APPLICATION STUDY ON ADAPTIVE NEURAL FUZZY INFERENCE MODEL IN COMPLEX SOCIAL-TECHNICAL SYSTEM

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Abstract: The adaptive neural fuzzy inference system (ANFIS) is used to make a case study considering features of complex social-technical system with the target of increasing organizational efficiency of public scientific research institutions. An integrated ANFIS model is built and the effectiveness of the model is verified by means of investigation data and their processing results. The model merges the learning mechanism of neural network and the language inference ability of fuzzy system, and thereby remedies the defects of neural network and fuzzy logic system. Result of this case study shows that the model is suitable for complicated socio-technical systems and has bright application perspective to solve such problems of prediction, evaluation and policy-making in managerial fields.

Key words: complex adaptive system; adaptive neural fuzzy inference system (ANFIS); complex social-technical system; organizational efficiency

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INTRODUCTION

Socio-technical systems are typical complex systems that have the complex functional mechanism among multiple internal factors and the self-adaptive features, and therefore can be analyzed and studied with adaptive theory for complex systems. Complex adaptive system (CAS)[1] theory was put forward by Holland in 1994 and has been applied in researches on organizations such as organizational complexity, creativeness and cultural complexity, self-adaptability and management ideology. The feasibility of applying CAS theory in researches on complex system decision and optimization is as follows:

First, CAS takes system members as active subjects that have their own aims.

Second, CAS emphasizes the interactivity between subjects and their environment, and takes individuals and the interactive functions among them as the base of the whole system. Subjects in complex system take adaptation as basic means to attain the status of evolving together with their environment. They develop in a co-ordinate way, influence and evolve mutually and continuously.

Third, subjects of CAS have features of surge. Surge phenomena in a complex system mean some features that have never been seen in the previous systems. These features are attributes, characteristics, behaviors and functions that exist only at a higher layer but exist no longer when restoring to the lower layers.

1 ADAPTIVE NEURAL FUZZY INFERENCE MODEL

Multi-criteria, non-linear, non-differential and uncertainty are basic features of complex systems. This seriously challenges traditional decision and optimization methods. To deal with problems of complex adaptive systems, biological evolution method should be adopted to take the

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advantage of its mechanism of non-linear and mutual function and evolution. In order to solve problems of complex system, either fuzzy logic system or neural network can be used independently to simulate human behaviors by means of simulating experts in specific areas. Nevertheless, if we combine the above two methods, in other words, adopt the adaptive neural fuzzy inference system (ANFIS) method to deal with such problems, we can merge the advantages of learning mechanism in neural network and language inference ability in fuzzy system and make up their disadvantages. As stated in Refs. [2-4], ANFIS method has been used to solve decision, prediction and analysis problems in engineering, social and management areas. Lee et al[5] applied a knowledge based AMFIS method to decision making by representing candlestick patterns with fuzzy time series. Tan et al[6] used ANFIS method supplemented by reinforcement learning (RL) as a non-arbitrage algorithmic trading system, which is capable of identifying a change in a primary trend for trading and investment decisions. Mellit et al[7] dealt with the modeling and simulation problems of photovoltaic power supply systems using ANFIS method and proposition of a new expert configuration PVPS system. Noori et al[8] analyzed the uncertainties on artificial neural network (ANN) and ANFIS method models in predictions. Salahshoor et al[9] used support vector machine (SVM) and ANFIS method for fault detection and diagnosis of an industrial steam turbine. Dogantekin et al[10] built an intelligent diagnosis system for diabetes with linear discriminant analysis (LDA) and ANFIS.

It can be concluded from the current research and application status that: First, ANFIS method is applied much wider in engineering systems than in social and economic systems; Second, applications of ANFIS method depend much on data quality and amount, which limits its applications in social and economic systems where large amount of high quality data are not obtainable; Third, it is very few to see theoretical verification in documents that ANFIS is more advantageous than other biological learning methods, and its advantages are generally shown by comparison and analysis between conclusions; Forth, since ANFIS method has some shortcomings itself, it is often used with other artificial intelligent methods[9-10]. With the above in mind, in the process of ANFIS modeling in this paper, data processing and analysis are specially studied to increase the applicability of ANFIS method. And comparisons with other artificial intelligent methods are made to show the effectiveness of ANFIS model.

1.1 Structure of ANFIS model

ANFIS put forward by Roger is a fuzzy system of Sugeno type. For a first order fuzzy system of Sugeno type with two inputs (x, y) and one output (z), there are two rules as follow

If (x is A_1) and (y is B_1) then $f_1 = p_1 x + q_1 y + r_1$

If (x is A_2) and (y is B_2) then $f_2 = p_2 x + q_2 y + r_2$

The ANFIS model structure that is equivalent to the first order fuzzy system of Sugeno type is shown in Fig. 1[11].

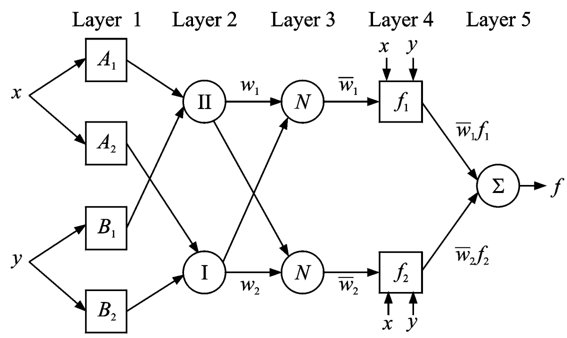

Fig. 1 Structure of ANFIS model

Fig. 1 is a typical structure of five layers of knots. Arrows among knots only mean directions of signal flows but no weights are related to them. Square knots mean that these knots have adjustable parameters and circle knots mean those have no adjustable parameters. All knots within layer 1 are self-adaptive ones, which is the layer of membership functions of input variables and can usually be chosen as Gaussian functions. Described in language variables, outputs of these knots can be expressed as follows

$$O_i^1 = \mu_{A_i}(x) \qquad i = 1,2 \tag{1}$$

$$O_j^1 = \mu_{B_j}(y) \qquad j = 1,2 \tag{2}$$

where x, y are the input knots, O_i^1, O_j^1 the outputs of knots in layer 1. Shapes of membership functions μ_{A_i}, μ_{B_j} are determined by some parameters, which are called forward parameters.

Layer 2 is a fixed (not self-adaptive) layer, which is called the intensity release layer of rules and multiplies input signals. Product output of input signals is shown as follows

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_j}(y) \tag{3}$$

Layer 3 normalizes adaptivities of the rules. Normalized adaptivity of the rule i is shown as follows

$$O_i^3 = \overline{w}_i = w_i/(w_1 + w_2) \tag{4}$$

All knots in layer 4, which are used to calculate the outputs of fuzzy rules, are self-adaptive ones and their outputs are expressed as follows

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \tag{5}$$

where $\{p_i, q_i, r_i\}$ means the set of parameters at that knot, and they are called backward parameters.

Layer 5 composes only one fixed knot, which calculates the total output for all the input signals as follows

$$O_i^5 = f = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{6}$$

Both forward and backward parameters are unknown ones that can be obtained by training ANFIS model with mixed learning algorithm in order to build a fuzzy model.

1.2 Mixed learning algorithm for ANFIS

Mixed learning algorithm combines least square method and gradient reduction method, and can reduce the dimension number of search space in gradient method and increase the convergence speed. For every time of sample training, there are two transfer procedures in mixed learning algorithm, one is forward and the other is backward. First, forward parameters are fixed. Inputs are then transferred forward to layer 4 of ANFIS. Now, total output of the system can be expressed as a linear combination of backward parameters, that is

$$\boldsymbol{z} = (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + \overline{w}_1 r_1 + (\overline{w}_2 x)p_1 + (\overline{w}_2 y)q_2 + \overline{w}_2 r_2 = \boldsymbol{A} \cdot \boldsymbol{X} \tag{7}$$

where $\{p_1, q_1, r_1, p_2, q_2, r_2\}$ compose a vector $\boldsymbol{X}$; $\boldsymbol{A}$, $\boldsymbol{X}$, $\boldsymbol{z}$ are matrixes with the dimension numbers of $P\times 6$, 6×1, $1\times P$ and P is the set number of training data. Backward parameters can be obtained by means of least square method.

Errors are calculated with Eq. (8). Signals obtained are transferred backward, forward parameters are renewed with gradient reduction method, and shapes of membership functions are then changed.

$$\boldsymbol{X}^* = (\boldsymbol{A}^{\mathrm{T}}\boldsymbol{A})^{-1}\boldsymbol{A}^{\mathrm{T}}\boldsymbol{z} \tag{8}$$

2 CASE STUDY

2.1 Case background

Public scientific research institutions (PSRIs) are an important part in the national innovative system and main providers of social public products in the area of science and technology. They have some significant features such as non-profit aims, strategic and critical core tasks, public and highly overflowing main achievements, non-market examination for organization performance, relatively open activities, and high risk investment of various resources. Therefore, how to increase the efficiency of PSRIs and their creative capability is an important problem focused by every country in the world. Motivating PSRI employees scientifically is an effective way to increase the operational efficiency of these organizations. Nevertheless, it is quite complex to motivate PSRI employees. It is reflected in the characteristics of their employees that they are knowledge worker engaging in intellectual work, they are highly independent and self-relying and have clear aim and strong sense of self value, and they have high psychological expectation for the challenge and creativeness of work, for the satisfactory of work, for the work environment and the development space of work given to the individuals, as well as human concerns in their organizations. Owing to the above, traditional material motivation cannot satisfy the requirements of employee motivation in PSRIs. Whereas, motivation based on work value, which complies with the internal contract theory in modern human resource management, can avoid role confusions and interest conflicts caused by mismatches between the value of an organization and its members and keep employees from bad behaviors that lose organizational interests. In comparison with feasibility study of work value motivation, it is more difficult to determine its result quantitatively. Researches made before by scholars were often constrained in the area of qualitative researches and far from realizing quantitative. Owing to the difficulty to analyze the result of work value motivation quantitatively, it is also difficult to provide auxiliary policy-making support for making relevant motivation policies. To overcome such difficulties effectively, complex adaptive system theory is used to study the functional mechanism of employee motivation based on work value in PSRIs. And self-adaptive neural fuzzy inference system is used to build a model in order to realize quantitative analysis on the result of work value motivation.

2.2 Data acquisition and processing

(1) Questionnaires on work value of employees in PSRIs

Questionnaires are specially designed for PSRIs on the base of collecting factors related to the work value of their employees. They include 53 items, as shown in Table 1.

Table 1 is a factor structure consisting of external environment and internal operational sys-

Table 1 Related factors for work value of PSRI employees

No.	Factor	No.	Factor
C_1	Consciousness of national development strategy	C_{28}	Reasonable mechanism for achievement sharing and transfer
C_2	National level of science and technology development	C_{29}	Perfect personnel training mechanism
C_3	National system and total amount of economy development	C_{30}	Performance appraisal system leading personnel to key and strategic research fields
C_4	Position of institution and legal assurance	C_{31}	Performance appraisal system leading personnel to concern for comprehensive benefits
C_5	Relevant policies and implementation		
C_6	Basic conditions and funds income	C_{32}	Appraisal system for higher research performance
C_7	Bright development prospects	C_{33}	Salary system encouraging competitions
C_8	Position in national construction	C_{34}	Consummate and reasonable promotion mechanism for management staffs
C_9	Development plan and objectives	C_{35}	Consummate and reasonable evaluation mechanism for professional titles
C_{10}	Reputable academic leaders	C_{36}	Rational and orderly exchange mechanism for talented staffs
C_{11}	Satisfactory work facilities	C_{37}	Good relationship between leaders and personnel
C_{12}	Advocating conventions and inheritance	C_{38}	Atmosphere of union and co-operation among personnel
C_{13}	Encouraging to pay attention to virtue and be indifferent to fame and gains	C_{39}	Reasonable post setting
C_{14}	Encouraging to pursue individual interests	C_{40}	Clear understanding of post responsibility and duty
C_{15}	Encouraging academic freedom	C_{41}	Jobs in accordance with career plan
C_{16}	Generous environment of allowing failures	C_{42}	Aesthetic feeling from work
C_{17}	Advocating fair competitions and equal opportunities	C_{43}	Jobs in accordance with personal interests
C_{18}	Advocating organization atmosphere of Golden Mean	C_{44}	Jobs inspiring creativity
C_{19}	Balance and coordination of life and work	C_{45}	Job challenge
C_{20}	Atmosphere and system guarantee for talented persons	C_{46}	Jobs improving quality and developing ability
C_{21}	Centralized organization structure with clear levels	C_{47}	Jobs with more autonomy
C_{22}	Decentralized flat organization structure	C_{48}	Achievement feeling from work
C_{23}	Decision mechanism with broad participation of staffs	C_{49}	Adequate respect from work
C_{24}	Research projects established according to organization objectives	C_{50}	Satisfactory salary and welfare
C_{25}	Effective management of research projects	C_{51}	Job stability
C_{26}	Reasonable scientific evaluation mechanism for research achievement	C_{52}	Relaxing body and mind
C_{27}	Advocating to team study	C_{53}	Traffic convenience

tem of organizations, employee growth, material and mental rewards and so on. Questionnaires are remarked with five-point method from least importance to most importance. All questionnaires are distributed and collected in a lumped way. 362 questionnaires are distributed and 292 ones are collected.

(2) Data acquisition and processing for comprehensive employee performance based on work value

The function of work value motivation can be an increase of current work performance but can also be a potential influence on employees that cannot measured with current performance. So, some indexes are selected to measure the effects of work value motivation in a way of weighted sum. Main indexes are as follows:

① Current performance of employees;

② Employee commitment to organization;

③ Satisfactory of employees;

④ Compliance of employee's target with that of organization;

⑤ Long term growth of employees.

Among the above, index ① is mainly collected from the year-end examination results of employees, indexes ②—④ are obtained with the questionnaires, and index ⑤ is according to the comprehensive remark points by personnel manager. Weights for all indexes are determined in the light of expert comments and weight for index ① is 0.5, for index ② 0.2, and for indexes ③—⑤ are all 0.1.

(3) Dimension reduction for data

Factor analysis is made for original data in order to reduce data dimension, avoid data intercross and overlap, and reduce the difficulty to train the neural network. Statistical analysis is made with the software of SPSS13.0. And eight factors are selected with the criteria that their information amount is more than 70%. Rotated load factors and their contributions are shown in Table 2.

Table 2 Rotated factors and their meaning

Factor	Eigen value	Meaning
F_1	7.339	Influence of research project operations
F_2	6.899	Influence of external factors
F_3	6.436	Influence of employee growth and value realization of organization members
F_4	3.976	Influence of internal environment
F_5	3.116	Influence of material and mental rewards
F_6	2.509	Influence of performance
F_7	2.266	Influence of factors such as health and traffic
F_8	1.797	Influence of leading style

All the points collected for the above eight factors are used as input variables to train the neural network.

(4) Setting up fuzzy rule database

The 576 rules are set up for eight input knots. Basic expressions of the rules are as follows:

Rule 1 if $F_1 \in B$, $F_2 \in B$, $F_3 \in B$, $F_4 \in B$, $F_5 \in B$, $F_6 \in B$, $F_7 \in B$ and $F_8 \in B$, then output $\in B$.

Rule 2 if $F_1 \in M$, $F_2 \in B$, $F_3 \in B$, $F_4 \in B$, $F_5 \in B$, $F_6 \in B$, $F_7 \in B$ and $F_8 \in B$, then output $\in M$.

⋮

Rule 576 if $F_1 \in W$, $F_2 \in W$, $F_3 \in W$, $F_4 \in W$, $F_5 \in W$, $F_6 \in W$, $F_7 \in W$, $F_8 \in W$, then output $\in W$.

(5) ANFIS training and verification

Among the 292 questionnaires, 200 questionnaires are randomly chosen and divided into two sets, i.e., one set as training samples and the other as testing samples. Based on the given input/output data sets, a fuzzy inference system (FIS)[12] is built with the ANFIS model structure in MATLAB fuzzy toolbox. Parameters of the membership function in the system are adjusted to their minima with both BP algorithm and least square method, which allows the fuzzy system to learn with silent data. ANFIS model learns with the training samples under a condition that keeps the error rate less than 0.05. After being trained for 1 000 times with the sample data, a good data structure is obtained and the effectiveness of the structure is verified in the application of the samples. Further, normalized connection weights for the input knots are obtained as shown in Table 3.

It can be concluded from the above analysis

Table 3 Connection weights for input variables

Factor	F_1	F_2	F_3	F_4
Weight	0.155	0.031	0.129	0.306
Factor	F_5	F_6	F_7	F_8
Weight	0.227	0.162	0.028	0.009

that it is an effective way to increase the employee performance in PSRIs by means of setting up better internal environment and increasing their material and mental rewards.

(6) Simulation results with ANFIS model

In combination with analysis of (5), it is determined that main motivation measures for the specific employees can include the followings:

① Increasing income for employees;

② Improving internal mode and system for project management;

③ Strengthen rule-breaking promotion mechanism.

Three motivation schemes are designed in combination with ①, ② and ③ respectively, with increasing the motivation strength of 10% compared with the original schemes.

Ten samples are chosen and their responses to the motivation schemes are determined by means of expert comments and inference. ANFIS model inputs are adjusted and the related results are shown in Table 4.

(7) Comparison and analysis for results

The main viewpoint of this paper is to build a model with ANFIS method. In order to verify the effectiveness of the method in this paper, a comparison is made with the results obtained in Ref.[5] that adopted pure neural network method and used input/output data to train the network, as shown in Table 5.

Table 4 Simulation results with ANFIS model for different motivation schemes

No.	Initial P	Scheme 1		Scheme 2		Scheme 3	
		P	S	P	S	P	S
1	0.75	0.827	7.7	0.765	1.5	0.779	2.9
2	0.67	0.752	8.2	0.778	10.8	0.817	14.7
3	0.72	0.791	7.1	0.797	7.7	0.839	11.9
4	0.95	0.961	1.1	0.950	0.0	0.960	1.0
5	0.81	0.907	9.7	0.825	1.5	0.852	4.2
6	0.65	0.692	4.2	0.671	2.1	0.715	6.5
7	0.91	0.917	0.7	0.917	0.7	0.921	1.1
8	0.78	0.905	12.5	0.817	3.7	0.853	7.3
9	0.83	0.901	7.1	0.850	2.0	0.869	3.9
10	0.88	0.927	4.7	0.895	1.5	0.919	4.43

Note: P means the performance and S the sensitivity.

Table 5 Simulation results for different motivation policies with pure neural network method

No.	Initial P	Scheme 1		Scheme 2		Scheme 3	
		P	S	P	S	P	S
1	0.75	0.840	12.00	0.770	2.67	0.781	4.13
2	0.67	0.768	14.63	0.799	19.40	0.828	23.58
3	0.72	0.790	9.72	0.821	13.89	0.854	18.61
4	0.95	0.96	1.05	0.950	0.00	0.962	1.26
5	0.81	0.921	13.70	0.850	4.94	0.842	3.95
6	0.65	0.715	10.00	0.661	1.54	0.691	6.31
7	0.91	0.935	2.75	0.921	1.10	0.907	−0.33
8	0.78	0.921	18.08	0.829	6.41	0.875	12.17
9	0.83	0.905	9.04	0.851	2.41	0.881	6.14
10	0.88	0.927	0.47	0.895	0.15	0.920	4.55

Comparing the results of Tables 4, 5, we can conclude the followings:

(1) For same motivation policies, performance results of ANFIS simulation are somewhat lower than those of neural network;

(2) For same motivation policies, sensitivities of ANFIS simulation are also somewhat lower than those of neural network.

In order to make a further comparative verification between the two methods, the simulation results are used to calculate the error rates for test samples and different motivation policies. It is found that the error rates of ANFIS model are significantly lower than those of neural network. Therefore, it is in better compliance with practices to adopt complex adaptive system to study work-value based employee motivation processes in PSRIs.

3 CONCLUSION

In view of the features of complex adaptive system, a model is built by means of self-adaptive neural fuzzy inference system. The model merges the learning mechanism of neural network and language inference ability of fuzzy system, and remedies the defects of neural network and fuzzy logic system. Work-value based employee motivation in PSRIs is studied in application of complex adaptive system. Policy-making analysis model for employee motivation in PSRIs is built using self-adaptive neural fuzzy inference system. Employee performance increases for different motivation schemes are predicted by means of simulation analysis. Effectiveness of the method is proved compared with the simulation results of traditional neural network. The related results can provide an effective support for making employee motivation policies in PSRIs.

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自适应神经模糊推理模型在复杂社会技术系统中的应用

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摘要:考虑复杂社会技术系统的特点,运用自适应神经模糊推理模型对提高公益科研机构的组织效率进行了实例研究。建立了针对公益科研机构员工激励决策的自适应模糊推理完整模型,利用调研数据及其处理结果验证了模型的有效性。该模型融合了神经网络的学习机制和模糊系统的语言推理能力,弥补了神经网络和模糊逻辑系统各自的不足。研究结果表明,自适应神经模糊推理模型适用于复杂社会技术系统,在解决管理领域的预测、评估和决策问题中有广阔的应用前景。

关键词:复杂适应系统;自适应神经模糊推理系统;复杂社会技术系统;组织效率

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