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APPLICATION OF FACTOR NEURAL NETWORK IN MULTI-EXPERT SYSTEM FOR OIL-GAS RESERVOIR PROTECTION

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ABSTRACT

Knowledge representation and reasoning model play an important role in multi-expert system. In this paper, a new knowledge representation method, factor neural network theory(FNN), is used in multi-expert system for oil-gas reservoir protection. Firstly, by introducing factor and factor space theory, knowledge representation model based on factor state space is presented. Secondly, analog factor neural network structure is analyzed to solve reasoning problem of expert system. For illustration, fuzzy reasoning theory is utilized in factor neural network to verify the effectiveness of our proposed method. The application of the expert system shows that factor neural network theory is valid in knowledge representation and reasoning model and blackboard mechanism based on point-to point can solve the communication problem among sub-expert systems better. As a result, our proposed method based on FNN can effectively improve the accuracy of inference results.

Keywords: *Analog Factor Neuron, Agent, Oil-Gas Reservoir Protection, FNN*

1. INTRODUCTION

Oil reservoir protection technology is one of the important ways to improve good effects in exploration and development of oil-fields and a key technology of maintaining peak production in oilfields[1].In the evaluation of reservoir damage, it is necessary for relevant subject experts to discuss and research together to get an intelligent solution[2].The evaluation way not only needs to expand a large amount of manpower, material resources and financial resources, but also delays oil development progress. So, it is very important to design a comprehensive multiple experts system with recognition, evaluation, prediction, diagnosis and processing of oil layer damage to expand the application scope of reservoir protection and enhance the application effect of reservoir protection[3-4]. Factor neural network provides a new method for expert system of oil-gas reservoir protection, which can effectively solve prediction and diagnosis problems of reservoir damage.

In the factor neural network (FNN) theory for information processing systems engineering, factor knowledge representation is the basis, factor neurons and factor neural network are formal framework. It aims to achieve storage and application of knowledge and to complete engineering simulation process of the intelligent behavior. An expert system is a program system that includes a large number of specialized knowledge and experience, which applies artificial intelligence technology and computer technology to a field in order to simulate human experts' decision-making process, such as reasoning and judgment process, and then solves complex problems which need human experts processing.

The paper first applied FNN theory to establish an expert system for oil-gas reservoir protection, which predicted the occurrence of reservoir damage in advance, so that people could timely take measures to protect oil-gas reservoir.

The remainder of this paper is organized as follows. In Section 2, factor and factor state space are introduced to describe knowledge representation in expert system. Section 3 gives formal description of analog factor neuron, which can construct analog factor neural network to solve reasoning of expert system. In section 4,we introduce analog neural network based on fuzzy reasoning model and implement fuzzy reasoning. Implementation of multi-expert system for oil-gas reservoir protection is presented in Section 5.Finally, we conclude our paper in Section 6, and provide suggestions for future work.

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2. EXPERT SYSTEM BASED ON FNN

2.1 Factor

As a vocabulary of the factor space theory, factor has three meanings as follows. The first is that when looking for reasons from the results, factors are defined as the things which cause some results. While we understand factor concept from state or feature, the factors are symbols of a kind of state or a set of features[7, 8]. The second is analyticity, factors can be regarded as a way to resolve the real world, a thing can be described from different aspects in a different way, and the analysis process is the process of looking for factors. The third is descriptive; everything is the intersection of the various factors, which means that it can build a broad cross-coordinate system. Such system can be described as a point of the generalized coordinates, and factor is the name of the dimension of the generalized coordinates [9, 10].

2.2 Factors State Space Based on Object

The object u is related to factor f, and also there is a corresponding state $f(u)$. If U and F are the sets comprised of some objects and some factors, and for $\forall u \in U$,all factors related to U are in F $(f \in F)$. For a practical problem, we can always assume that there is an approximate matching. For a given matching (u, f), a relation R between u and f is defined and written as $R(u, f)$. Only when $R(u, f) = 1$, f and u are relevant. So u space which is related to f and f space which is related to u can be defined as:

$$D(f) = \{u \in U \mid R(u, f) = 1\} \qquad (1)$$

$$F(u) = \{f \in F \mid R(u, f) = 1\} \qquad (2)$$

Factor $f\,(f \in F)$ can be regarded as a mapping, and function on a certain object $u\,(u \in U)$ is written as: $f : D(f) \to X(f)$, among them, $X(f) = \{f(u) \mid u \in U\}$, $X(f)$ is the state space of f.

2.3 The Knowledge of Factors Express

[Definition 1] In the domain of U, the atomic model of knowledge factors is a triple,

$$M(o) = < o, F, X > \qquad (3)$$

Where ○ is a set of objects of the knowledge description about U.
F is a factor set when U is used to describe ○.
X is a state set about F when F is used to described ○, and

$$X = \{X_O(f) \mid f \in F, o \in O\} \qquad (4)$$

[Definition 2] In the domain of U,the relation of knowledge mode is defined as

$$R(O) = < RM, M(O), XM > \qquad (5)$$

Where RM is a knowledge model.
M(O) is atomic model of knowledge representation in knowledge model.
XM is structure group state and state transformation relation of the atomic model M(O) in RM.

The atomic model of the knowledge factor representation gives a discrete set that describes objects; this is the basis of knowledge representation with factors. The relation mode of knowledge factor representation can associate with various related knowledge or different knowledge representation; this can realize the transformation of the different ways of knowledge and knowledge reasoning. They provide the basis of representation and processing of knowledge in using factors neural network.

3. FORMAL DESCRIPTION OF ANALOG FACTOR NEURON

The analogous FNN is based on the analogous factor neuron, and the center is the object of system domain, the factors are used to build functional knowledge storage, with external matching implicit way ,it can complete the processing of information. Analog factors neurons and its network mainly simulate the human brain nerve network system, it simulates the behavior of human intelligence from the outside of things and macro functions. Analog factors neural network is the basis of analog factors neurons, the key of their work is to build a functional analog characteristics of this simulation unit which has some characteristics, such as associative knowledge storage properties, network stability properties and rapid recalling function, etc.

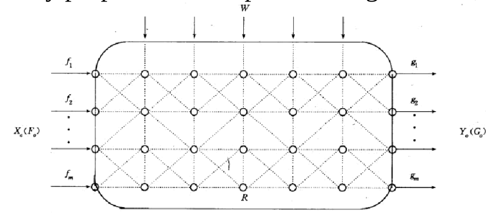

Figure 1:Analog Factor Neural Network Structure

In Figure 1, f1……fm are input factors that have some connections with O, each input factors are called a perceived channel of analog factors neurons, g1……gn are output factors of the O, they represent different output response.

$$F_o = \{f_1, f_2, ..., f_m\} \qquad (6)$$

$$G_o = \{g_1, g_2, ..., g_m\} \qquad (7)$$

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$$X_o(F_o) = \{X_o(F_i) \mid i = 1, 2, ..., m\} \quad (8)$$

$$Y_o(G_o) = \{X_o(g_j) \mid j = 1, 2, ..., m\} \quad (9)$$

For one of analog factors neurons, the external function can be used to express by $Y_o(G_o) = R(X_o(F_o))$, to build the simulation model of neurons within the network module ,to try to achieve the purpose of processing this information.

Analog factors neurons achieve the process of intelligent simulation with the following mathematical formula:

$$Y = F(X, W, T) \quad (10)$$

where

(X,Y) is called the input and output set mode of analog factors neurons,

X is called the stimulated or input mode set,

Y is called its corresponding response or output model set, and W, T is controllable parameters of the simulation model of neurons within the network module.

Make (X,Y) relatively fixed when learning, according to the network characteristics, try to adjust W, T to establish the above mapping relationship. Make W,T relatively fixed when recalling, analog factors neurons can make Y response according to input X.

4. FUZZY REASONING BASED ON FACTOR NEURAL NETWORK

4.1 Fuzzy Reasoning Model

As shown in Figure 2, a structure of an expert system includes 8 parts: knowledge base, inference machine, knowledge acquisition, explanatory mechanism, blackboard system, man-machine interface for experts and Interface for users. Through knowledge acquisition interface, users can establish knowledge base and get fact information into the blackboard system, then inference machine extracts factual information from blackboard system and matches rules in knowledge base repeatedly, in this process, intermediate conclusions will be put to blackboard system, until the system gets final conclusion output according to user questions. Explanatory mechanism explains the final conclusions and gives the solving process.

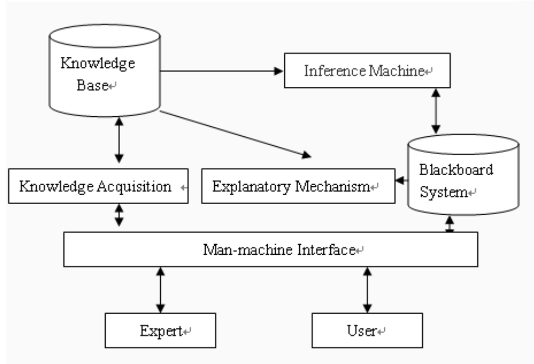

Figure 2:Structure of expert system

When reasoning more complex output conditions, at this point we use multi-stage implies fuzzy reasoning model.

Rule 1 if x is A1 and y is B1，then z is C1,else

Rule 2 if x is A2 and y is B2，then z is C2,else

……………………………………

Rule n if x is An and y is Bn，then z is Cn,else

Fact x is A'and y is B'

Conclusion z is C'

$$C' = \bigcup_{i=1}^{n} \{[A' \circ R(A_i; C_i)] \cap [B' \circ R(B_i; C_i)]\} \quad (11)$$

Firstly, obtain adaptation degree $\omega_{\tilde{A}_1}$ and $\omega_{\tilde{B}_1}$ of rule 1 from the following formula:

$$\omega_{\tilde{A}_1} = \vee_{x \in X} [\mu_{\tilde{A}^*}(x) \wedge \mu_{\tilde{A}_1}(x)] \quad (12)$$

$$\omega_{\tilde{B}_1} = \vee_{x \in X} [\mu_{\tilde{B}^*}(x) \wedge \mu_{\tilde{B}_1}(x)] \quad (13)$$

Adaptation degree $\omega_{\tilde{A}_2}$ and $\omega_{\tilde{B}_2}$ of rule 2 can be obtained:

$$\omega_{\tilde{A}_2} = \vee_{x \in X} [\mu_{\tilde{A}^*}(x) \wedge \mu_{\tilde{A}_2}(x)] \quad (14)$$

$$\omega_{\tilde{B}_2} = \vee_{x \in X} [\mu_{\tilde{B}^*}(x) \wedge \mu_{\tilde{B}_2}(x)] \quad (15)$$

Similarly, we can obtain Adaptation degree $\omega_{\tilde{A}_n}$ and $\omega_{\tilde{B}_n}$ of rule n

$$\omega_{\tilde{A}_n} = \vee_{x \in X} [\mu_{\tilde{A}^*}(x) \wedge \mu_{\tilde{A}_n}(x)] \quad (16)$$

$$\omega_{\tilde{B}_n} = \vee_{x \in X} [\mu_{\tilde{B}^*}(x) \wedge \mu_{\tilde{B}_n}(x)] \quad (17)$$

Then, activation degree ω_1 , ω_2 … ω_n can be calculated:

$$\omega_1 = \omega_{\tilde{A}_1} \omega_{\tilde{B}_1} \quad (18)$$

$$\omega_2 = \omega_{\tilde{A}_2} \omega_{\tilde{B}_2} \quad (19)$$

……

$$\omega_n = \omega_{\tilde{A}_n} \omega_{\tilde{B}_n} \quad (20)$$

Finally, by using product compositional operation between activation degree and consequent of its fuzzy rule, we can get the conclusions of a rule and get the final conclusion by max operation.

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$$\mu_{\tilde{C}^*}(y)=\omega_1\mu_{\tilde{C}_1}(y)\vee\omega_2\mu_{\tilde{C}_2}(y)\vee...\omega_n\mu_{\tilde{C}_n}(y) \quad (21)$$

Two-antecedent and two-consequent Larsen fuzzy reasoning process is shown in Figure 3.

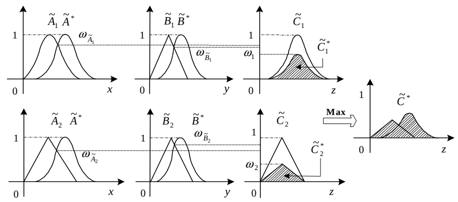

Figure 3:Two-Antecedent And Two-Consequent Larsen Fuzzy Reasoning Process

4.2 Experiment Verification

In the expert system for oil-gas reservoir protection, predictions factors are rock types (T), particle size of rock (C), pressure (P), particle density of rock (D), inference result are solid particle damage (F), wetting transition damage (W), and velocity sensitivity damage (V) and etc.

An inference rule is as follow:

if C(particle size of rock is large) and P(pressure is high) then F(solid particle damage is serious)

Where C ,P,D,F is respectively defined as a fuzzy set.

When C*(particle size of rock is little large) and P*(pressure is a little higher) ,the result can be inferred from the above rule.

Let $X=\{x1=0.2, x2=0.8\}$ be the domain of C; Let $Y=\{y1=0.1, y2=0.5, y3=0.8\}$ be the domain of P; Let $Z=\{z1=0.2, z2=0.8\}$ be the domain of F. In the rule,

$$C=\frac{1}{x1}+\frac{0.5}{x2} \quad (22)$$

$$P=\frac{0.1}{y1}+\frac{0.5}{y2}+\frac{1}{y3} \quad (23)$$

$$F=\frac{0.2}{z1}+\frac{1}{z2} \quad (24)$$

Given that

$$C^*=\frac{0.8}{x1}+\frac{0.1}{x2} \quad (25)$$

$$P^*=\frac{0.5}{y1}+\frac{0.2}{y2}+\frac{0}{y3} \quad (26)$$

The inference result F* can be calculated from the Larsen fuzzy model.

The calculating steps are as follows:

Step 1: Calculate adaptation degree ω_c between C* and C, adaptation degree ω_p between P* and P

$$\omega_C=\bigvee_{x\in X}\left(\frac{1\wedge 0.8}{x1}+\frac{0.5\wedge 0.1}{x2}\right)=\bigvee_{x\in X}\left(\frac{0.8}{x1}+\frac{0.1}{x2}\right)=0.8 \quad (27)$$

$$\omega_P=\bigvee_{y\in Y}\left(\frac{0.1\wedge 0.5}{y1}+\frac{0.5\wedge 0.2}{y2}+\frac{1\wedge 0}{y3}\right)=\bigvee_{y\in Y}\left(\frac{0.1}{y1}+\frac{0.2}{y2}+\frac{0}{y3}\right)=0.2 \quad (28)$$

Step 2:Obtain activation degree ω

$$\omega=\omega_C\omega_P=0.8*0.2=0.16 \quad (29)$$

Step 3: Activation degree ω products membership function F

$$\mu_{F^*}(z)=\omega_{\mu_F}(z)=0.16*\left(\frac{0.2}{z1}+\frac{1}{z2}\right)=\frac{0.032}{z1}+\frac{0.16}{z2} \quad (30)$$

Step 4: Search the best matching membership function $\mu_{F'}(z)$ of $\mu_{F^*}(z)$ and then F' is the inference result.

From step 1 to step 4,we can get the inference result F'(olid particle damage is a little serious);the inference result is consistent with the practice.

When predicting reservoir damage in using of reservoir parameters and rules of experience, sometimes you can get the status display function or correlation matrix changes, in this case, analytical methods can be used for reservoir prediction. However, in practice, the relationship between the parameters of change is very complex, so it is very difficult to get these relationships; in this case, it is more feasible to use analog factor neural network module to simulate and reasoning experience. For the parameter relation is not easy to be expressed, the principle of treatment is to establish a corresponding simulation prediction model. Simulation prediction model learns from the experience, and continuously improves in practice.

The analogous diagnostic mode through the main experience learning can predict reservoir damage, the function entity is the forward-type factor neurons, it is also set to reverse diagnosis function to show the results, reaction to the people on the basis of reverse validation. First of all, we must establish factors space based on the analysis of reservoir damage factors. The space including the output, input data based on FNN can timely forecasts reservoir damage and other damage, make a prediction to the possibility of impending damage.

5. IMPLEMENTATION OF MULTIPLE EXPERT SYSTEMS FOR OIL-GAS RESERVOIR PROTECTION

5.1 Sub-expert Agent Structure Based on Blackboard Model

Expert systems for oil-gas reservoir protection mainly consists of the following five sub-systems: reservoir sensitivity prediction sub-system, reservoir potential damage sub-system, reservoir damage diagnosis sub-system, reservoir damage

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prediction sub-system and reservoir damage processing sub-system. We take sub-systems as sub-agents, which can reason and judge. Each sub-expert system includes its own independent knowledge base, reasoning machine, local blackboard, knowledge acquisition component, and etc. Their main task is to maintain its own knowledge base ,then, reason and design in terms of design task document and its own knowledge on the global blackboard, finally, return final results to users after completing task. Sub-agent structure is illustrated in Figure 4.

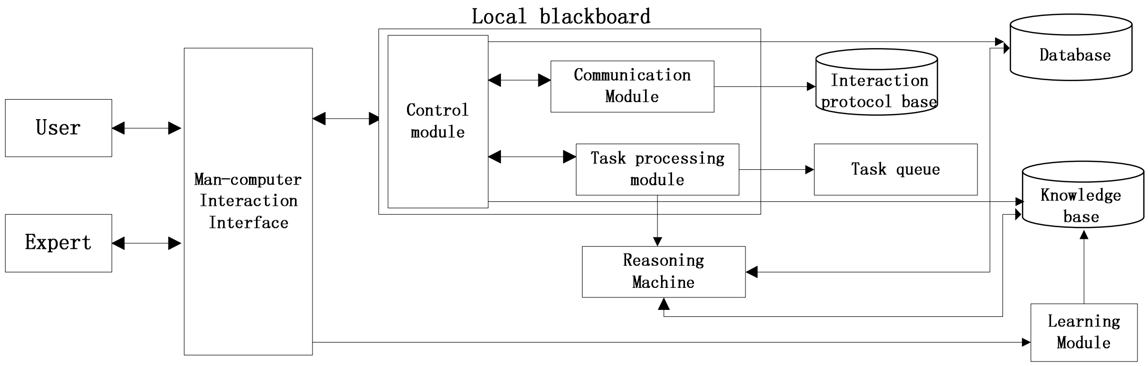

Figure.4:Task.Sub-Agent Structure

Expert agent not only has main functions of its own, but also has relevant features of other sub-expert system. The new functions in expert agents make collaboration among multi-expert agents more convenient.

Learning module makes expert agent have intelligence, it can acquire new knowledge through user interface and update knowledge base in time with combining intermediate collaboration result in database. Local blackboard includes communication module and task processing module, which are controlled by a master module. Task queue includes local task queue, collaboration task queue and delegation task queue. Local task queue stores the tasks which can be solved by local agent, collaboration task queue stores tasks which are asked for by other expert agents, delegation task queue stores tasks which local agents need other agents to cooperatively solve.

5.2 Implementation of Expert Agent

5.2.1 Class of expert agent

In the expert system, class of expert agent, ExpertAgent, is classified into two sub-classes,ManagerAgent class and CoAgent class. ManagerAgent class and CoAgent class form many-to-one relation,that is to say,a ManagerAgent object can collaborate with one CoAgent object or many CoAgent objects;ManagerAgent class depends on Announcement class,Award class;CoAgent class depends on Bid class,Execute class;Announcement class,Award class, Bid class and Execute class all depends on Connection database class, Sqlcon.Class diagram of expert agent is shown in Figure 5.

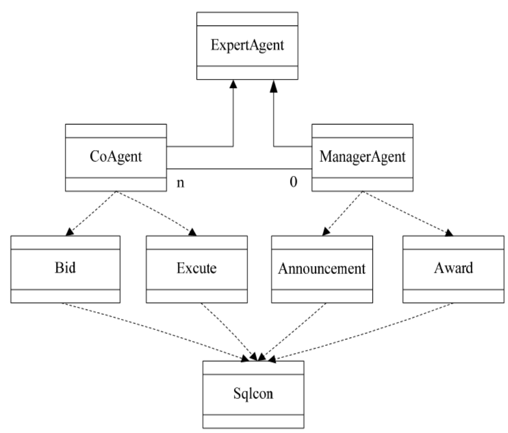

Figure.5: Class Diagram Of Expert Agent

5.2.2 Create function of agent class

Public void newAgent(String AgentName,String className,Object arg[],String containerName)
{
requestMsg.setOntology(AgentManagementOntology.NAME);
content object; fillContent(requestMsg,l);
addBehaviour(new AMSClientBehaviour("CreateAgent",requestMsg));
}

5.2.3 Implementation of message sending and receiving

In Java virtual machine, there exists a single thread named event distribution thread which is responsible for continuously reading event objects from system event queue, then calls event listener to listen user operation. Event listener runs in event distribution thread, so we add new method to event

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listener to implement message sending and receiving.

Message sending function head:myAgent.addBehaviour(new SenderBehaviour(msgToSend));

Message receiving function head:myAgent.addBehaviour(new ReceiverBehaviour(msgToRecv));

5.3 The main interface of the system

As shown in Figure 6,basic data for reasoning is shown on the top of the figure. By collaboration of multi-expert agent, Inference result and suggestion from multiknowledge base, such as reservoir damage knowledge base and sensibility damage knowledge base, are shown at the bottom of the figure.

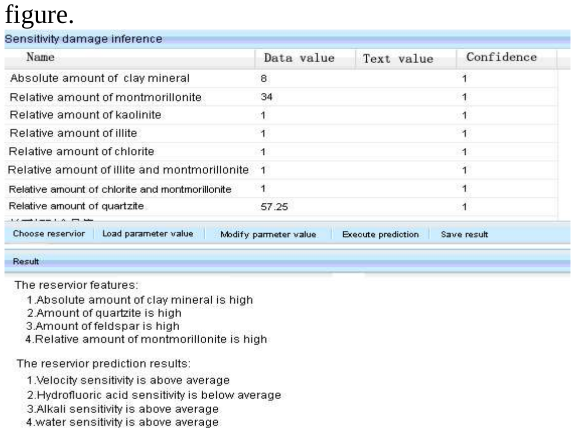

Figure.6 Inference Interface Of Reservoir Damage

6. CONCLUSION

The expert system based on FNN theory can effectively forecast and diagnose reservoir damage and sensitivity damage through dealing with reservoir category, rock particle size, amount of clay mineral, permeability, and other factors of the rock, the intermediate factors reasoned by the expert system. This paper provides a new method for the expert system for oil-gas reservoir protection which plays an essential role in protecting the oil-gas reservoir from damage. The next work is to research on collaboration mechanism between analog factor neural network and analysis factor neural network.

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