

Extracting fuzzy rules based on fusion of soft computing in oil exploration management

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Abstract

This paper proposed a self-learning, self-adapting algorithm (ANN-GA-Cascades) for extracting fuzzy rules, which is based on fusion of soft computing. We could use it to attain the fuzzy rules of oiliness in oil exploration: firstly, supervised learning of training sample is performed by using neural networks, with the inputs being the simplest well-logging attribute set which is relevant to the oiliness attributes, and the outputs being the corresponding oiliness partition C_k (dry layer, water layer, inferiority layer and oil layer). When the neural network attained precision or the maximum iteration steps, the k th output node of neural network will be the corresponding partition of decision character, with the output function being $\psi_k = f(x_i, (WG1)_{ij}, (WG2)_{jk})$, in which $(WG1)_{ij}$ are the connection weights between input layer and hidden layer, $(WG2)_{jk}$ are the connection weights between hidden layer and output layer. Then, the genetic algorithm (GA) was used to randomly assemble the input character and ψ_k as the fitness function. In this way, the optimal chromosome will be the fuzzy rule of partition C_k . Finally, the empirical study application of this algorithm on oil well oilsk81 and oilsk83 of Jiangnan oilfield in China has proved to be satisfactory.

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Keywords: Soft computing; Artificial neural networks; Genetic algorithm; Fuzzy rules; Reservoir; Well-logging

1. Introduction

There are much raw data in the procedure of oil exploration, which covers certain information that could become knowledge and even be formed to if–then fuzzy rules, thus is helpful for a better decision-making. Artificial neural networks and genetic algorithms are both commonly used in extracting fuzzy rules. When the input and output variables as well as the fuzzy partition of the variables become too much, fuzzy rules extracted by neural networks will be obtained and at the same time the rules will be exponentially growing (Benitez & Castro, 1996). Using genetic algorithms to extract fuzzy rules (Lim, Rahardja, & Gwee, 1996) could, on the one hand, achieve the global optimization search, and, on the other hand, be hard to get the expression of chromosome and conformation of fitness function.

At the same time, two main goals should be considered in extracting fuzzy rules: one is the maximizing accuracy; and the other is the minimizing complexity, which means a good interpretability for fuzzy rules. But the two goals are often conflicted with each other. Based on the tradeoff of accuracy and interpretability, the main consideration of fuzzy rule sets should be accuracy maximization and complexity minimization. Then, fuzzy rules selection should be considered based on the following three main parameters (Ishibuchi, Murata, & Turksen, 1997; Ishibuchi, Nakashima, & Murata, 2001; Ishibuchi & Yamamoto, 2004): $f_1(S)$, $f_2(S)$ and $f_3(S)$, where S is the set of fuzzy rules, $f_1(S)$ being the number of correctly classified training patterns by S , $f_2(S)$ is the number of fuzzy rules in S and $f_3(S)$ is the total number of antecedent conditions of fuzzy rules in S . The larger value of $f_1(S)$ denotes the higher recognition accuracy of fuzzy rules set, and the smaller value of $f_2(S)$, $f_3(S)$ denotes the better interpretability of fuzzy rules set.

This paper presents an algorithm of extracting fuzzy rules from trained neural network using genetic algorithm

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(Wang & Cao, 2002; Guo & Chen, 2001), which is ANN-GA-Cascades. The ANN is trained on the encoded vectors of the input attributes and the corresponding vectors of the output classes. The training of ANN is processed until the convergence rate between the actual and the desired outputs will be achieved. Then we obtain the function of the k th output node of ANN $\psi_k = f(x_i, (WG1)_{ij}, (WG2)_{jk})$ which will be the corresponding partition of decision character, where $(WG1)_{jk}$ is the connection weights of the input layer to the hidden layer and $(WG2)_{jk}$ is the connection weights of the hidden layer to the output layer. The function ψ_k represents the input patterns of the k th cluster. Finally, we use genetic algorithms to obtain the best chromosome which maximizes the fitness function ψ_k . For extracting the rule of k th cluster ($class_k$), the best chromosome must be decoded as follows:

- (1) The attribute values exist if the corresponding bits in the best chromosome equal one and vice versa.
- (2) The operators “OR” and “AND” are used to correlate the existing values of the same attribute and the different attributes, respectively.
- (3) The set of rules makes rule refinement and cancels redundant attributes, e.g. if an attribute has three values, such as A, B and C, the rule will be as follows:

If the k th attribute has a value A or B or C, then $class_k$ attribute can be dropped (redundant).

2. The algorithm of extracting fuzzy rules (ANN-GA-Cascades)

ANN-GA-Cascades is the cascade fusion mode of soft computing, which combines ANN with GA. The scheme of ANN-GA-Cascades is shown in Fig. 1.

The algorithm of ANN-GA-Cascades is divided into two steps. The first step is to obtain the fitness function of each cluster or decision attribute by training ANN. The inputs of ANN are the simplest well-logging attribute set which is relevant to the oiliness character and the outputs of ANN are the oiliness cluster (dry layer, water layer, inferiority layer and oil layer). The inputs and outputs are all binary. When the convergence accuracy or the maximal iterative loop is reached, the output function $\psi_k = f(x_i, (WG1)_{ij}, (WG2)_{jk})$ of output node k is obtained, where $f(\cdot)$ is the sigmoid active function and $(WG1)_{ij}$ and $(WG2)_{jk}$ are the weight groups between the input and hidden nodes, and the hidden and output nodes, respectively. ψ_1 , ψ_2 , ψ_3 , and ψ_4 denote the objective function of dry layer, water layer, inferiority layer and oil layer, respectively. The function ψ_k is the objective function corresponding to cluster k and ψ_k is the maximal function. Since the objective function ψ_k is nonlinear and the constraints are binary, it is a nonlinear integer optimization problem. The genetic algorithm (GA) can be used to solve it. Assume that the fitness function is ψ_1 , ψ_2 , ψ_3 , and ψ_4 , respectively, then the best chromosome corresponding to each cluster k is obtained.

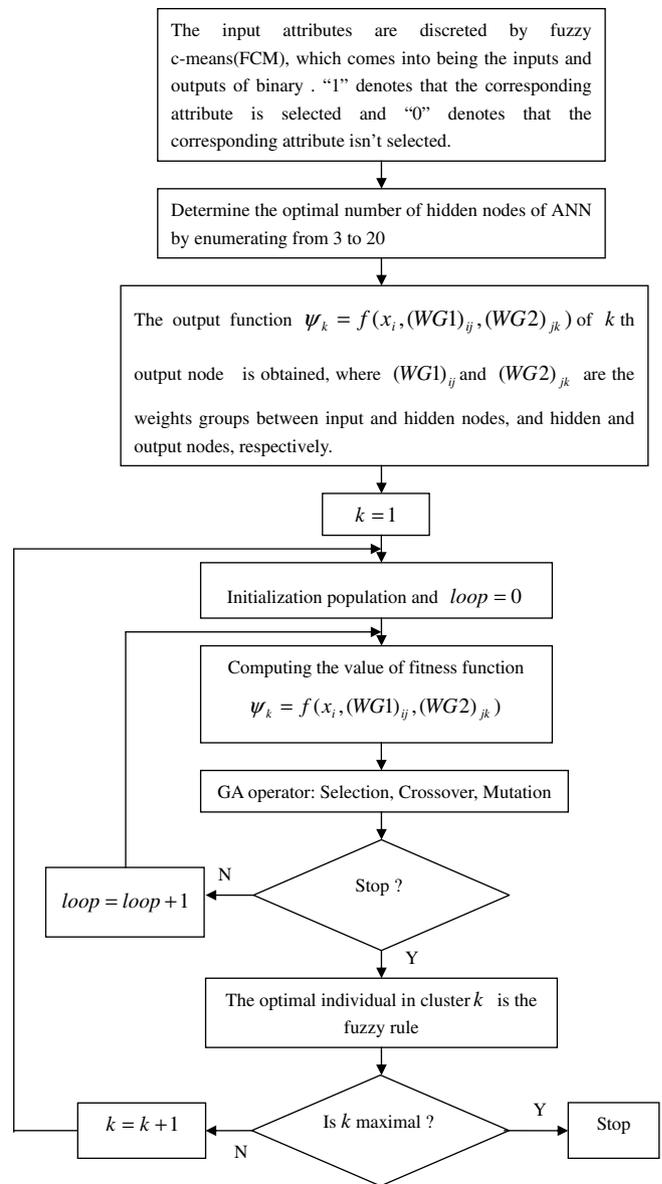


Fig. 1. The scheme of ANN-GA-Cascades.

The best chromosome can be decoded into fuzzy rule. We take the data of oilsk81 as the training data and obtain the fuzzy rules, then take the data of oilsk83 as the testing data.

2.1. Reduction of input logging attributes

From Table 1 and 2, we know that the number of attributes set for recognizing oiliness is six, just as AC, CNL, RT, POR, So and PERM. We can use GA-FCM (Zhu, Su, & Li, 2005) to reduce the attribute set to get the subset which is the optimal and simplest to recognize oiliness. GA-FCM is nesting GA and FCM, in which GA searches each combination of attributes while FCM evaluates each combination by recognizing accuracy obtained by comparing the recognizing result and real result. In this way, we

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