a strong focus for researchers and committees at all levels of institutions. To date, numerous evaluation methods have been suggested, but some of these depend more on personal experience; as a result, subjective opinions rather than objective assessments influence the evaluation of proposals.

Currently, for the evaluation of research project proposals at the Natural Science Foundation of Guangdong Province, People's Republic of China, project proposals are assessed by several experts in their own fields according to sixteen evaluation criteria which are combined into an evaluation index structure. The structure consists of four generalized parts, and each part has three or more material criteria, represented by the following set:

- $I = \{I_1, I_2, I_3, I_4\}$
- = {application basis, research schemes, research basis, comprehensive opinions}
- *I*₁={scientific significance, application prospect, innovation level, application basis, present, tate of research in the domain}
- *I*₂={content of project, research approaches and methodology, possibility of realizing research goal, expenditure budget and planning}
- *I*₃={accumulation of relevant research about the project, research conditions provided, research staff}
- *I*₄={expert's familiarity with project, comprehensive evaluation, whether it is a cross subject or a new subject, to subsidize or not}
- Or $I = \{ d_1, d_2, \dots, d_{16} \}$, where *di* is the *i*th index, and $i = [1, \dots, 16]$.

The goal of IMSESRP is to provide accurate evaluations using the knowledge of academic experts while minimizing human error, so that significant, meaningful, applicable and technically feasible projects can be selected from the great number of project candidates and funds can be used efficiently.

3.1.2 Feasibility Study

In order to remedy the defects of the current evaluation method and improve its objectivity, by building an intelligent management system of evaluating scientific research proposals, a hybrid approach based on synergies of FNGs is proposed in this paper. The framework for processing information by using the intelligent management system is shown in Figure 1.

The data that the system needs are divided into two parts. One part is the learning set derived from experts' historical experiences; the other one is the evaluation set. The two parts are manipulated by the learning program module and the evaluation program module of the intelligent management system respectively. In Figure 1 the procedure of building the intelligent management system



Figure 1. Intelligent management systems processing structure

is marked by a solid line, and that of the evaluation procedure by a dotted line. The two groups of data are pre-processed using fuzzy sets approaches. Then, the learning set used to train the system's network is put into the learning program module and genetic algorithms which accelerate the pace of training and optimization employed here to establish the expert system. When users input the project candidate data into the trained management system, evaluation outputs are calculated directly.

(1) Economic feasibility

Only relevant information used to build the system is needed, and the programming of the system occurs according to the algorithm purposed in the paper. This keeps the cost of development relatively low. Once the system is built, the workload and the human subjectivity involved in evaluating projects will be reduced greatly. This means large economic and social benefits.

(2) Technical feasibility

The technologies used in the paper have been used successfully in many applications of intelligent control systems. They can be applied to management systems but, of course, the corresponding hybrid algorithms of soft computing should be studied for any special purpose system. Nevertheless, these technologies lay a solid foundation for the feasibility of IMSESRP. Once it is completed, the system should be easy to operate, be stable, and should satisfy with the requirements of evaluation.

(3) Legal feasibility

The system is developed independently so that there is no problem of legal intrusion or responsibility.

(4) Selectivity

As an intelligent management system, besides the

approaches employed by the system, other approaches of intelligent information processing can be applied, such as rough sets and support vector machine.

3.2 Design of IMSESRP

3.2.1 Analysis of Demand

A data flow diagram (DFD) is a graphical technique that depicts information flow and transformation as data move from input to output. A DFD may be used to represent a system or software at any level of abstraction. According to the objective and range of the system software proposed in the problem proposal section, a DFD of the structured analysis of the IMSESRP based on fuzzy neural networks with genetic algorithms is pre-sented.

The fundamental system model of IMSESRP, as the level 0 DFD, is shown in Figure 2.

The intelligent management system in the level 0 DFD can be analyzed into three subsystems: learning system, evaluation system and inquiry system as the level 1 DFD (see Figure 3).

In Figure 3, the intelligent management system in the level 0 DFD consists of the learning system, evaluation system and inquiry system in the level 1 DFD. In particular, the matrix of network weights of the system and the predetermined error rate of learning and the number of training iterations are recorded in the parameter table; the fitness rates of retrospective evaluations by historical project data and the information of each project including score, ranking, degree of subsidy and expert assessments are recorded in the parameter of results table; evaluation system produces the final decision as to whether or not the project will be subsidized.

In level 2 there are three DFDs, which specify the procedures for processing data from the learning, evaluation and inquiry systems in the level 1 DFD.



Figure 2. Fundamental system model of IMSESRP (level 0)







Figure 4. Level 2 DFD of the learning system

The procedure for processing learning system data is shown in Figure 4. Users input or renew the learning set manipulated by fuzzification to train the network of the expert system of the IMSESRP.

The procedure for processing evaluation system data is shown in Figure 5. In this system, the large data are input in the form of a matrix, and the small data are input by experts who assess according to the table provided by the intelligent management system. Before the evaluation set is estimated, the network of the expert system will call-in the trained network weights recorded in the parameter table to prepare for evaluation computing.

The procedure for processing the inquiry system data is shown in Figure 6.

3.2.2 IMSESRP Software

The IMSESRP software system is programmed in Matlab Programming Language under a Windows system, and consists of a learning module, an evaluation module, an inquiry module and a system brief. The learning and evaluation modules consist of a number of branch modules. Experimental data used for training and testing come from science research project proposals of the



Figure 5. Level 2 DFD of the evaluation system



of project

Figure 6. Level 2 DFD of the inquiry system



Figure 7. Software structure of IMSESRP

Natural Science Foundation of Guangdong Province. The main functions of the components of the IMSESRP, which are a data input (experts' scoring tables) module, a data integration module, a building expert systems module, a decision reasoning module and an output evaluation results module (see Figure 7) are introduced as above.

(1) Data input module

In this module, there are two ways to input data entering the system. One is to input data in the form of a matrix directed to large data; the other is experts' assessments according to the table provided by the system, which is directed to the small evaluation set. Both can be renewed and re-edited.

(2) Data integration module

Fuzzification enables the scoring of data of a specific proposal by several experts to be transformed into a uniform format so as to avoid the influence of a different number of experts scoring different cases. Weights of experts are regarded as the same. By corresponding discrete methods to genetic algorithms, the integrated scoring data are ranked and used in the decision reasoning module.

(3) Building the expert system module

The network of IEMSSRP based on FNG is a threelayered feedforward network, which is the supervised learning mode of an ANN. As the input, the integrated values of evaluation set $I = \{d_1, d_2, ..., d_{16}\}$, which have been pre-processed by the integrated data module, are regarded as the input of the network. The first layer is the rule layer, which realizes fuzzy reasoning rules to perform the logic multiply operation. The second layer is the conclusion layer, which performs logic OR operation, in which there are four conclusion items: to proceed to subsidize; to agree to subsidize; to modify project content; not to subsidize. The third layer outputs the final result, which is the decision (to subsidize or not) given by the intelligent management system.

The function of this module is to train the FNG network with learning sets (historical input and output data of project candidates) so as to build the expert system, which prepares for decision reasoning.

The genetic algorithm employed in this module is to optimize data (learning set), structure and parameters of the neural network, whose fitness values are all equal to the fitness rates of learning samples used to train the network.

| Table 1. | Fitness rates of evaluations of four intelligent |
|----------|--|
| | management systems |

| Techniques applied to Intelligent management system | Fitness Rate |
|--|--------------|
| Fuzzy Systems | 58.4% |
| Artificial Neural Networks | 74.5% |
| Fuzzy Neural Networks | 87.4% |
| Fuzzy Neural Networks with Genetic Algorithms | 93.75% |

(4) Decision reasoning module

The decision reasoning to output the final evaluation results of the IMSESRP is performed by this module. On the basis of the model and FNG algorithms ,and the strategies of qualitative and quantitative analysis, the expert system of decision reasoning of the IMSESRP is constructed. The reasoning results consist of project scores, project rankings and subsidy or funding rankings.

Candidates' scores and rankings can be obtained directly from the output of the IMSESRP, but subsidy or funding rankings are obtained by another approach; that is, the eligibility of the project for funding is ranked using the qualitative part of the evaluation indexes (*Comprehensive Opinions*), the quantitative evaluation results , the outputs of the IMSESRP, and the current annual overall situation of project candidates' scores.

(5) Evaluation result output module

Functions such as output evaluation results, interpretation projects results, inquiry results and printing results are completed by this module.

3.2.3 Testing of IMSESRP

To test the system software, a black box method is employed. The intelligent management systems based on FSs, ANNs, FNNs and FNGs are separately applied to the evaluation of science research projects of the Natural Science Foundation of Guangdong Province. Then, the efficiency of these four is examined. This was done by taking the 764 valid projects from 1999 as the learning set to set up the intelligent management system (after FNG network's training, the training samples' fitness rate based on FNG was 99.7 percent) and the 704 projects from 1998 as evaluation samples. The evaluation samples' fitness rates obtained by these four methods are shown in Table 1 below.

4. CONCLUSION

According to the above fitness rates, the IMSESRP based on a FNG simulates technically and practically the thinking of experts in the evaluation process and optimizes the experts' experiences; its fitness rate is 93.75 percent higher than that of other approaches. Although it took a great deal time to train the expert system, the IMSESRP is still more scientific and rational than traditional evaluation methods. In the field, combining the decisions of experts with the results of this kind of intelligent evaluation system can decrease the influence of human interference and make evaluation results and decisions more equitable and reasonable.

Moreover, along with deeper studies of intelligent systems, some techniques of soft computing could also be applied to improve the performance of the IMSESRP, such as rough set theory (RS). Because of its particular nature, it would be interesting to investigate whether RS could optimize the IMSESRP by optimizing the evaluation index structure by reducing the redundant index without loss of precision, thus enhancing the training speed of the system. Above all, the study in this paper lays a solid foundation for future deeper studies of intelligent information processing based on synergetic techniques of soft computing, which can present a great challenge in all kinds of developing intelligent management systems.

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