Multi-BP expert system for fault diagnosis of power system

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ABSTRACT

Fault diagnosis and assessment is a crucial and difficult problem for power system. Back propagation neural network expert system (BPES) is an often used method in fault diagnosis. However, with the layer numbers increasing, BPES becomes time consuming and even hard to converge. To solve this problem, we divide the whole networks into many sub-BP groups within a short depth and then propose a novel Multi-BP expert system (MBPES) based method for power system fault diagnosis. We use two real power system data sets to test the effectiveness of MBPES. Experimental results show that MBPES obtains higher accuracy than two commonly used methods.

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1. Introduction

In modern times, power system becomes larger and more complex than before. With its fast development, higher demand for the sustainability and stability of power system is of great requirement. However, some common faults in power system have never been resolved very well and are still hindering the stability of power system, such as transmission fault, network distribution fault, power variable fault (Mizutani et al., 2007). Sometimes, even only one fault could destroy the equipments in power system, and might affect the whole power system. An even worse damage could cause conflagration and casualties, and leading to a huge pecuniary loss. Therefore, it is of great significance to do researches for preventing those faults from power system. And fault diagnosis is a powerful tool to guarantee the safety and reliability of power system.

In power system, transformer is a kind of major equipment and plays an important role in power transmission. It can raise voltage so that power can be transported to the user with less loss. On the other hand, the transformer can reduce power into different voltage levels, which can satisfy variety needs of users. Because of its complex structure and function, transformer is tending to cause fault. Unfortunately, transformer fault is very difficult to predict. Moreover, if some accidents take place in transformer, the whole system has no choice but to stop to check and maintain the equipments. Therefore, it is believed that keeping the transformer running in perfect situation plays a key role in power system diagnosis (Lin and Zeng, 2009). High voltage circuit breaker (over 3 kV) is another important element in power system. It has two main functions, namely controlling and

protecting. Firstly, it decides when and which parts of the power system should be started or stopped according to the requirements; secondly, when some errors occur in power networks or equipments, the high voltage circuit breaker will quickly break off the error parts from power system, so that other parts can work without influence. In other words, high voltage circuit breaker is able to control the normal current in power lines, and to deal with the overload current, short-circuit current and other abnormal current within a limited time. When a mistake happens in high voltage circuit breaker, it will usually expand to other parts of the power system and finally lead to a worse accident.

There are some classical artificial intelligence technologies have been used in power system fault diagnosis, for example: the expert system (Ma et al., 2010), artificial neural networks (El-madany et al., 2011; Zhu et al., 2006; Huang et al., 2002; Karthikeyan et al., 2005), decision tree theory (Qu and Gao, 2008) etc. In recent years, some new theories have been applied in this field, such as data mining (Athanasopoulou and Chatziathanasiou, 2009), fuzzy set theory (Lee et al., 2000; Zhang et al., 2010), rough set theory (Li and Wang, 2010, Li et al., 2011), petri-network (Yang et al., 2004), support vector machine (Eristi and Demir, 2010), multi-agent systems (Zaki et al., 2007), and so on. Li and Liu had performed a comprehensive review of the above-mentioned methods (Li and Liu, 2010). They pointed out that there are some problems in the existing intelligent fault diagnosis expert system theology, such as the difficulty for knowledge gaining and managing, low on-line usage of fault diagnosis, high error rate, poor efficiency of inference process, and so on. Back propagation neural network (BPNN) expert system is an often used method in fault diagnosis. In real applications, BPNN usually has many layers. However, the training time of BPNN will grow exponentially with the layer number increasing. While more serious problem is that it is difficult to converge when BPNN has a large number of layers. Another problem is that the diagnostic accuracy

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of BPNN is still not satisfied. To solve those problems, we propose a so called multi-BP expert system (MBPES) method. In MBPES, the whole BPNN networks are divided into many sub-BP groups within a short depth, saying about 5 layers. In this manner, the consumed training time is greatly reduced and it is easy to achieve the convergence of the training process.

In the experiments, we firstly compare the performance of BPNN with different number layers according to a XOR problem. Numerical results show that when the layer number is more than 6, BPNN is very time consumed and even hard to converge. To test the effectiveness of the proposed MBPES method, it is applied to two real power system data sets, namely that the transformer data set and high voltage circuit breaker data set. Experimental results show that MBPES is very efficient, and it is more accurate than two other compared methods.

2. Back propagation expert system

Back propagation (BP) algorithm is one of the most classical and successful learning methods of feed forward artificial neural network, which is based on gradient descent algorithm. For its success, those feed forward neural networks using BP algorithm are always called BPNNs. Fig. 1 shows an architecture of BPNN model with K hidden layers. There are n nodes in the input layer, which is corresponding to the sample vector's dimension. And the inputs of the input layer are the components of the sample's vector. Denote the node's number of the jth hidden layer as N_j, then the outputs of first hidden layer are

$$Y_j^1 = \frac{1}{1-(\sum_{i=1}^n X_i \cdot w_{ji}^1)} \quad j=1,\dots,N_1 \tag{1}$$

And the outputs of the other hidden layers are

$$Y_j^k = \frac{1}{1-(\sum_i^{N_{k-1}} Y_i^{k-1} \cdot w_{ji}^k)} \quad k=2,\dots,K; \quad j=1,\dots,N_k \tag{2}$$

Suppose the related problem has m expected outputs, then the output layer should have m nodes, and their outputs are

$$Z_j^1 = \frac{1}{1-(\sum_{i=1}^{N_K} Y_i^K \cdot w_{ji}^0)} \quad j=1,\dots,m \tag{3}$$

Here w_{ji} is the weight between the jth node of one layer and the ith node of its former layer. The weights should be trained before application. The training method could be referred to Rumelhart et al. (1986).

BPNN also can be used as an expert system, which is called back propagation expert system (BPES). In BPES, the rules with the form

of IF-THEN in knowledge database are represented by the weights of networks. An example of BPNN expert system is shown as Fig. 2. In the networks, the nodes represented by rectangles are the antecedents or consequents of the rules, while the nodes represented by circles are corresponding to the rules. The initial structure of the networks is generated by rules in knowledge database, as well as the values of the weights. If we could obtain enough known sample data, the weights can be improved by training process, even the topology of the networks might be amended. The training algorithm is the same as that of BPNN.

In BPES networks, each rule creates a 3-layer sub-network. The first layer represents the antecedents of the rule, the second layer represents the transform relationship including only one node, the third layer represents consequent of the rule, also including one node. Therefore, the nesting of different rules may extend the length of the network structure. Unfortunately, it is often the case in the knowledge database. However, when the BPNN networks have more than 5 layers, the training time and iteration number will grow exponentially and even hard to converge. To solve such problem, a called Multi-BP Expert System (MBPES) is proposed in this paper, in which the networks are divided into sub-networks with small scale.

3. Multi-BP expert system (MBPES)

3.1. The structure of MBPES

In a BPNN, a rule is corresponding to a substructure of the networks with 3 layers. Accordingly, 2 and 3 nested rules are corresponding to a substructure with 5 and 7 layers, respectively. Because those BPNN networks with more than 5 layers are difficult to train and even hard to converge, we divide the whole networks into sub-networks with 5 or less layers. Fig. 3 shows the division of a BPNN in serial structure.

However, in real applications, rules are not always nested in serial. For example, the inputs of a rule might be the outputs from other 2 or more rules. For 2 independent rules, the accordingly sub-networks are in parallel. Moreover, the inputs of a rule could come from different rules in different layers. For such a complicated BPNN, we also need to divide it into sub-networks with 5 or less layers, namely that Multi-BP expert system (MBPES). A classical structure of MBPES is depicted as Fig. 4.

3.2. The construction algorithm of MBPES

Given a knowledge base, the structure of the MBPES should be determined firstly. To begin with the construction algorithm of
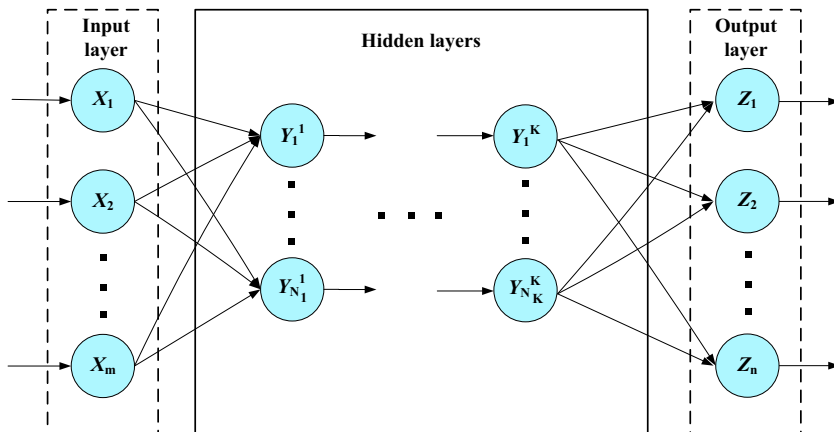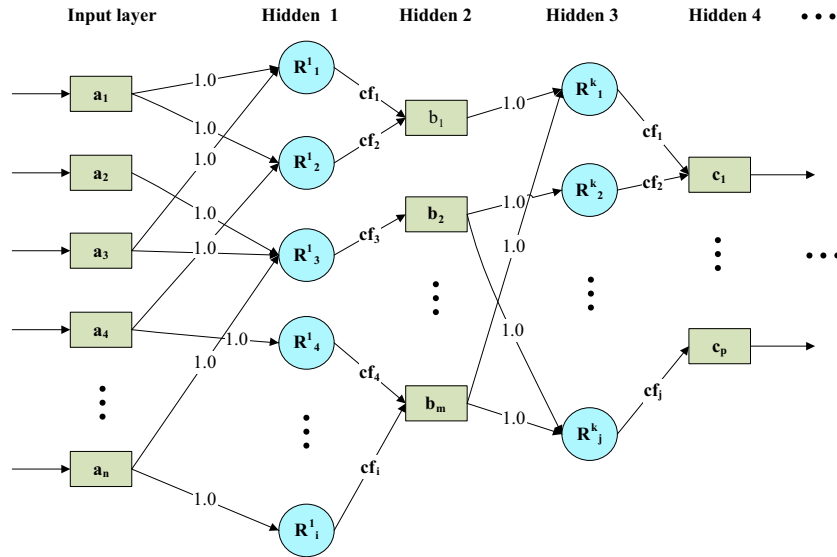

Fig. 1. Architecture of BPNN.
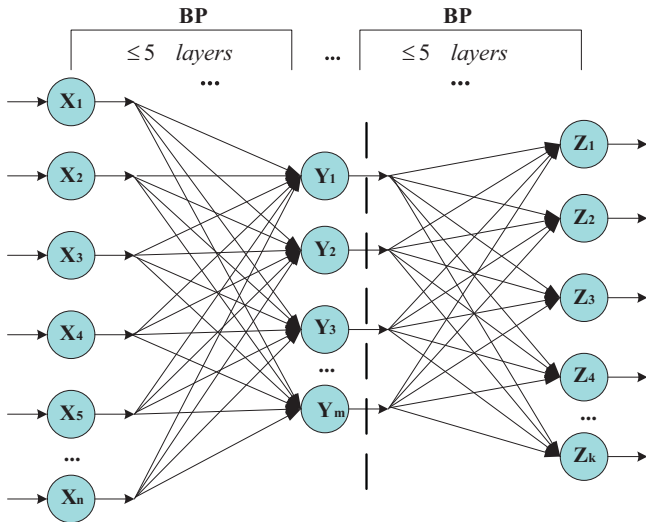
Fig. 2. Architecture of BPES.

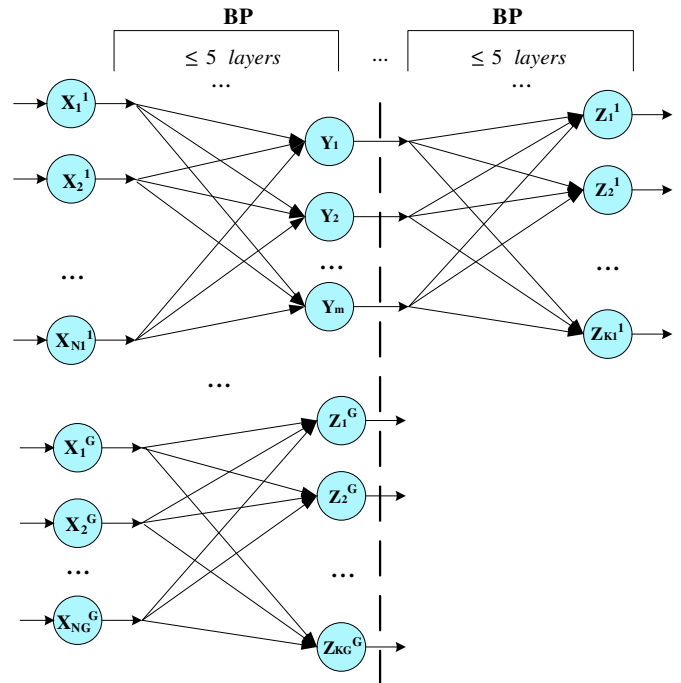**Fig. 3.** Division of a BPNN in serial structure.

Fig. 4. A classical structure of MBPES.

MBPES, we look at how to build up a digraph from only one rule (Shi et al., 2006). Denote an empty digraph as Φ, and assume we have a rule $R1$ as

$R1$: IF a_1 AND a_2 THEN b_1 (0.8)

Then, $R1$ could be input into Φ, and a new digraph D is created which is shown as Fig. 5.

Next, if we have rules which have antecedents or consequents associated with D, they could be added into the digraph. For instance, in Fig. 6 there are seven rules (from $R2$ to $R8$) having related antecedents or consequents to digraph D. Then D can be updated as Fig. 7 shown, which has 5 layers.

However, when more rules are added into digraph, it might exceed 6 layers. Taking aforementioned rules as an example, the antecedents of the following rule $R9$ are associated with D:

$R9$: IF c_1 AND c_2 THEN c_3 (0.8).

But if $R9$ is added into D directly, it will be changed into 7 layers. Therefore it is divided into 2 sub-digraphs according to the 5th layer. It is shown in Fig. 8.

Now considering a knowledge database KD which includes N rules, a MBPES could be built up similarly. Denote R_i is the ith rule in KD ($i=1,2,\dots,N$), D is the digraph, D_k is the kth divided
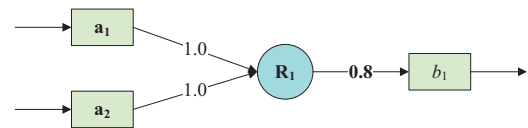

Fig. 5. The digraph generated from $R1$.

sub-digraph ($k=1,2,\dots j$), j is the number of sub-digraphs, L_{Dk} is the layer number of D_k. Then the main steps of the construction algorithm are described as follows:

(1) Initialization: Set $i=1$, $j=1$, $D_1=\Phi$, $D=\{ D_1 \}$;
(2) Determination: If all the rules in KD have been read, namely $i>N$, output MBPES, END the algorithm, else go to step (3);

(3) Input of rule R_i:
(3.1) Search R_i in sub-digraphs.
If $\exists k$, s.t. the antecedents or consequents of R_i are related to sub-digraph D_k, then check if D_k has more than 5 layers. If yes, $j{+}{+}$, create a new sub-digraph D_j, input R_i into D_j, else, input R_i into D_k. go to step (3.3).
(3.2) Create a new sub-digraph for R_i.
If $\forall k$, the antecedents or consequents of R_i are not related to sub-digraph D_k, $j{+}{+}$, create a new sub-digraph D_j, input R_i into D_j, go to step (3.3).
(3.3) $i{+}{+}$, go to step (2).
The flowchart of the algorithm is depicted in Fig. 9.

3.3. The training algorithm of MBPES

The constructed MBPES could be considered as a weighted digraph. However, there are lots of noises in the rules saved in KD. So a training process is necessary to improve the accuracy of the system. By the training process, the weights in digraph are updated according to a real data set, which are more reliable compared to the rules in KD. Even some weights can be deleted and some new ones can be added.

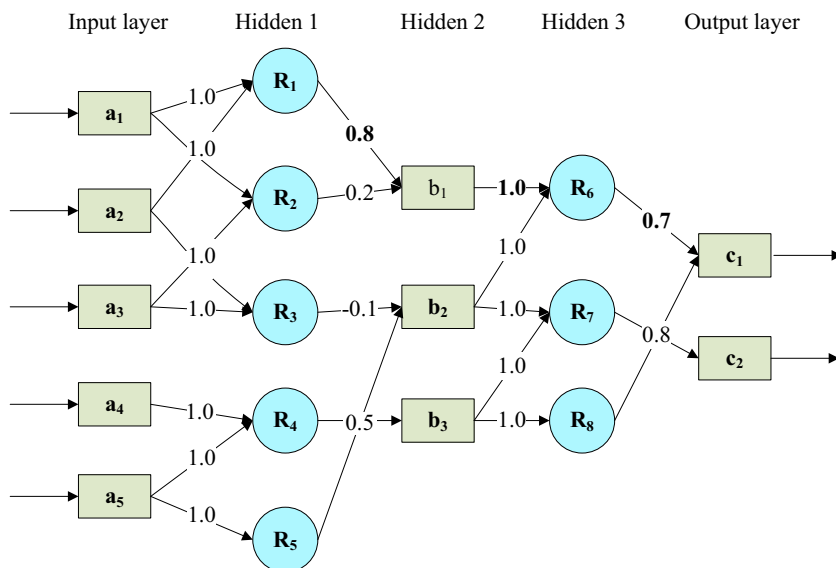| |
|---|
| $R\,2$: IF a_1 AND a_3 THEN b_1 (0.2) |
| $R\,3$: IF a_2 AND a_3 THEN b_2 (0.8) |
| $R\,4$: IF a_4 AND a_5 THEN b_3 (-0.1) |
| $R\,5$: IF a_5 THEN b_2 (0.5) |
| $R\,6$: IF b_1 AND b_2 THEN c_1 (0.7) |
| $R\,7$: IF b_2 AND b_3 THEN c_2 (0.8) |
| $R\,8$: IF b_3 THEN c_1 (0.2) |

Fig. 6. Rules from R2 to R8.

Assume there are J sub-digraphs in MBPES D. Denote D_k as the kth of sub-digraphs, N_k the output number of D_k, T_j^k and Y_j^k the jth expected output and the jth real output of D_k, respectively. Then the main steps of the training algorithm are as follows:

(1) For each sub-digraph D_k ($k=1,2,\dots,J$), define an error function as

$$E_k = \tfrac{1}{2}\sum\nolimits_{j=1}^{N^k}(T_j^k - Y_j^k)^2 \tag{4}$$

(2) According to the basic BP training algorithm, train each sub-digraph D_k.
(2.1.) If E_k reaches a value less than the error threshold E_{thr}, then terminate the training process of D_k, and remove those weights with 0 values.
(2.2.) Else, if E_k could not decrease below to E_{thr} within the max iteration number $N_{\max}$ loops, then add new links between unlinked nodes with 0 weights, and retrain D_k.
(3) When all the sub-digraphs finish the training procedures, update the whole structure of MBPES.

4. Results and analysis

4.1. Comparison for different network layer numbers

To test the performance of BPNNs with different layer number, we take XOR problem as an example. In the experiment, the main parameters are set as follows: the inertial weight α is 0.5, the momentum coefficient η is 0.9, the threshold β is -0.5, and the error threshold E_{thr} is 0.001, respectively. To get the statistical results, each experiment is repeated for 100 times. Numerical results are shown in Table 1 and Fig. 10. From Table 1 and Fig. 8, we can see that the training time is raising with the increasing of BPNN layer's number. On the contrary, the convergence rate is falling in a converse manner. It is noteworthy that there is a steep slope between the layer numbers 5 and 6 for both training time and convergence rate. When the layer number is more than 5, training time for BPNN is increasing exponentially and the convergence rate is decreasing sharply. In fact, that is just the reason we want to divide the BP subgroup within 5 layers.
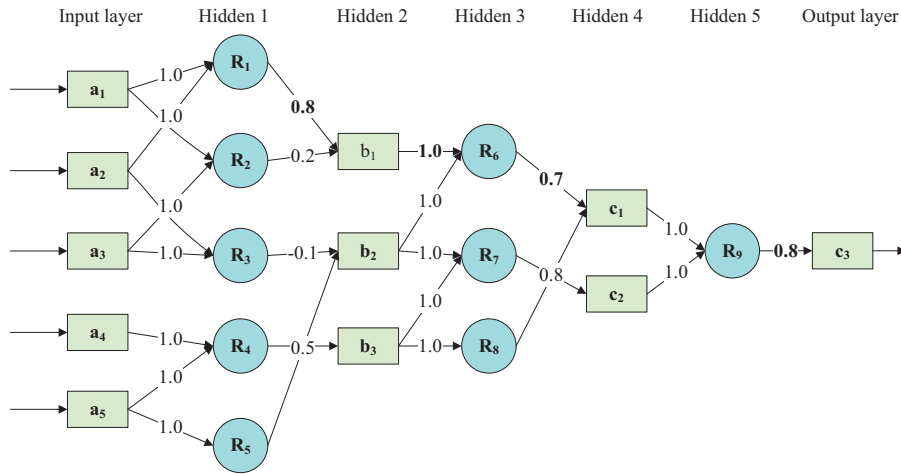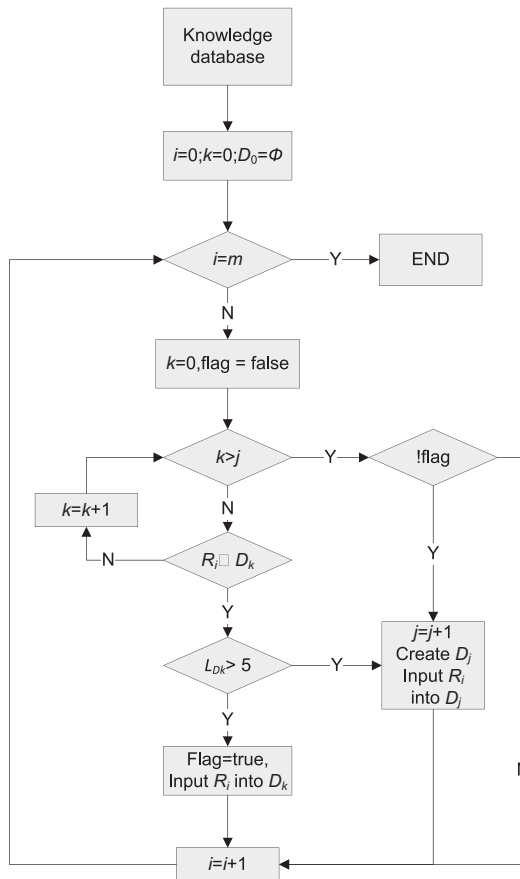

Fig. 7. The Updated digraph D by $R2$ to $R8$.

Fig. 8. The Updated digraph D by $R9$.

Fig. 9. The flowchart of construction algorithm of MBPES.

Fig. 10. training time and convergence.

contains 8 gas acquisition data (in the unit of μL/L), namely H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, CO_2, and HC, together with "Fault type" which indicates the real fault type of the sample. In our experiment, there are five real fault types: final superheater, medium superheater, primary superheater, spark discharge and arc discharge (Wang et al., 2006) etc. For the preprocessing procedure, the values of the eight gas acquisition data are normalized into interval [0,1] using the following equation:

$$\bar{y}_i = \frac{y_i - y_{\min}}{y_{\max} - y_{\min}} \tag{5}$$

where y_i, $y_{\min}$, $y_{\max}$ represent the original i-th sample data, the minimum and maximum values of all of the samples with the same input attribute respectively, and $\bar{y}_i$ indicates the normalized i-th sample data.

Firstly, according to the construction algorithm proposed in Section 3.2, an MBPES structure has been built using the 700 rules which are related to transformer fault diagnose. And then it is updated according to the learning algorithm in Section 3.3. The final topology of MBPES is shown as Fig. 11. It is interesting that our groupment result is highly consistence with the theoretical results in Li (2010) about the relationship between fault type and the partition of gas inputs.

To test the effectiveness of MBPES, it is compared with BPNN and BPES on the prediction results of the 50 test sample data. The comparison results are shown in Table 3. From the table, it could be found that the correct predicted diagnosis record numbers of BPNN, BPES and MBPES are 39, 40 and 43, with the accuracy rates

4.2. Experiment on transformer data

Our experimental data used in this section are the real data from the on-site transformer in an electric power design institute. The rules in knowledge base are provided by the engineers in the institute and arranged by authors. There are more than 1200 knowledge rules, of which more than 700 rules are about transformer fault diagnose. For comparison, BPNN, BPES and our proposed MBPES methods are all applied as the inference engines, respectively. There are 150 sample data in all, 100 of which are set as the training data and the other 50 ones are set as the testing data. The first 15 sample data are shown in Table 2. Each sample
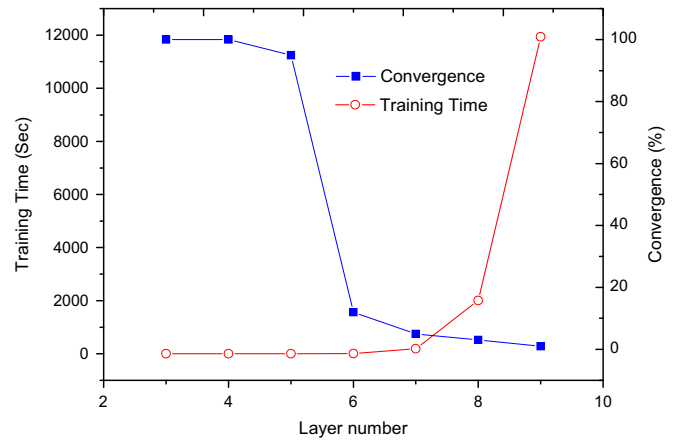
Table 1
XOR BPNN data of experiments.

Layer Number	3	4	5	6	7	8	9
Time (Sec)	0.043	0.272	1.85	8.96	190.65	2000.72	11,935.84
Iteration	5642.25	7914.56	20,143.84	1,340,879.96	3,095,324.14	7,971,254.69	30,326,842.44
Convergence (%)	100	100	95	12	5	3	1

Structure of BPNNs with different layer number: 3 layers:2-4-1; 4 layers: 2-4-3-1; 5 layers: 2-4-3-2-1; 6 layers: 2-4-3-2-2-1; 7 layers: 2-4-3-3-2-2-1; 8 layers: 2-4-3-3-2-2-2-1; 9 layers: 2-4-3-3-3-2-2-2-1.

Table 2
The first 15 data in transformer ($\mu L/L$).

ID	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	CO	CO_2	HC	Fault type
1	0.00	16.18	10.26	63.76	5.27	141.69	2096.60	95.74	Final superheater
2	0.00	15.65	11.99	63.21	6.05	153.05	2284.45	96.90	Final superheater
3	0.00	200.00	222.00	826.00	0.00	84.00	1114.00	1248.00	Final superheater
4	0.00	179.00	189.00	137.00	0.00	108.00	1075.00	1405.00	Primary superheater
5	0.00	59.00	15.90	111.10	0.00	262.20	764.90	186.50	Final superheater
6	3.00	198.00	191.00	701.00	0.00	396.00	2256.00	1093.00	Final superheater
7	4.00	79.00	112.00	312.00	0.00	45.00	4155.00	503.00	Primary superheater
8	5.49	35.89	28.08	156.00	0.00	12.79	304.56	219.97	Final superheater
9	6.50	38.30	15.50	73.60	0.00	120.60	67.40	127.40	Final superheater
10	54.60	7.20	5.00	37.20	7.00	63.00	571.00	116.80	Spark discharge
11	86.13	31.82	8.58	8.52	21.05	564.48	4837.00	678.00	Arc discharge
12	11.70	55.00	111.40	23.60	0.90	308.90	669.30	190.90	primary superheater
13	14.00	221.00	199.00	804.00	0.00	138.00	1193.00	1227.00	Final superheater
14	29.00	26.30	1.80	27.00	82.40	522.90	398.30	344.90	Arc discharge
15	14.6	98	42.2	204.7	0	715.1	1611	344.9	Final superheat
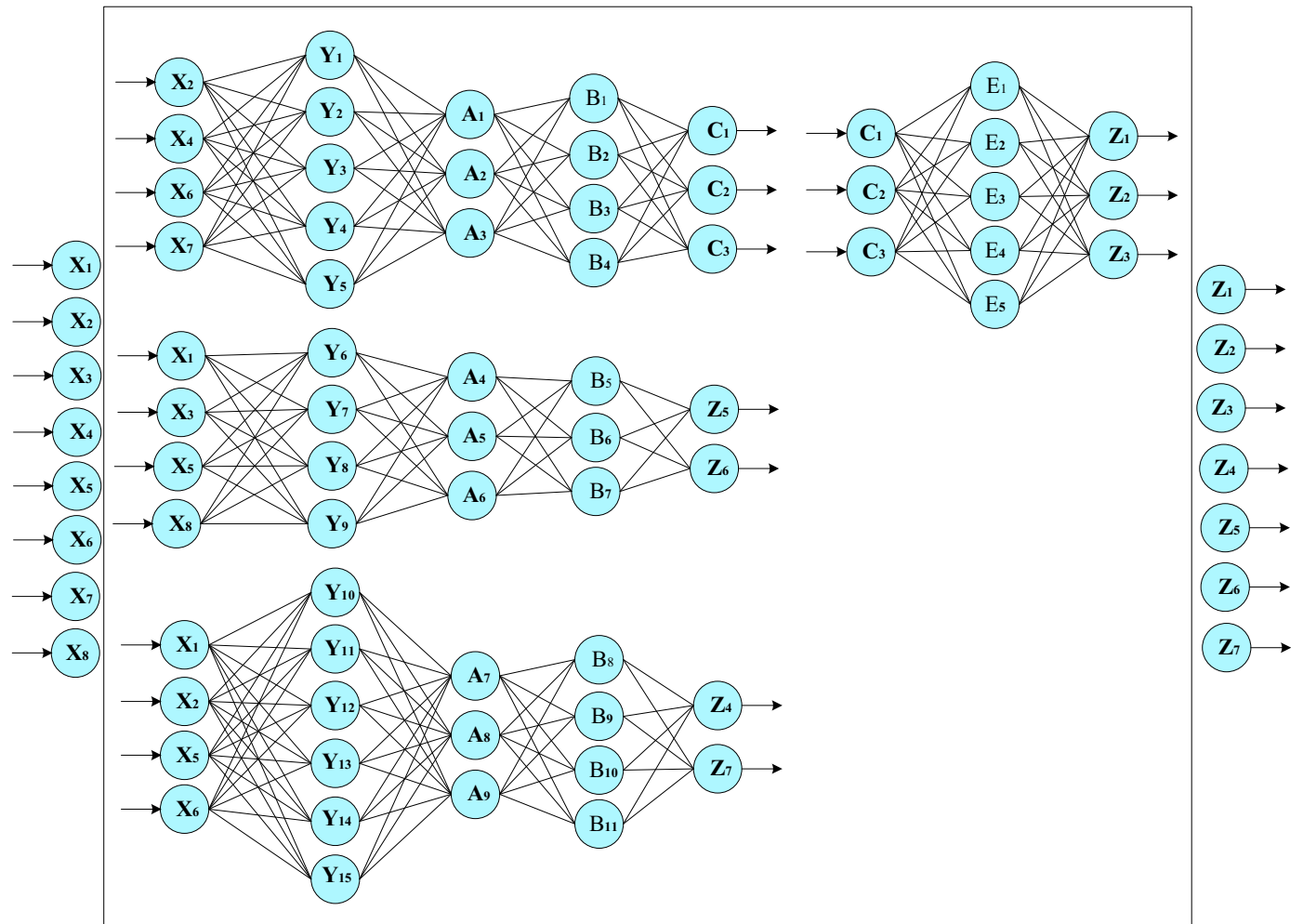
Fig. 11. MBPES topology graph for transformer fault diagnose.

Table 3
Comparison results (I).

ID	BPNN	BPES	Mutli-BP
Accuracy rate	78%	80%	86%

BPNN: training error is 0.001; main parameters: $\alpha = 0.5$, $\beta = -0.5$; structure: 8-16-10-6 BPES: rules available in database: 31; training error 0.001; main parameters $\alpha = 0.5$, $\beta = -0.5$.

Table 4
The first 15 data in high voltage vacuum circuit breaker.

ID	I_1/A	I_2/A	I_3/A	t_1/ms	t_2/ms	t_3/ms	t_4/ms	t_5/ms	T
1	1.61	1.14	2.21	24.5	37.8	43.6	46.7	50.3	ZC
2	1.64	1.16	2.2	24.59	37.78	43.57	46.54	50.35	ZC
3	1.23	0.91	1.81	23.8	36.7	42.3	45.8	50.1	GD
4	1.26	0.95	1.82	23.82	36.84	42.29	45.81	49.97	GD
5	1.61	1.11	2.25	30.1	43.5	49.1	52.4	56.1	HKS
6	1.62	1.08	2.26	30.17	43.47	49.11	52.48	55.99	HKS
7	1.63	1.17	2.21	24.21	37.57	43.25	50.02	54.09	CKS
8	1.62	1.15	2.31	24.2	37.5	43.3	49.9	54.1	CKS
9	1.61	1.13	2.26	24.09	39.75	42.86	45.89	49.79	TD
10	1.64	1.14	2.22	24.15	39.73	42.83	45.94	49.82	TD
11	1.65	1.13	2.23	23.95	37.53	43.35	48.17	52.21	FK
12	1.63	1.16	2.22	23.93	37.47	43.3	48.09	52.09	FK
13	1.62	1.19	2.18	24.36	37.88	43.39	46.59	50.21	ZC
14	1.61	1.15	2.19	23.9	37.49	43.28	48.09	52.19	FK
15	1.22	0.92	1.81	23.76	36.8	42.27	45.77	50.1	GD

of 78%, 80% and 86%, respectively. Obviously, MBPES outperforms the other two compared algorithms. Taking the first record in Table 2 as an example to describe the output of MBPES, the predicted diagnosis result is "final superheater" which is just met the real fault type of the sample. Furthermore, MBPES gives an advice for the fault type as

(1) Please check the wire connector to see whether it is badly contacted and many spots of the iron core touch floor.
(2) Please check the current of iron core touching floor.
(3) Please check the iron core insulation resistance.
(4) Please check DC Resistance.

4.3. Analysis of vacuum circuit breaker experimental data

Similarly as stated in Section 4.2, MBPES is compared with BPNN and BPES in another real data set in this section. The experimental data are from a power plant, which are related to high voltage vacuum circuit breaker. There are 300 rules and 120 sample data in all. 80 of the sample data are used for learning and the other 40 data are used for testing. Table 4 lists the first 15 sample data, each of them contains 3 current data (I_1, I_2 and I_3), 5 time data (t_1, t_2, t_3, t_4 and t_5) and the real fault type (T). Here t_1, t_2, t_3, t_4 and t_5 are five time points, and the current variation within each time range could reflect mechanics transmission system's working performance. I_1, I_2 and I_3 are the current values corresponding to time points t_1, t_2 and t_4, respectively. In this experiment, there are 6 real fault types: running properly (ZC), power in low (GD), Jam in the beginning (HKS), Jam in operation mechanism (CHK), Iron core idle running too long (TD), Auxiliary switch contacts badly (FK) (Lei and Liu, 2010). The same as the above experiment, the values are also normalized according to Eq. (5).

According to the construction algorithm and learning algorithm, we obtain the final MBPES structure. A sub-digraph is shown as Fig. 12. Wang had described that the Jam related faults (HKS and CHK) are relevant to the current values at time points
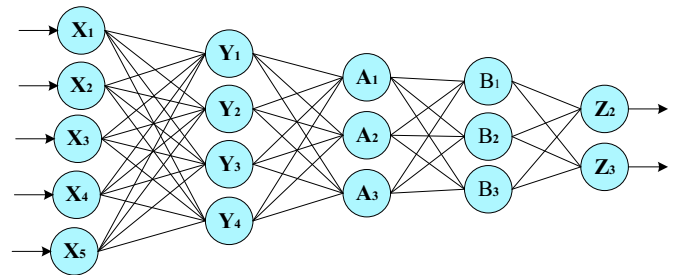

Fig. 12. A sub-digraph of MBPES for high voltage breaker fault data.

Table 5
Comparison results (II).

ID	BPNN	BPES	Mutli-BP
Accuracy rate	80%	82.5%	90%

BPNN: training error is 0.001; main parameters: $\alpha = 0.5$, $\beta = -0.5$; structure: 8-16-10-6 BPES: rules available in database: 19; training error 0.001; main parameters $\alpha = 0.5$, $\beta = -0.5$.

t_1 and t_2 (Wang, 2008). Analyzed the inputs and the outputs of the sub-digraph in Fig. 12, we could find that it is highly concordant with Wang's conclusion.

The comparison results of MBPES, BPNN and BPES are shown in Table 5. The accuracy rates of BPNN, BPES and MBPES are 80%, 82.5% and 90%, respectively. MBPES is also better than the other two compared algorithms. Taking the first record in Table 4 as an example, the predicted diagnosis result is "Auxiliary switch contacts badly (FK)", the same with the real fault type of the sample. And an advice for the fault type is given as

(1) Please check all the possible leaking points and block them.
(2) Please install sealing sleeve in the output link.
(3) Please open the heating and drive wave device in the box.

5. Conclusions

In this paper, facing the real data in transformer and high voltage breaker, with serial, parallel and hybrid grouping algorithm, we proposed two typical new Multi-BP networks. Moreover, they successfully solved the problem of low convergence speed caused by the large number of network layers and also greatly increased the speed of diagnosis. Furthermore, by the comparison with BPNN and BPES, we can see that the results from Multi-BP are more accurate. Using multi-BP network to diagnosis power system, not only can we diagnose the transformer online and offline, but also the system will give us the diagnosis advice quickly.

References

Athanasopoulou, C., Chatziathanasiou, V., 2009. Intelligent system for identification and replacement of faulty sensor measurements in thermal power plants. Expert Syst. Appl. 36 (5), 8750–8757.

El-madany, H.T., Fahmy, F.H., El-Rahman, N.M.A., Dorrah, H.T., 2011. Spacecraft power system controller based on neural network. Acta Astronaut. 69 (7–8), 650–657.

Eristi, H., Demir, Y., 2010. A new algorithm for automatic classification of power quality events based on wavelet transform and SVM. Expert Syst. Appl. 37 (6), 4094–4102.

Huang, Y.C., Yang, H.T., Huang, K.Y., 2002. Abductive network model-based diagnosis system for power transformer incipient fault detection. IEE Proc. Gener. Transm. Distrib. 149 (3), 326–330.

Karthikeyan, B., Gopal, S., Vimala, M., 2005. Conception of complex probabilistic neural network system for classification of partial discharge patterns using multifarious inputs. Expert Syst. Appl. 29, 953–963.

Lee, H.J., Park, D.Y., Ahn, B.S., Park, Y.M., Park, J.K., Venkata, S.S., 2000. A fuzzy expert system for the integrated fault diagnosis. IEEE Trans. Power Del. 15 (2), 833–838.

Lei, H.Y., Liu, J.G., 2010. Common fault and disposal methods of vacuum circuit breaker. Econ. Res. Guide 12, 205–254.

Li, C., 2010. Research of Power Transformer Fault Diagnosis System. Shanghai University of Electric Power 6–8.

Li, J.R., Wang, Q.H., 2010. A rough set based data mining approach for house of quality analysis. Int. J. Prod. Res. 48 (7), 2095–2107.

Li, Q., Li, Z.B., Zhang, Q., 2011. Research of power transformer fault diagnosis system based on rough sets and Bayesian networks. Adv. Mater. Res. 320, 524–529.

Li, Z.H., Liu, M.K., 2010. Review of intelligence fault diagnosis in power system. Electr. Eng. 8, 21–24.

Lin, Y.X., Zeng, Q.J., 2009. Development of on-line monitoring system for high voltage vacuum circuit breaker. Electron. Des. Eng. 17 (12), 21–23.

Ma, D.Y., Sun, C., Li, Z.H.X., Guan, R.C., Liang, Y.C., 2010. Uncertain management in rule-based power system using object-oriented design. In: Proceedings of the 3rd International Conference on Power Electronics and Intelligent Transportation System (PEITS 2010), 363–366.

Mizutani, Y., Takahashi, T., Ito, T., 2007. Lifetime evaluation method for pole transformer based on transient temperature analysis. IEEE Trans. Power Energy 127 (5), 653–658.

Qu, Z.Y., Gao, Y.F., Nie, X., 2008. Network fault diagnoses expert system model based on decision tree. Comput. Eng. 34 (22), 215–217.

Rumelhart, D.E., Hinton, G.E., Williams, R.J., 1986. Learning representations by back-propagating errors. Nature 323 (6088), 533–536.

Shi, Y., Qiu, T., Chen, B.Z., 2006. Fault analysis using process signed directed graph model. Chem. Ind. Eng. Prog. 25 (12), 1484–1488.

Wang, J., Liu, J.X., Wu, L.Z., 2006. Fault forecast of the transformer using new theory of grey system. In: Proceedings of the International Conference on Electricity Distribution (CICED 2006), 20, 340–345.

Wang, N., 2008. Study on Fault Diagnosis of High Voltage Circuit Breaker Based on Neural Network Expert System. Henan University 37–40.

Yang, B.S., Jeong, S.K., Oh, Y.M., Tan, A.C., 2004. Case-based reasoning system with Petri nets for induction motor fault diagnosis. Expert Syst. Appl. 27 (2), 301–311.

Zaki, O., Brown, K., Fletcher, J., Lane, D., 2007. Detecting faults in heterogeneous and dynamic systems using DSP and an agent-based architecture. Eng. Appl. Artif. Intell. 20 (8), 1112–1124.

Zhang, L.L., Li, P., Wang, T.T., Wang, H., 2010. Research of fault diagnosis based on fuzzy neutral network to power transformer. Ind. Instrum. Autom. 5, 3–5.

Zhu, Y.L., Huo, L.M., Lu, J.L., 2006. Bayesian networks-based approach for power systems fault diagnosis. IEEE Trans. Power Del. 21 (2), 634–639.