Immune Genetic Evolutionary Algorithm of Wavelet Neural Network to Predict the Performance in the Centrifugal Compressor and Research

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Abstract—**Prediction of the performance of centrifugal compressors, the traditional methods using BP neural network. This single neural network for forecasting problem is not high enough precision, slow convergence and easy to fall into local optimal solution. In order to more accurately predict the performance of centrifugal compressors, the implicit commit identify problems early. Are the immune algorithm, genetic algorithm, wavelet theory, the combination of neural networks, established immune genetic algorithm optimization of wavelet neural network model (IGA-WNN). Realized to predict the performance of centrifugal compressor, and the predicted results with the BP neural network model prediction results and the wavelet neural network model prediction results were compared. Simulation results show that: the prediction model, can achieve the centrifugal compressor performance prediction and monitoring. Which, IGA-WNN optimal prediction results: with a simple algorithm, structural stability, the convergence speed and generalization ability of the advantages of prediction accuracy of 99% over traditional methods of prediction accuracy of 15%, with a certain Theoretical study and practical value.**

Index Terms—**immune algorithm, genetic algorithm, wavelet theory, centrifugal compressor, performance prediction.**

I. Introduction

As centrifugal compressor owns the features of high rotating speed, small size, small occupancy area, etc, therefore, it is widely used in the petrochemical industry. The following stages in the process of new product development for centrifugal compressor are needed: theoretical design, modeling production, performance test and prototype production. When designing, we must test on centrifugal compressor's performance, which can help us know whether the centrifugal compressor meet the requirements or not. If the result is not good, then a further optimization is needed. However, this approach will inevitably need large input of manpower, material and financial resources, so applying a new method can predict the performance of centrifugal compressor before designed to provide theoretical guidance for the optimal design. Artificial neural networks can train the existing samples in order to predict the conditions of centrifugal compressor's best performance, shorten the testing time, increase the efficiency and cut down the cost. In the past, the BP neural network approach is often considered as the main network approach, however, for complex centrifugal compressors, in order to obtain a better prediction, the further optimization is a must. When conventional neural network recognizes centrifugal compressor, there exists the defects with low identification accuracy, poor convergence speed, and easily falling into local optimal solution. Therefore, it's necessary to seek for an optimal identification model with high identification accuracy, fast convergence speed and strong global searching optimization, which is significant for the research and understanding of centrifugal compressor's fault and performance.

To solve these problems, the immune genetic algorithm is proposed wavelet neural network model (IGA-WNN). Advantages of this model are:

(1) structure determination, avoiding the blindness in the structure design of BP network;

(2) the linear distribution of network weight factors and the convexity of study objective function fundamentally prevent issues such as the local optimization in network training process;

(3)simple concept of algorithm, faster convergence speed;

(4) strong function learning ability, able to approach any nonlinear function in high precision.

The results show that: the immune genetic algorithm for wavelet neural network model (IGA-WNN) prediction accuracy 99%.

II. Immune Genetic Algorithm Optimization of Wavelet Neural Network Model (IGA-WNN)

Wavelet neural network WNN is based on the wavelet theory, put forward artificial neural network as a feedforward network. It is based on the wavelet function as the neuron activation function, wavelet scaling, translation factors, as well as connection weights, the error energy function in the optimization process to be adaptive. Use of models such as (1) type shown.

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$$y(x)=f(\sum_{j=1}^{M}\omega_j\varphi_{a,b}[\sum_{i=1}^{N}v_{ji}x_i]) \quad (1)$$

Type in xi (i = 1,2,3, ... N) is the i-input; y (x) for the network output; ωj first j for the hidden layer nodes to output layer weights; vji for the first i- input to the j-node hidden layer weights; f (•) for the hidden layer to output layer activation function; $\varphi_{a,b}(\bullet)$ for the wavelet function, a, b are scaling and wavelet function for the translation factor; N input number; M is the number of hidden layer neurons

Error energy function is:

$$E=\frac{1}{2}\sum_{k=1}^{K}[T-f(x_k)]^2 \quad (2)$$

Type in: x_K as the sample; K for the sample number.

Wavelet theory, Zhang and Benveniste first proposed wavelet neural network (WNN), its forward neural networks as a new form of training with back propagation algorithm to approximate WNN arbitrary nonlinear function. Wavelet neural network (WNN)'s structure shown in Figure 1.

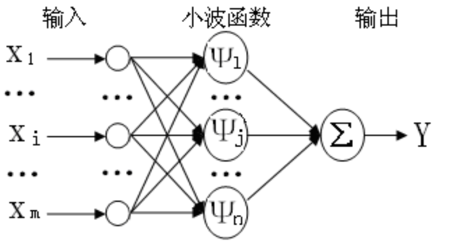

Figure1. Schematic diagram of wavelet neural network

Wavelet neural network is basically divided into three layers: input layer, wavelet function and output layers. The output expression is:

$$y=\sum_{j}^{m}w_j\psi_j(\bar{x}) \quad (3)$$

Type in: $\bar{x}=x_1 ...,x_i,...,x_m$, ψ_j That the wavelet function layer node function, w_j equivalent to the wavelet coefficients after the wavelet decomposition.For a multi-variable nonlinear coupled system, need to build multi-dimensional wavelet function as the wavelet layer WNN node, where more than scalar wavelet function using the product to build multidimensional wavelet function.Therefore, WNN output expression to read:

$$y=\sum_{j}^{n}w_j\prod_{i}^{m}\psi(\frac{x_i-b_{ij}}{a_{ij}}) \quad (4)$$

Among them, the scalar function ψ, multi-dimensional wavelet function in wavelet layer node number n, coefficient of *W*j, scale parameters a_{ij} and b_{ij} are the translation parameters need to be identified and estimated.Here choose ψ (x) =- xexp (-1 / 2x2). For the parameters n, a_{ij} and b_{ij} , using immune algorithm is estimated that in the course of the iterative algorithm for updating coefficients *W*j.

Immune algorithm is a combination of deterministic and stochastic selection heuristic random search algorithm, which is considered to be adaptive immune response in a simple simulation, this study of antibodies and antigen response process to complete. Immune algorithm includes initialization antibody group, clonal selection, antibody clones, affinity mutation, clone inhibition, immune selection, new members of the other steps. each step corresponds to an evolutionary mechanism for the immune system. The evolution process of antibody optimization problem as a candidate solution, antigen as the optimal solution, process of finding the optimal solution can be achieved by the immune algorithm.

For a set of training data St={(xk , yk), k = 1,…, nd} , Objective function obtained here:

$$J\left(\left(a_{ij}\right)_{m\times n},\left(b_{ij}\right)_{m\times n},n\right)=\frac{1}{n_d}\sum_{k}^{n_d}\left(y_k-\hat{y}_k\right)^2 \quad (5)$$

Where, $\hat{y}_k$ is the y_k estimate.

Calculated using the following formula between the antibody and antigen affinity:

$$f_{aff}\left(\left(a_{ij}\right)_{m\times n},\left(b_{ij}\right)_{m\times n},n\right) =\frac{1}{1+\exp\left(\eta_{aff}J\left(\left(a_{ij}\right)_{m\times n},\left(b_{ij}\right)_{m\times n},n\right)\right)} \quad (6)$$

Where, 0 <ηaff <1. J on the type that the smaller affinity, the more close to the optimal solution. Immunization goal is to find a maximum affinity between antigens and antibodies.

IA-WNN parameters of immune optimization steps are as follows:

Step 1: Generate initial antibody group (a set of parameters ((a_{ij}) m × n, (b_{ij}) m × n, n) as a antibody);

Step 2: Get a WNN corresponding coefficient for each antibody by the iterative formula (7) - (9) and training data is estimated for each w;

$$e_k=y_k-\sum_{j=1}^{n}w_{jk-1}\psi_j(\bar{x}_k) \quad (7)$$

$$Q_{jk}=\lambda Q_{jk-1}+\psi_j^{\,2}(\bar{x}_k) \quad (8)$$

$$w_{jk}=w_{jk-1}+e_k\psi_j^{\,2}(\bar{x}_k)Q_{jk} \quad (9)$$

Step 3: Group in the antibody affinity antibody and antigen (type (9)), and select the affinity of antibody formed a larger ηaff a new antibody group;

Step 4: According to the affinity of antibodies size, degree of similarity and incentive on the antibody clone, mutation, suppression and selection;

Step 5: Obtained from step 4, remove the new antibody population in one of the largest affinity antibodies to determine the antibody corresponding objective function value is less than the set value, if less than, the end of the algorithm; Otherwise, return to step 2.

Genetic Algorithm (GA) is a global optimization algorithm based on natural selection and natural heredity, and it uses the selection, crossover and mutation of the three genetic operators abstracted from the mechanism of natural selection to operate on the parameters encoding string, which features with overall importance, rapidity, good adaptability and strong robustness, etc and is able to achieve global search in complex, multimodal, nonlinear and non-differentiable space. The general steps of using it to solve problems are:

Step1:conduct chromosome bit string encoding on the parameters that need to be optimized;

Step2:generate initial population;

Step3: evaluate the group and solute the fitness value of each individual;

Step4: apply genetic operators on groups and generate new population, executing circularly. Specific genetic manipulation includes selection, crossover and mutation. When carrying out network training, the author applies genetic algorithm to optimize the network parameters of wavelet neural network predictive model and determine hidden layer nodes---the number of wavelet in order to simplify network structure and improve the accuracy, adaptability and robustness of anode effect prediction.

The author uses genetic algorithm optimization approach to identify the number of hidden nodes is the number of wavelet basis, while the second part is the training method of training: first with the genetic algorithm to train the network's scale factor, translation factor and weights the same time determine the wavelet Number, and then use gradient descent on the scale, translation factors and weights, the threshold for secondary training. The specific steps:

1. encode

For chromosomes to mixed binary and real coded form of the binary code to each network that the effectiveness of Cain layer unit, randomly generated N (determined based on experience) one structure, each individual corresponds to a structure, the wavelet network The number of input and output nodes to reflect the anode effect by the number of parameters determined by the actual situation, when encoding only the number of hidden layer wavelet encoding, 0 for invalid connections, 1 connection is valid;On the network weights, scale factor, translation factor to real coding, the wavelet corresponding to each individual network, weight, scale factor, translation factor compiled a code string sequence as a gene. Code string obtained by mixing the form of coding

$$\phi_1^h w_{11}^h \cdots w_{11}^h a_1^h b_1^h \cdots \phi_H^h w_{H1}^h \cdots w_{H1}^h a_H^h b_H^h \phi_O^o w_{11}^o \cdots w_{H1}^o$$

1…0…1 （10）

Where: h is hidden, O for the output layer.

2. Swarm initialization

For the initialization for weights, threshold, scale factor and shift factor, the initialization interval is [-1, 1]. Set the population size to S, crossover probability to Pc, mutation probability to Pm, and the maximum number of genetic iterations to Gmax.

3. Calculation of individual fitness

Evaluate the training results according to the fitness function, and the evaluation evidence is:

$$f = \frac{1}{1+E} \tag{11}$$

4. determine whether the fitness value meets the overall requirements, if it satisfies, refer to 6, otherwise execute 5.

5. Selection, crossover and mutation

Adopt the roulette selection method to get a large number of individuals with strong fitness, and then use them to directly copy the next generation. At the same time, carry out crossover and mutation on the individuals which need to be conducted these operations according to the crossover probability Pc and mutation probability Pm in order to generate the next generation, then refer to 3, to evaluate its fitness value.

6. if it meets the pre-conditions or maximum iterations, end the loop to obtain the optimal chromosome and decode it into corresponding number of hidden layer wavelet basis, weight, scale factor and shift factor.

7. Secondary Training

After determining the number of hidden layer network nodes, use gradient descent algorithm to conduct secondary optimization training on parameters such as weight, threshold, scale factor, scale factor and shift factor. The parameters obtained after two optimizations will be used as the final parameters of genetic wavelet network prediction model, and furthermore used to predict the performance of centrifugal compressors.

III. THE EXTRACTION OF MODEL IDENTIFICATION PARAMETER

The factors affecting the performance of centrifugal compressor own the following performance parameters: flow(Q), blade incidence(β_A)， rotational speed(n)， number of leaves(Z), number of guide vanes($Z1$), impeller diameter(D), ratio of impeller outer and inner diameter($D1/D2$), the impeller outlet width($b2$), pressure ratio(Pd/Ps), etc. Simply calculating, select 4 main performance parameters: flow(Q), installation angle of the impeller outlet (β_{2A}), pressure ratio($\varepsilon=Pd/Ps$)and efficiency(η)to establish predictive model. Research on the centrifugal compressor with the same rotate speed, and take the pressure ration corresponding to 4 different installation angles of the impeller outlet（β_{2A}） and the performance curve of efficiency changing with the flow. Utilize partial data of these known performance curve to conduct training for BP neural network, and then make use of other data to test the network prediction ability that has been trained. According to the efficiency and pressure ratio of 16 flow points of each blade angle obtained through 4 performance testing data, divide the data into groups, as shown in table 1. These data constitute 64 pairs of sample points. The input mode of each sample is constituted by 1 angle value and 1 flow value, while the output mode is constituted by 1 efficiency or pressure ratio. Divide the samples into 2 groups: there are 40 samples in group (1), which are mainly used in the network training to establish predictive model; there are 24 samples in group (2) used to test the predictive model.

Table 1
Sample Centrifugal Compressor Performance Prediction

β_{2A}°	Q m^3/s	ε	η %	β_{2A}°	Q m^3/s	ε	η %	β_{2A}°	Q m^3/s	ε	η %	β_{2A}°	Q m^3/s	ε	η %
30	1.52	1.21	71.00	32	1.67	1.31	74.00	34	1.84	1.42	78.00	36	2.01	1.61	82.00
	1.51	1.31	73.00		1.66	1.41	76.00		1.83	1.52	80.00		2.00	1.72	83.00
	1.50	1.40	75.00		1.65	1.60	77.00		1.82	1.71	81.00		1.99	1.80	84.00
	1.49	1.50	77.00		1.64	1.70	78.00		1.81	1.90	82.00		1.98	1.90	86.00
	1.48	1.66	79.00		1.63	1.81	80.00		1.80	2.00	83.00		1.97	2.12	87.00
	1.47	1.71	81.00		1.62	1.90	81.00		1.79	2.10	85.00		1.96	2.33	88.00
	1.46	1.80	83.00		1.61	2.00	82.00		1.78	2.20	86.00		1.95	2.43	89.00
	1.45	1.91	84.00		1.60	2.11	83.00		1.77	2.31	87.00		1.94	2.52	90.00
	1.44	2.00	86.00		1.59	2.30	84.00		1.76	2.40	88.00		1.93	2.61	91.00
	1.43	2.10	89.00		1.58	2.40	86.00		1.75	2.61	89.00		1.92	2.70	92.00
30	1.52	1.21	71.00	32	1.67	1.32	74.00	34	2.01	1.35	82.00	36	2.06	1.34	85.00
	1.51	1.32	73.00		1.66	1.41	76.00		2.00	1.53	83.00		2.04	1.56	86.00
	1.50	1.34	75.00		1.65	1.65	77.00		1.99	1.74	84.00		1.99	1.71	87.00
	1.49	1.47	77.00		1.64	1.73	78.00		1.98	1.95	86.00		1.96	1.85	88.00
	1.48	1.58	79.00		1.63	1.82	80.00		1.97	2.02	87.00		1.93	2.10	89.00
	1.47	1.66	81.00		1.62	1.96	81.00		1.86	2.14	88.00		1.88	2.16	90.00

IV. SIMULATION RESULTS

Immune genetic algorithm to optimize the initial antibody population or the population size S = 50, the maximum number of iterations Gmax = 10000, training for gradient descent learning rate η = 0.85, momentum factor α = 0.921, learning error to set ε = 0.001 , The maximum number of learning steps epoch = 10, crossover probability Pc = 0.25, mutation probability Pm = 0.01, the maximum number of learning steps epoch = 10. For the learning rate η, used in the training process adaptive method for faster convergence rate and improve the prediction of real-time.

To paragraph (1) group of 40 samples of data input, after several training comparison, the number of hidden layer neurons is taken as 10, to build the prediction model. To subsection (2) group of 24 samples to be predicted forecast data generation model identification, in the iteration stops after 4800 time iterations, the correct identification rate of 99%, At this point, pressure ratio(ε) and efficiency (η)errors are 1.0406×10^{-6}, 1.0386×10^{-6}; Recognition rate WNN model is greater than 90%; BP network model is over 85% recognition accuracy. Figure 2 and Figure 3 is IGA-WNN, WNN and BP training error comparison chart, we can see from the figure: IGA-WNN's convergence speed.

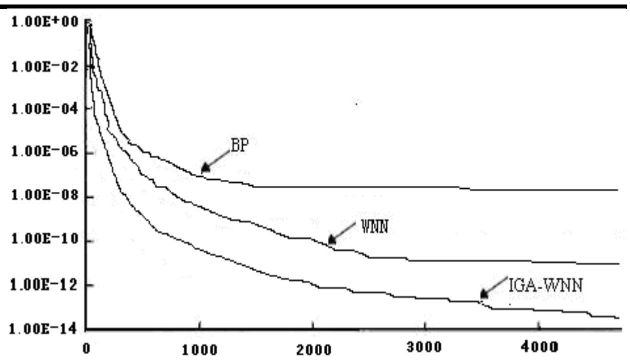

Figure 2. ε training error comparison chart

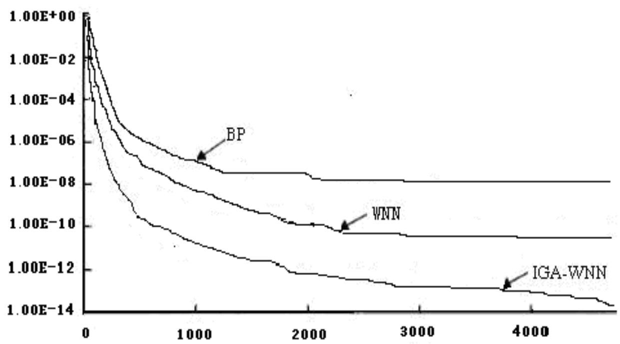

Figure 3. η training error comparison chart

In order to better understand and explain the immune genetic algorithm neural network model to predict the performance advantages of centrifugal compressors. Of the study, also using BP neural network and wavelet neural network WNN data were processed using the same training samples, and establish a three-layer neural network model, the number of hidden neurons is set to 1O, and the immune genetic Algorithm optimization of wavelet neural network model has the same structure of the network, the training sample to predict recognition. The simulation results from Matlab, you can obviously see, IGA-WNN and BP in the 4800 iteration of the changes within the training error, IGA-WNN method of convergence speed and accuracy of better than WNN method; WNN method of convergence Speed and accuracy is obviously better than the BP method. Table 2 shows the centrifugal compressor pressure ratio (ε) and efficiency (η) predictions.

In order to better observe the centrifugal compressor pressure ratio (ε) and efficiency (η) of the predicted results, the measured value and the IGA-WNN, WNN, BP predicted values with the scatter plot to display. It is clear that: IGA-WNN best prediction. Figure 4, Figure 5, Figure 6, Figure 7, Figure 8 and Figure 9.

Table 2
Pressure ratio (ε) and Efficiency (η) prediction table

β_{2A} °	ε	BP	WNN	IGA-WNN	Q(m^3/s)	η (%)	BP	WNN	IGA–WNN
30	1.21	1.01	1.16	1.21	1.52	71.00	71.30	71.12	71.01
	1.32	1.30	1.33	1.32	1.51	73.00	73.10	73.06	73.01
	1.34	1.40	1.38	1.35	1.50	75.00	75.40	75.16	75.02
	1.47	1.50	1.50	1.47	1.49	77.00	77.30	77.12	77.00
	1.58	1.61	1.61	1.58	1.48	79.00	79.60	79.23	79.02
	1.66	1.68	1.69	1.66	1.47	81.00	81.20	81.09	81.00
32	1.32	1.25	1.32	1.32	2.01	82.00	82.40	82.15	82.00
	1.35	1.40	1.39	1.36	2.00	83.00	83.20	83.09	83.01
	1.34	1.41	1.39	1.35	1.99	84.00	84.50	84.19	84.02
	1.73	1.71	1.74	1.73	1.98	86.00	86.40	86.15	86.00
	1.82	1.80	1.83	1.82	1.97	87.00	87.10	87.05	87.00
	1.96	1.81	1.93	1.95	1.86	88.00	88.30	88.12	87.99
34	1.35	1.40	1.39	1.36	1.67	74.00	74.20	74.09	74.00
	1.53	1.46	1.53	1.53	1.66	76.00	76.50	76.18	75.99
	1.74	1.71	1.75	1.74	1.65	77.00	77.40	77.16	77.01
	1.95	1.91	1.96	1.95	1.64	78.00	78.50	78.19	78.01
	2.02	1.92	2.01	2.02	1.63	80.00	80.20	80.09	80.00
	2.14	2.10	2.14	2.13	1.62	81.00	81.50	81.19	81.02
36	1.34	1.42	1.39	1.34	2.06	85.00	84.40	84.82	84.99
	1.56	1.53	1.57	1.56	2.04	86.00	85.20	85.75	85.99
	1.73	1.71	1.74	1.73	1.99	87.00	86.50	86.86	87.01
	1.85	1.81	1.85	1.84	1.96	88.00	87.40	87.82	88.00
	2.10	2.07	2.11	2.10	1.93	89.00	88.50	88.85	89.00
	2.16	1.91	2.10	2.16	1.91	90.00	89.30	89.79	90.01

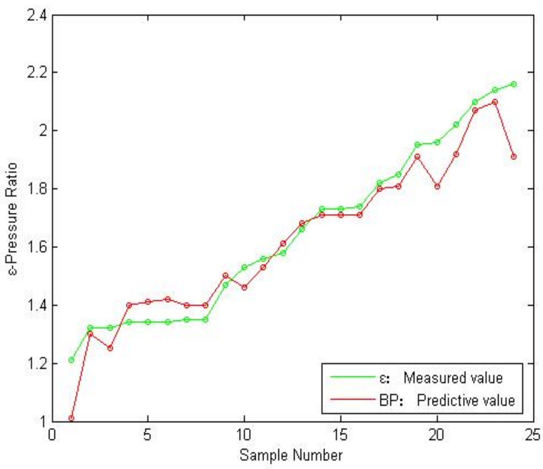

Figure4. BP to centrifugal compressor's pressure ratio forecast contrast chart

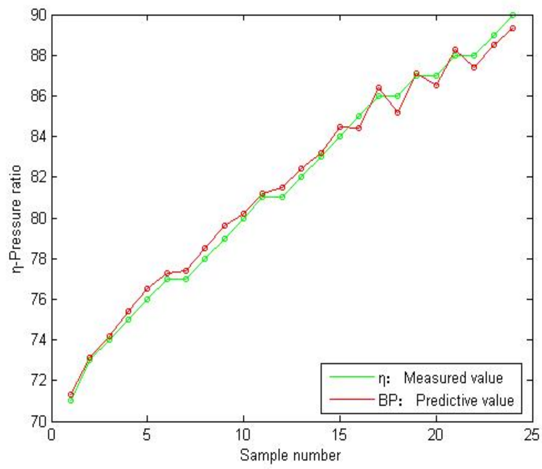

Figure5. BP to centrifugal compressor's potency forecast contrast chart

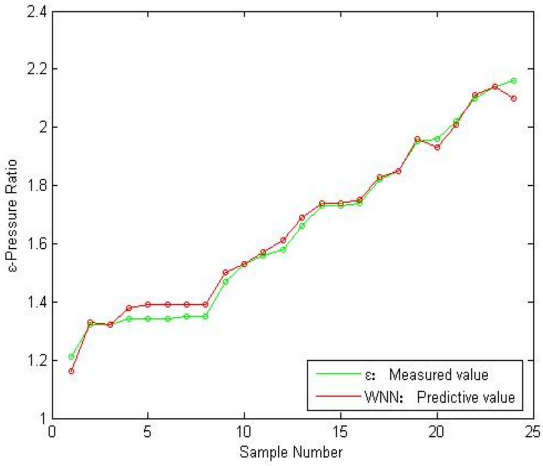

Figure6. WNN to centrifugal compressor's pressure ratio forecast contrast chart

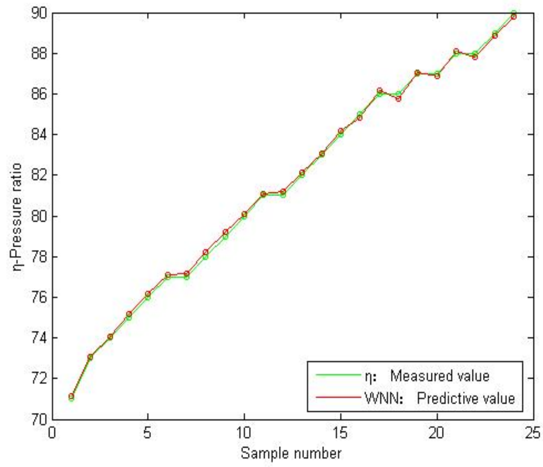

Figure7. WNN to centrifugal compressor's potency forecast contrast chart

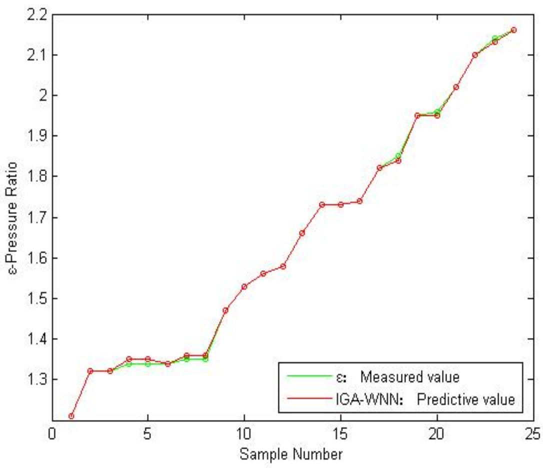

Figure8. IGA-WNN to centrifugal compressor's pressure ratio forecast contrast chart

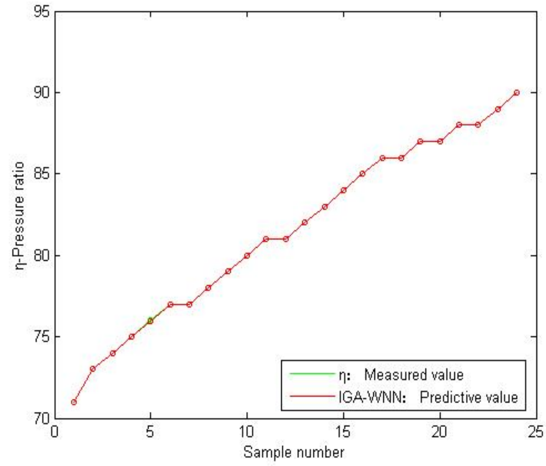

Figure9. IGA-WNN to centrifugal compressor's potency forecast contrast chart

V. CONCLUSIONS

Simulation Description: immune genetic algorithm neural network model(IGA-WNN) with structural stability, simple algorithm, global search capability and convergence speed, generalization ability, etc., can reflect the nonlinear centrifugal compressor performance Problem. The measured performance of the centrifugal compressor 40 samples for training, 24 samples to predict, predict the correct rate of 99%. Predicted effect, centrifugal compressor performance monitoring presents a fast convergence and high accuracy, low cost performance prediction model developed in the experiment, the centrifugal compressor to improve efficiency, reduce costs and has practical value to the similar Problem with some guidance.

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