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Application of a fuzzy neural network based on particle swarm optimization in intermittent pumping[1]

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Abstract. In the intermittent pumping, due to the complexity and uncertainty of oil production process, it is difficult to accurately determine the pumping running status, and pumping unit start-stop cannot match the downhole oil quantity change. To more effectively evaluate the pumping running status, this paper presents an improved fuzzy neural network evaluation model. The model uses particle swarm optimization to optimize the membership function and the final output layer connection weights of the fuzzy neural network, improving the fuzzy neural network parameter selection randomness, avoiding falling into local optimal solution and enhancing the accuracy and the convergence speed. By comparison, the improved model has higher accuracy and faster convergence rate. Through field application, it shows the evaluation results of the model are consistent with the actual situation, verifying the feasibility of the model.

Key words. Intermittent pumping, PSO, fuzzy neural network.

1. Introduction

In the oil field exploitation, beam pumping plays a decisive role in oil exploitation machinery because of its simple structure, reliability, practicability and handiness. But on account that beam pumping rated extraction capacity is greater than oil well's actual load and that there are different degrees of empty pumping , it makes electric motor light relatively and its power factor low, and makes pumping backlash increasing and energy waste [1]. If the motor can stop when it works lightly and the oil storing is less, and start up when the oil storing increases to the degree to

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which that the pumping can full pumping continuously, intermittent pumping can be realized, and thus it can save energy, reduce wear, and improve economic benefit. In intermittent pumping, evaluating the running status of pumping, such as accurate judgement of full pumping and empty pumping, is the key to determine the start-stop interval of pumping. However power supply of each well, weight and position of counterbalance, motor power and suspension center's load are different, and these factors are interconnected, which makes it difficult to have a clear criterion to judge the state of full and empty pumping. So how to use limited information to judge operation status of pumping is of practical significance for formulating reasonable intermittent pumping control plan.

At present, intelligent control for pumping has become a hot spot. Among that, neural networks control, fuzzy logic control and expert control are typical control methods. However due to the complexity, randomness and nonlinearity of oil extraction systems, there is not a unified approach so far.

Fuzzy neural network has been widely applied with good approximation ability of nonlinear function and learning capacity. The article proposed rule self-tuning RL fuzzy neural network, and has applied it to the intermittent pumping control with power-saving rate of 30 %. The article [2] proposed a simplified fuzzy neural network intelligent control program and has energy-saving result. The article [3] proposed self-adapting fuzzy control system and has applied it to the energy saving retrofit of pumping oil production successfully. However, it still exists randomness of fuzzy neural network's parameter selecting and local optimal solutions when modeling with fuzzy neural network.

In view of this, this paper improves fuzzy neural network using Particle Swarm Optimization algorithm through combinatorial optimization of center value and width value of membership function and the connection weights of final output layer of the fuzzy neural network. Particle Swarm Optimization algorithm improves fuzzy neural network's learning ability and generalization ability. Through using this for evaluating of operation state and being verified by the actual data, the modified method improves the evaluation model's accuracy and convergence rate.

2. Methodology

Fuzzy neural network is the combination of fuzzy logic and neural network, which has the advantages of reasoning process is easily understood, sample requirement is low, and stronger ability of self-learning. However, when modeling by fuzzy neural network, the relationship between learning ability and generalization ability of fuzzy nervous system is not direct ratio, only when the fuzzy neural network has moderate complexity, it has good generalization ability. Moreover, when parameters of the network front section arbitrarily selected, improper selection will result in the convergence speed of fuzzy neural network slower, and falling into the local optimum [4]. Thus, according to the performance requirements of model, select the best combination values of fuzzy neural network parameters.

In this paper, $T-S$ fuzzy neural network model is divided into five levels, namely input layer, fuzzification layer, fuzzy inference layer, normalization layer and defuzzification layer. The first layer and the second layer represent the predictor of fuzzy rules, namely the input space division of fuzzy systems; the left three parts represent the consequent of fuzzy rules, namely completing fuzzy inference rules of the system.

The input layer is the first layer in graph 1, and its nodes are the entrances of fuzzy information. The input layer transfers the information to the next layer, and each node represents input message $x_i,\ i = 1, 2, ..., n$, respectively. Therefore, the number of input layer nodes depends on the dimension of the input message, $N_1 = n$. There are three input quantities in this paper, namely current I of the pumping unit motor, differential value $\mathrm{d}I/\,\mathrm{d}t$ and integral value $\int I\,\mathrm{d}t$, so that $n = 3$. The second one is the fuzzification layer, where each node represents a language variable value. The layer is used to calculate the membership function of each input component which belongs to the fuzzy set of linguistic variables $\mu_{ij},\ i = 1, 2, ...n,\ j = 1, 2, ...m$. We select the Gaussian function as the membership function that is defined by the formula

$$\mu_{ij} = \exp\left[-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}\right],\ i = 0, 1, 2, ..., n,\ j = 1, 2, ..., m\,. \tag{1}$$

Here, c_{ij} and σ_{ij} represent the center and width of the membership function in this equation, respectively. Symbol n is the dimension of input, m is the number of the fuzzy rules. In this article, we select $n = 3$ and $m = 5$. So the total number of nodes of this layer is $N_2 = n \cdot m = 15$.

The third is fuzzy inference layer, where each node represents a fuzzy rule. The layer is used to match premises of fuzzy rules and calculate fitness value of each rule. This will be normalized by the fourth layer that is the normalization layer. The normalized fitness value is calculated as follows:

$$\alpha_j = \frac{\alpha_j}{\sum_{i=1}^{m} \alpha_i},\ j = 1, 2, ..., m. \tag{2}$$

There are equal numbers of nodes between the third and fourth layers, that is, $N_3 = N_4 {=} \prod_{i=1}^{n} m$ ($n = 3$ and $m = 5$ in this paper), so there are equal node numbers between fuzzy inference and normalization layers, which is 125. The fifth is the output layer, also known as defuzzification layer, which realizes clear calculations in fuzzy neural network as shown in the following expression [5]:

$$y_i = \sum_{j=1}^{m} \omega_{\mathrm{ij}} \overline{\alpha_j},\ i = 1, 2, 3..., r. \tag{3}$$

Here, ω_{ij} represent the connecting weight between the ith output node and jth inference layer node. Symbol r is the number of nodes of the output layer. As there is only one output in this paper, $r = 1$.

By the above analysis, there are two kinds of learning parameters in Fuzzy neural network: one is the central value and width value of membership function, given by c_{ij} and σ_{ij}, respectively; another one is the output weight $omega_{ij}$ in the last layer.

First, the population of particles must be encoded and then the optimization for central values and width values of membership function and the final output layer connection weights of the fuzzy neural network are conducted again and again. The optimization stops until it reaches the prescribed scope of mean square error function and outputs the optimal parameters.

The particle population is composed by n vectors of dimension D. The position vector X of the particle in the population represents the center value c_{ij}, the width value σij of the membership function of the fuzzy neural network, and final output layer connection weights ω_{ij}. Initialization of the particle swarm and updating the velocity and position of the particle is performed according to the following formulae

$$V_{is}^{t+1} = V_{is}^{t} + c_1 r_{1s}^{t}\left(P_{is}^{t} - X_{is}^{t}\right) + c_2 r_{2s}^{t}\left(P_{gs}^{t} - X_{is}^{t}\right) . \tag{4}$$

$$X_{is}^{t+1} = X_{is}^{t} + V_{is}^{t+1} . \tag{5}$$

Here, c_1 and c_2 are learning factors, r_{1s}, r_{2s} are uniform random numbers ranging from zero to one. Symbol V_{is}^{t} is the speed of sth dimension in tth iteration for particle i, X_{is}^{t} is the current position, P_{is}^{t} is the individual optimal position, and P_{gs}^{t} is the global optimal position of sth dimension in tth iterations for the entire population.

In this paper, the output mean square error of the fuzzy neural network is used as the fitness function of the particle swarm algorithm, and the output mean square error function of the fuzzy neural network is expressed as

$$SE = \frac{1}{2k}\sum_{i=1}^{k}\left(y_{di} - y_i\right)^2 , \tag{6}$$

where, y_{di} and y_i represent expected output and actual output, respectively, and K is the total number of the samples.

Parameter optimization of fuzzy neural network: the output mean square error of the fuzzy neural network is used as the fitness function of the particle swarm optimization algorithm. The maximum error is 0.005 and the maximum number of iterations is 800. When the error reaches the specified range or reaches the maximum number of iterations, the optimization stops and network model achieves the best.

3. Result analysis and discussion

Since the oil pumping control system has the characteristics of model uncertainty, highly nonlinear, and the system main equipment is placed underground, the measurable state variable are quite less. The most convenient, reliable and relatively low-cost method determining whether the pumping unit is empty or not is to detect current.

Therefore, the evaluation model established in this paper has three inputs and one output. The inputs include the current I, differential value $\mathrm{d}I/\mathrm{d}t$ and integral value $\int I\,\mathrm{d}t$ of motor of pumping unit, namely the load current, load changes, the load accumulated. The output stands for the levels of pumping unit operating status, that are full pumping, half pumping and empty pumping and the corresponding values are 0,1,2. Table 1 shows input and output data of two representative wells.

Table 1. Data of two wells

time	A				B			
	I	$\mathrm{d}I/\mathrm{d}t$	$\int I\,\mathrm{d}t$	Output	I	$\mathrm{d}I/\mathrm{d}t$	$\int I\,\mathrm{d}t$	Output
1	24	0	1	0	31	0	1	0
2	25	1	2	0	32	2	2	0
3	29	4	4	0	32	0	4	0
4	31	2	7	0	34	2	4	0
5	34	3	9	0	35	1	7	0
6	34	0	12	0	35	0	8	0
7	34	0	14	0	35	0	10	0
……	……	……	……	……	……	……	……	……
28	21	1	38	2	26	-1	35	1
29	19	-2	38	2	26	0	36	2
30	18	-1	38	2	25	-1	36	2
31	18	0	38	2	25	0	37	2
32	18	0	38	2	25	0	37	2

According to the data of Table 1, it can be seen the trends of current, current changes and current accumulation of motor of pumping unit, the running status of the pumping unit could be evaluated in turn.

1. Full pumping phase: After pumping starts, current has increased and current change will be larger and current accumulation will be small, these data show that pumping unit is in "full pumping" state. However, during the downtime to start, oil pump should be filled in a short time as oil flow from the pump back to the oil wells.

2. Stable full pumping phase: After pumping start-up, current I remains stable, current change $\mathrm{d}I/\mathrm{d}t$ is smaller.

3. Half pumping transitional phase: The current decreases slowly and the load of oil pumping reduces since the pump suction capacity is greater than the oil seepage ability of oil well.

4. Empty pumping phase: At oil production later period,the current stabilizes at a lesser extent, current change is small and current integration reaches the maximum, indicating the pumping unit to "empty pumping" [6].

3.1. Network training and evaluation model

1) Sample data: as Table 1 shows, input and output data of two representative wells being given, it is possible to select 32 sets of data in group A as the training sample data for training the model and another 32 sets of data in group B as the testing sample for model testing and inspection. Due to the large differences between the data, data normalization is done beforehand.

2) Network structure: according to the characteristics of current parameters, the first layer has three input variables and their fuzzy division numbers by the second layer are selected as 5, i.e., $m = 5$. Now, the second layer has 15 nodes, and the number of membership functions corresponds to 15. By the second section analysis, the number of nodes in the fuzzy inference layer is same as in the normalized layer and its value is 125. And output layer node number is 1, which can determine the topology of the fuzzy neural network based on PSO for the 3-15-125-125-1 type.

3) Determination of model parameters: the determination of model parameters is done through fuzzy neural network training process. Further parameters adjustment through continuous training of the model, actually the training process is a correction procedure for the parameters.

In this paper, the learning rate of the network is set as $\eta = 0.2$, the maximum number of iterations is set to 800, and the error is set to 0.005. 32 sets of sample data are input for specific training process of the model. First, enter a set of sample data namely data A, the output could be obtained after the gradual spread between the layers, and then calculate the change amount of neurons' weight in each layer of the data A, including $\Delta_{\mathrm{A}}\,\omega$, $\Delta_{\mathrm{A}}\,c$ and $\Delta_{\mathrm{A}}\,\sigma$. Second, repeat the first step process until completing the calculation of all the sample. According to $\Delta\omega = \sum \Delta_{\mathrm{A}}\,\omega$, $\Delta c = \sum \Delta_{\mathrm{A}}\,c$, $\Delta\sigma = \sum \Delta_{\mathrm{A}}\,\sigma$, the change of the connection weights of this round training are calculated, as $\Delta\omega$, Δc, $\Delta\sigma$. Again, according to the output mean square error, the center value and width value of the membership function of network with network connection weights can be adjusted through iteration. If the mean square error of the output is less than the present value or the maximum number of iterations is reached, the iteration stops; otherwise it continues. Thus, the fuzzy neural network evaluation model based on particle swarm optimization is established and it can be used to evaluate the running state of the pumping unit.

3.2. Comparative example simulation and evaluation results

1) Convergence speed comparison

The training for the traditional fuzzy neural network (called FNN) was done with the same sample data and consistent parameters, as the learning rate is $\eta = 0.2$, the maximum number of iterations is set to 800, error is set to 0.005. The FNN model reaches steady state after 583 iterations and the fuzzy neural network model based on particle swarm optimization (referred to the PSO-FNN) after 352 iterations is stabilized. The training error curves are shown in Fig. 1 and 2. Table 2 contains the performance analysis of two kinds of models. From the figures and the table, when the MSE objective value is 0.005, PSO-FNN model can meet the requirements after

352 iterations, which is less 231 iterations than the FNN's. Also the running time is shorter than the latter. Therefore, PSO-FNN model has the advantages of less iteration number and faster convergence speed.

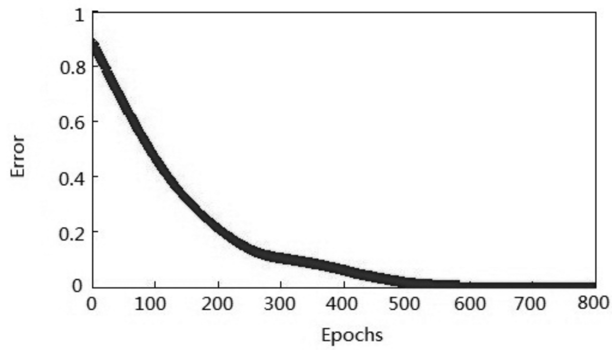

Fig. 1. Mean square error curve of FNN

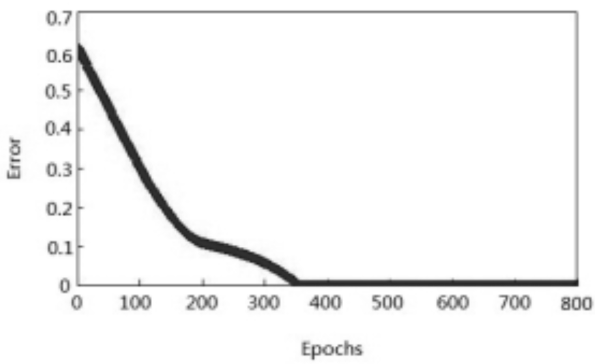

Fig. 2. Mean square error curve of PSO-FNN

Table 2. The performance analysis of two models

Performance	FNN	PSO-FNN
MSE	0.005	0.005
iterations	352	583
run time/s	23.6	37.3

The network is trained and tested by the normalized training sample and test sample data. Using the already trained fuzzy neural network, the model is tested by 32 sets of data of group B in Table 1. In contrast the model actual output to the expected output, the accuracy of the PSO-FNN model could be checked, furthermore, comparing with the output results of the FNN model. Figures 3 and 4 represent the test output results from the FNN model and PSO-FNN model, respectively. Table 3 shows output average error comparison of test data of two models.

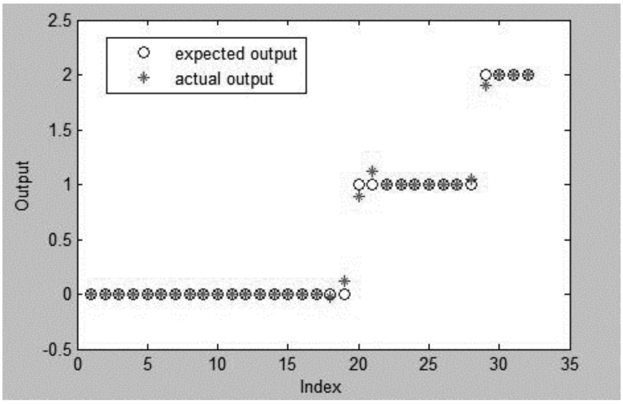

Fig. 3. FNN model test output diagram

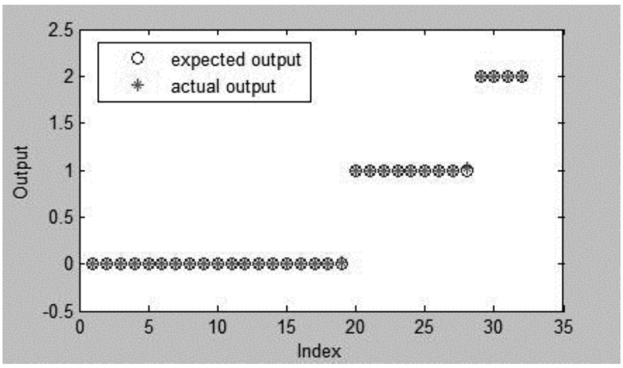

Fig. 4. PSO-FNN model test output diagram

Table 3. Comparison of average errors of two model test data

	FNN	PSO-FNN
Average error	0.0693	0.0083

Comparing the two methods by the above figures and tables, the PSO-FNN has better fitting degree since the actual output of it is very close to the expected output and average error of its test output is 0.0083 contrasting the FNN model's providing 0.0693. It is visible that PSO-FNN model is more accurate.

Comparative verification of the particular cases shows that the fuzzy neural network model based on PSO significantly improved on the convergence rate and accuracy of the evaluation results in contrast to the traditional fuzzy neural network model. The improved pumping state evaluation model has a strong self-learning ability, good generalization ability and precision, so it will be more suitable for the pumping operating status evaluation.

3.3. *Application of pumping unit operating state evaluation model*

A field well is selected as the research object and its basic situation is as follows: pumping speed is $3.52\,\mathrm{min}^{-1}$, the length of stroke is 3 m and pump diameter is 28 mm. Data acquisition time is on 2016/3/9 15:00:23. A stroke of the current acquisition curve is shown in Fig. 5. The full part of the line represents the process of downstroke while the dotted part represents upstroke. The indicator diagram curve of the well is shown in Fig. 6.

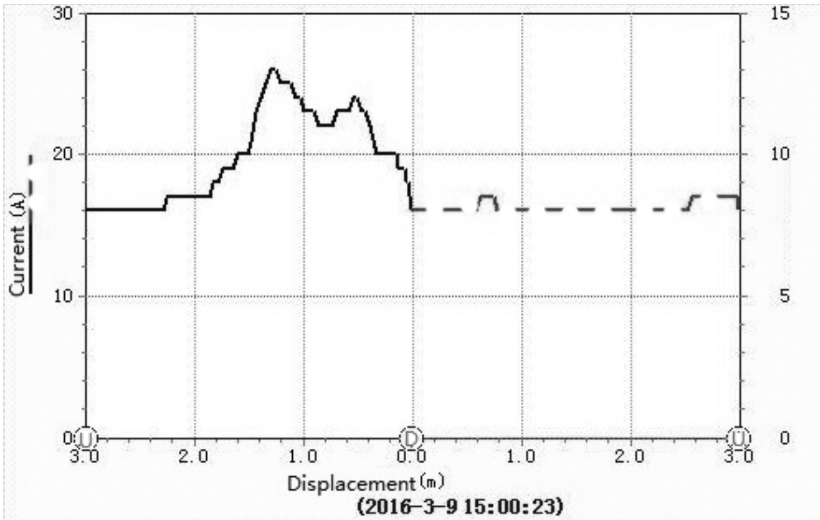

Fig. 5. Current curve in a stroke of the well

Figure 6 shows that the well has a "knife-type" indicator diagram that is typical characteristics for insufficient liquid supply of a well. Therefore, the well is currently in a state of insufficient supply. The results of the evaluation model are consistent with the actual situation. In addition, combined with the data and output evaluation results, the model not only can output the evaluation level, but also can detail evaluation results through analyzing data reflected in the level location. This would contribute to the analysis and accumulation of typical current parameters and provide more help to the decision makers.

According to Table 1, the current parameters of the downhole stroke is selected as the research object with extracting 20 sets of current values from it, then corresponding calculations including current differentiation and current integration allowed forming 20 groups of current data of the well's downhole stroke, as shown in Table 4. Then these current data, as the input of PSO-FNN model established in this paper, are used for pumping unit operation status evaluation and the model's output is shown in Figure 7. The figure shows that there are 16 sets of data in 20

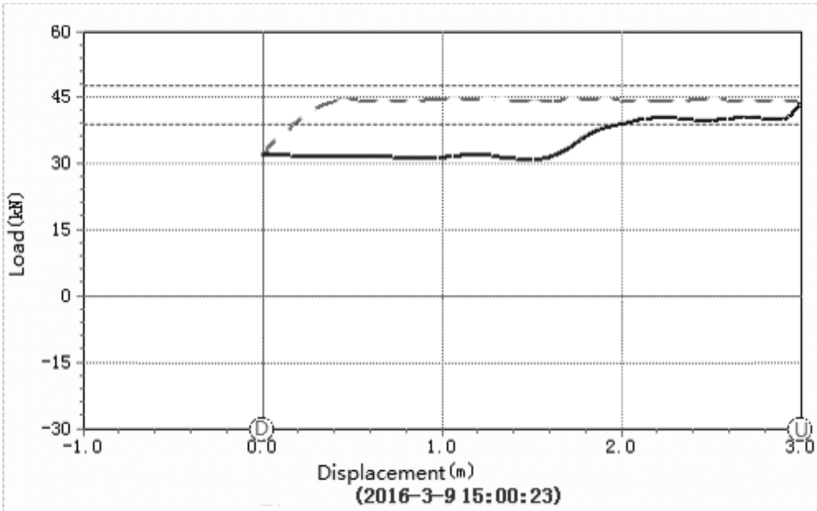

Fig. 6. Indicator diagram in a stroke of the well

groups output representing level 1 which stand for half pumping, while the remaining 4 sets represent level 0 standing for full pumping. Taking into account a certain chronological relationship among the 20 sets of data, the output results of the model can be evaluated according to the overall trend. Therefore, it can be judged that the operating state of the well pumping unit is half pumping, namely, liquid supply deficiencies and intermittent pumping measures need to be taken.

Table 4. Current parameters of the well

time	I	$\mathrm{d}I/\mathrm{d}t$	$\int I\,\mathrm{d}t$	time	I	$\mathrm{d}I/\mathrm{d}t$	$\int I\,\mathrm{d}t$
1	16	0	0	11	24	6	8
2	16	0	0	12	26	4	14
3	16	0	0	13	25	-2	19
4	16	0	0	14	23	-3	24
5	16	0	0	15	22	-2	28
6	17	2	0	16	23	2	32
7	17	0	1	17	24	2	36
8	17	0	1	18	21	-6	40
9	19	3	3	19	20	-1	42
10	20	2	5	20	17	-5	44

4. Conclusion

Improvement of fuzzy neural network uses PSO algorithm through combinatorial optimization of enter value and width value of membership function and the connection weights of final output layer of the fuzzy neural network, enhancing the learning ability and the generalization ability of fuzzy neural network. PSO-FNN model has good generalization ability and has been improved both in the rate of convergence and the accuracy of evaluation results compared with traditional FNN model. And influences of some human factors may be avoided through this model's ability of evaluation and prediction, saving human and material resources and improving the intelligent degree of the running status evaluation of pumping unit. The PSO-FNN model has been applied to an oil well and verified feasibly of the model as evaluation results are consistent with the actual situation. At the same time, detailing evaluation results by the data location reflected in evaluating grade, contributes to analyzing and accumulating typical current parameters and providing arguments for qualitative and quantitative evaluation, which is of guiding significance of decision in the field.

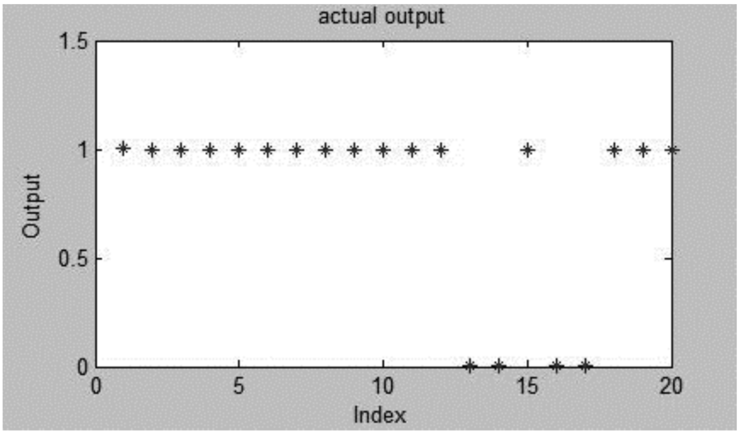

Fig. 7. PSO - FNN model output evaluation results

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