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Research Article

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Polymerizer fault diagnosis algorithm based on improved the GA-LMBP

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ABSTRACT

Aiming at the PVC production process is complex, the large critical devices polymerizer running need to constantly monitor the characteristics, performance monitoring and fault diagnosis polymerizer for the large PVC batch production process. First of all, for the lack of standard LMBP algorithm, the LMBP neural network algorithm is improved; Secondly, based on the genetic algorithm (GA) and improved LMBP algorithm that based on the GA-improved a LMBP Polymerizer device fault diagnosis algorithm is proposed; improved LMBP algorithm and genetic algorithm (GA) combined algorithm is applied to the study of fault diagnosis polymerizer. Finally, Combined with polymerizer industrial field history data set to carry out fault diagnosis simulation, results show the mentioned GA-improved LMBP fault diagnosis method. is effectiveness.

Keywords: Polymerizer, Fault Diagnosis, LMBP neural network, Genetic algorithm (GA)

INTRODUCTION

PVC production process is complex, production safety and product quality indicators of requirements is high. The main raw material for polyvinyl chloride production process is a vinyl chloride monomer (VCM), generated by the polymerization kettle After the reaction of PVC products. The polymerizer is the key equipment of PVC production unit, vinyl chloride in polymerization occur the polymerizer reaction of PVC, the polymerizer stability running directly related to the health of PVC production unit. Motor, speed reducer and machine closure is ensureded to the normal operation of key equipment polymerizer device. Once their malfunction will be a serious loss to bring to production. Therefore, early diagnosis the polymerizer fault type and the reason, can avoid polymerizer parking caused huge economic losses, improve the PVC product quality, reduce production costs has important practical significance.

In recent years, for the polymerizer fault diagnosis algorithm, many foreign scholars have proposed rough set neural network fault diagnosis method [1-3], The rough set method as neural network lead system, simplify the complexity of the neural network system, and improve the precision and efficiency of fault diagnosis. Many domestic scholars proposed reduction based on improved discernibility matrix ropperties polymerizer Rough Set - Neural network fault diagnosis [4-6], or the BP neural network expert system fault diagnosis [7-9], and principal component analysis in the polymerization production process fault monitoring and diagnosis [10-11].

The traditional theory of BP algorithm of convergence is slow and that is easy to fall into local minimum value of the shortcomings, it is difficult to determine the number of hidden layers and hidden layer nodes. Improved LMBP

algorithm is applied to the polymerizer fault diagnosis, at the same time using a genetic algorithm (GA) to optimize the improved LMBP neural network, select optimal weights and thresholds. Because the genetic algorithm in every iteration of the evolutionary process is competitive gene retention, which means that the result of genetic algorithm is in search of the evaluation function of the sense of the optimal value.

Therefore, the paper proposes a combination based on the improved LMBP neural network with GA polymerizer failure ddiagnostic algorithms. First, the right value and the offset value of the LMBP algorithm incremental

calculation method will be improved, G^{-1} moved to the left-hand side of the inverse matrix, Solving equations with LU decomposition method; And then, with a variable step size instead of a fixed step factor, which is avoid falling into the local minimum value, so the calculation is greatly reduced. LMBP neural networks of the proposed improvements combined with GA algorithms, combined with the industrial field history data polymerizer fault diagnosis, and effectively improve the accuracy of fault diagnosis and diagnosis efficiency.

THE LMBP ALGORITHM OF IMPROVED

STANDARD LMBP ALGORITHM Error objective function

$$F(x) = \sum_{j=1}^{q} \sum_{i=1}^{n} e_{ij}^{2} = \sum_{i=1}^{N} v_{i}^{2}(x)$$
(1)

Where

 $e_{ij} = t_{ij} - y_{ij}$ (2) is the network error vector.

 $v_i(x)$ is the error vector. By Newton's method is

$$x_{k+1} = x_{k} - \left(\nabla^{2} f(x_{k})\right)^{-1} \nabla f(x_{k})$$
(3)

Then

$$\Delta x = -\left[\nabla F^{2}(x)\right]^{-1} \nabla F(x)_{(4)}$$

Newton method has the advantages of rapid convergence, because each iteration of the calculation can not be guaranteed the Hessian matrix $\nabla F^2(x)$ are reversible, Available $J^T(x)J(x)+S(x)$ approximation instead $\nabla F^2(x)$, J(x), where e(x) is the Jacobian (Jacobian) matrix. Hession matrix

$$S(x) = \sum_{i=1}^{N} e_i(x) \nabla^2 e_i(x)$$
(5)
$$J(x) = \begin{vmatrix} \frac{\partial e_1(x)}{\partial x_1} & \cdots & \frac{\partial e_1(x)}{\partial x_n} \\ \frac{\partial e_2(x)}{\partial x_1} & \cdots & \frac{\partial e_2(x)}{\partial x_n} \\ \vdots \\ \frac{\partial e_n(x)}{\partial x_1} & \cdots & \frac{\partial e_n(x)}{\partial x_n} \end{vmatrix}$$
(6)

It can be shown $\nabla F(x) = J^T(x)e(x)_{(7)}$

When the solution near the extreme points S(x) = 0 (8) Then

$$\Delta(x) = -\left[J^{T}(x)J(x)\right]^{-1}J^{T}(x)e(x) \tag{9}$$

Formula to be improved, so that it only contains the Gauss - Newton method and a mixed form of the gradient descent method. The formula for

$$\Delta(x) = -\left[J^{T}(x)J(x) + IU\right]^{-1}J^{T}(x)e(x)$$
(10)

Where *I* is the unit matrix, *U* is a proportionality factor, If *U* is close to zero, compared with the Gauss - Newton method, If *U* value is large, similar to the gradient descent method $\Delta x \approx -\nabla F(x)/2U$, The usual adjustment strategy algorithm starts *U* that take a small positive value, If a step does not be reduced the error mesh value of the function F(x), *U* is multiplied by a stepping factor greater than 1 θ , that is $U = U\theta$, If a step produces a smaller F(x), *U* in the next step divided by θ , that is $U = U/\theta$.

THE LMBP ALGORITHM OF IMPROVED

LMBP algorithm to conduct in-depth research, involving matrix $\begin{bmatrix} J^T J + IU \end{bmatrix}^{-1}$ is found to affect its convergence, Matrix inversion, eliminating time-consuming by using LU decomposition is greatly reduced LMBP amount of calculation. Can be

$$A = \left[J^T J + IU\right]^{-1} (11)$$

 $-\Delta x = x_{(12)}$ $J^{T}e = b_{(13)}$

Then (9) can be replaced by

 $Ax = b_{(14)}$

Can take advantage of symmetric triangular decomposition LU direct decomposition of A.And Ax = b, the problem is equivalent to the calculated

$$A = LU (15)$$

. According to
$$Ly = b (16)$$

There
$$Ux = y (17)$$

Can be obtained x.

 Δx used LU decomposition to solve without require inverse matrix, Just $n^3/3$ times multiplication and division, The operation speed can be increased more than three times. Due to the reduction of the number operations, not only the Δx in order to save computation time, but also to reduce rounding errors, Therefore, this improvement makes a value calculated more accurately.

Happens in the actual calculation, with the increase of U of small step, resulting in one iteration cycle required in small steps in the cycle several times and spent a very long time to end. In order to solve this problem, the original fixed value of θ is designed to be variable step size, i.e. the step length factor θ is a variable amount. Variable step size formula is defined as

 $\theta' = 2^{k-\alpha} \theta_{(18)}$

Where k is the only enter this step the number of small cycles, $\alpha \in [0,1]$ for the adjustment variable. If a step does not reduce the value of the error mesh function F(x) is multiplied by a new stepping factor $\theta', v = v\theta'$. If a step produces a smaller F(x), then in the next stepping factor θ' divided by the new. That $U = U / \theta'$.

GA-IMPROVED LMBP ALGORITHM

GA-IMPROVED LMBP OPTIMIZATION ALGORITHM STEPS

The genetic algorithm (GA) is a simulation of Darwin's genetic selection and the natural selection process of biological evolution calculation model, it is first proposed in 1975 by the United States executive root (Michigan) University J.Holland professor, has a strong genetic algorithms macro-search capability and global optimization performance[13].

LMBP neural network structure, the choice of initial connection weights and thresholds of the network training performance is good or bad for a great impact, but can not be accurately obtained, for this feature, this paper uses a genetic algorithm neural network weights and valve values to be optimized.

A combination of genetic algorithm and improved LMBP algorithm and training weights and thresholds of the neural network using genetic algorithm to find narrow your search using improved LMBP network to the exact solution can reach a global find and fast efficiency purposes.

Has a three-layer BP network, I_i is the output of the j-th node of the input layer, H_i is the output of the i-th node in the hidden layer. O_i is the output of the i-th node in the output layer; WIH_{ij} is the i-th node and the j th hidden layer node in the input layer connection weights; WHO_{ji} is the j-th node in the hidden layer and output layer connection weights of the i-th node.

The genetic algorithm learning improved BP network, follow these steps:

() Initial population p, including cross-scale crossover probability pc and mutation probability pm, As well as any one of WH_{ij} and WHO_{μ} initialization; In the encoding, using the real number coding, the initial population value of 30.

() Calculated for each individual evaluation function, and sort. Press-probability values.

$$P_s = f_i / \sum_{i=1}^N f_i \tag{19}$$

Select network of individuals, where f_i is the individual i with the real value, Available to measure the sum of squared errors E.

$$f_i = 1/E(i)_{(20)}$$

$$E(i) = \sum_{p} \sum_{k} (V_{k} - T_{k})^{2}$$
(21)

Where $i = 1, \dots, N$ represents chromosome; $k = 1, \dots, 4$ is the output layer nodes; s is the number of learning samples; T_k for teachers signal.

() The probability pc the individual G_i and G_{i+1} crossover operator to produce new individuals $G_i^{'}$ and $G_{i+1}^{'}$ of no cross individuals directly copied.

() Using probability pm mutation produce G_i new individuals G'_i of.

() New individuals into the population p, and calculate the new evaluation function of the individual.

() If you find a satisfactory individual ends, otherwise go to (III). Achieve the required performance; the decoder can be obtained with the best individual in the final population optimized network connection weights.

GA- IMPROVED SIMULATION OF LMBP ALGORITHM

The fault diagnosis system of this article is based to polymerizer a large chemical group 70 M3, for example, the analysis of the measured data polymerizer fault monitoring system. The polymerizer failure include motor failure reducer failure Mechanical seal failure and mechanical seal failure. Decision table, select S1, S2, S3, S4, S5, S6, S7, S8, conditional attributes corresponding failure signs, Namely: water flow seal polymerization temperature (° C), polymerization reaction pressure (MPa), and stirred for current (A), Water flow seal((m3/h), the jacket flow (m3/h), the cooling water temperature (° C), cooling water, water pressure (Mpa)outlet shutter temperature (° C), the corresponding variables for the a, b, c, d, e, f, g, h. Typical LMBP neural network for the polymerizer fault diagnosis system in this article, the input layer nodes 6, the number of nodes of the output layer 4, and 10 experiments after

select hidden layer nodes. The polymerizer fault diagnosis LMBP neural network structure for N (6,10,4).

Sampla(II)	Historical datum of polymerizer										
Sample(U)	a, S1	b, S2	c, S3	d, S4	e, S5	f, S6	g, S7	h, S8			
1	54.78	0.788	119.1	473.0	0.2	10.6	0.66	23.72			
2	55.17	0.815	124.6	521.3	0.2	10.6	0.66	24.05			
3	56.42	0.817	129.3	510.5	0.2	10.9	0.68	24.73			
4	56.13	0.810	130.2	515.6	0.2	11.16	0.64	23.19			
5	56.31	0.819	138.9	515.4	7.13	11.38	0.69	25.29			
÷	:	÷	÷	÷	÷	÷	÷	÷			
50	56.21	0.761	155.3	499.8	56.3	21.72	0.60	26.44			

Table 1 Historical data of Polymerizer

Samela(II)	Historical datum of polymerizer										
Sample(U)	a, S1	b, S2	c, S3	d, S4	e, S5	f, S6	g, S7	h, S8			
1	54.78	0.788	119.1	473.0	0.2	10.6	0.66	23.72			
2	55.17	0.815	124.6	521.3	0.2	10.6	0.66	24.05			
3	56.42	0.817	129.3	510.5	0.2	10.9	0.68	24.73			
4	56.13	0.810	130.2	515.6	0.2	11.16	0.64	23.19			
5	56.31	0.819	138.9	515.4	7.13	11.38	0.69	25.29			
÷	÷	÷	÷	÷	÷	÷	÷	÷			
40	56.52	0.816	147.6	473.6	99.74	17.30	0.72	25.29			

Table 2 Traing sample data se

Comm1a(II)			Histori	cal datun	n of polyr	nerizer		
Sample(U)	a, S1	b, S2	c, S3	d, S4	e, S5	f, S6	g, S7	h, S8
41	63.52	1.320	150.6	508.3	70.89	13.60	0.69	24.19
42	56.55	0.820	141.2	513.2	74.22	13.96	0.72	23.86
43	56.50	0.818	175.6	514.3	78.54	14.50	0.69	23.76
44	56.54	0.817	159.9	510.5	78.54	14.96	0.68	28.50
45	56.52	0.816	153.6	508.4	73.15	16.07	0.65	24.30
÷	÷	÷	÷	÷	÷	÷	÷	÷
50	56.21	0.761	155.3	499.8	56.3	21.72	0.60	26.44

Table 3 Testing sample data set

Improved LMBP In order to compare the performance of the algorithm, simulation LMBP algorithm for standard and improved LMBP algorithm, GA-LMBP algorithm and the GA-improved LMBP comparison.

(i) The LMBP algorithm, improved with the preparation of their own Mytrainlm subroutine training times net.epochs = 1000, the training goals net.goal = 0.0001, learning rate LP.lr = 0.1.



Figure 1 Improved LMBP algorithm convergence times

(ii) GA-improved the the LMBP algorithm for (population size NIND = 40, hereditary algebra MAXGEIN = 50 individual length PRECI = 10, crossover probability pc = 0.7, mutation probability pm = 0.01).



Figure2 The LMBP algorithm in GA-improvement convergence Views

Can be summed up by the following Table 4: the four improved LMBP algorithm in standard LMBP algorithm the number of iterations is 21, the error is 0.0012057, is most unsatisfactory. Iteration of the GA-improved LMBP algorithm 11 times while the error is only 0.00036841 ideal result, training in the fastest, most accurate polymerizer fault diagnosis.

Table 4 Calculation times and Training error of four kinds of ameliorated BP algorithm

ImprovedBP Algorithm	LMBP algorithm	Improved LMBP algorithm	GA-LMBP algorithm	GA-improvedLMBP algorithm
The number of iterations	21	16	17	11
Training error	0.0012057	0.00090064	0.00088492	0.00036841

RESEARCH ON FAULT DIAGNOSIS ALGORITHM OF POLYMERIZATION KETTLE

Research on fault diagnosis Algorithm for Large polymerization kettle, fault code type is defined. The corresponding polymerizer five state based on LMBP Neural Network output codes are: normal running (0000), Motor failure (0001), Mechanical seal failure (0010), gear box failure (0100), machine component failure (1000). By GA-LMBP neural network fault diagnosis tests on polymerization kettle, first select the table that corresponds to 3 of the 10 sets of data, or 80 per cent sampled-data as a test sample, the simulation results as shown in figure 4, train number of steps is 11, the error is 0.00036841, the target error of 10-4.Fault diagnosis in table 5, this time fault diagnosis accuracy rate of 100.

Table 5 troubleshooting results

Test sample	1	2	3	4	5	6	7	8	9	10
	0.9963	0.0000	0.0000	0.0000	0.0012	0.0000	0.2000	0.0000	0.0000	0.0000
DD output	0.0561	0.0000	0.0021	0.0000	0.0000	0.0000	0.0000	0.9826	0.0102	0.0210
BP output	0.0070	0.0011	0.0000	0.9745	0.0011	0.0000	0.0000	0.0000	0.9542	0.0000
	0.0000	0.0000	0.9802	0.0000	0.0000	0.0106	0.0000	0.0000	0.0000	0.0000
Fault Code	$1\ 0\ 0\ 0$	0000	0001	0010	0000	0000	0000	0100	0010	0000
Diagnosis	Machina component		Matan	Mechanical seal		Normal	Normal	Gear	Gear	
Diagnosis	foilure	Normal	foilume		Normal			box	box	Normal
type	Tallure	Tan	Tanure	Tanure				failure	failure	

10 groups of data from historical databases and select troubleshooting, diagnostic results as shown in table 6, s7 the 7th set of data should be the normal operation of the data, diagnostic results show 0100, show that gear failure, the results of the 7th set of data is in error. Therefore, the diagnostic accuracy of 90.

	rable o troubleshooting results										
Test sample	1	2	3	4	5	6	7	8	9	10	
BP output	0.0000 0.0021 0.0000 0.0000	0.0000 0.0000 0.0011 0.0000	0.0000 0.0001 0.0000 0.9617	0.0000 0.0000 0.9065 0.0000	0.9716 0.0000 0.0000 0.0020	0.0000 0.0000 0.0000 0.0100	0.0000 0.9210 0.0000 0.0000	0.0000 0.9887 0.0000 0.0000	0.9614 0.0000 0.0000 0.0000	0.0000 0.0000 0.0013 0.0000	
Fault Code	0000	0000	0001	0010	$1\ 0\ 0\ 0$	0000	0100	0010	1000	0000	
Diagnosis type	Normal	Normal	Motor failure	Mechanical seal failure	Machine component failure	Normal	Gear box failure	Gear box failure	Machine component failure	Normal	

Table 6 transhlashaating regults

Another 10 sets of data import from the database troubleshooting, diagnostic results as shown in table 7, this time fault diagnosis accuracy rate is 100.

Table 7 troubleshooting results

Test sample	1	2	3	4	5	6	7	8	9	10
BP output	0.0000 0.0000 0.0000 0.0020	0.9450 0.0001 0.0011 0.0000	0.0000 0.0040 0.0000 0.0000	0.0000 0.0000 0.9513 0.0000	0.0000 0.0000 0.0000 0.0000	0.0000 0.1023 0.0000 0.0100	$\begin{array}{c} 0.0000\\ 0.0000\\ 0.0000\\ 0.0000\end{array}$	0.0000 0.9015 0.0000 0.0000	$\begin{array}{c} 0.0000\\ 0.0000\\ 0.0000\\ 0.0000\end{array}$	0.0000 0.0000 0.0000 0.0025
Fault Code	0000	$1\ 0\ 0\ 0$	0000	0010	0000	0000	0100	0010	0000	0000
Diagnosis type	Normal	Machine component failure	Norma	Mechanical seal failure	Normal	Normal	Normal	Gear box failure	Normal	Normal

You can see from three diagnostic results, with ga- lmbp algorithm for fault diagnosis of Polymerization kettle is very effective, failure the accuracy rate of 96.67.Fault Diagnosis by mutations in the variable data, you can determine the aggregation of faults in reactor equipment, such as mixing current for the failure of motor faults and gear box failure, water flow of the shaft seal failure is the failure of mechanical seal, Polymerization temperature is too high or high pressure will cause damage to the machine components directly.

CONCLUSION

This paper presents a fault diagnosis algorithm based on GA-improved a LMBP Polymerizer device of the weights and the bias value increment LMBP algorithm into the change, first of all, the inverse matrix moved the equation on the left, with LU direct decomposition method for solving equation, so that the computational complexity for reducing. Then, with a variable step size instead of the fixed stepping factor, reducing the number of cycles. The improved LMBP algorithm and genetic algorithm (GA) combined fault diagnosis algorithm applied to the polymerization kettle fault diagnosis research, simulation results show that this algorithm in fault diagnosis polymerizer training speed, high precision and practicality, failed the accuracy rate of 96.67.

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