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Fault prognosis for large rotating machinery using neural network

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Abstract

The way for predicting vibration value and forecasting serious malfunctions for large rotating machinery using neural networks is proposed in this paper. The topological architecture of a multi-layer neural network for this purpose and the training strategies are established. It is obtained that the back propagation neural network possess the strong ability in time series prediction by comparing it with the autoregresive modeling method. With the neural network, one-day prediction of the rotor vibration value for a 200 MW turbo-generator has been carried out quite accurately. The surging state in a CO_2 compressor has also been prognosed in the same way but taking multi related values of the process parameters as the input of the neural net.

1 Introduction

In recent years, artificial neural networks have played an active role in fault diagnosis. Skitt P.J.C.[1], Ahmet Duyar[2] and Leonard J.A.[3] made succesful application of it in jet engine diagnosis, space shuttle main engine diagnosis and chemical process diagnosis respectively. Much attention has been attracted by their powerful ability as a pattern classifier since the most diagnosis problem could be sorted as the one of the pattern recognition. Meanwhile, the interest in the feasibility of predicting output of a complex system using neural networks has been growing. Lapedes A.S. and Farber R.M.[4] made an systematically demonstration on nonlinear system mapping and prediction with neural networks. Based on these theoretical background, we have tried to lead

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neural network into the field of fault prognosis. It includes two kinds of works, one is to give a relative precised prediction of vibration value one or more days earlier for a working machine, the other is to forecast the malfunction of the machine before it occurred. It will give maintenance engineer a period of time to make a decision of weather doing adjustment or even making shutdown. In this paper, a three layer feedforword neural network with a back propagation algorithm is selected to be trained to accomplish the prediction of vibration value and serious malfunction of the large rotating machinery. The ability of time series prediction with a neural net is first compared to that of a autoregressive modeling method. Much more accuracy is gained with the former. An architecture of multi-parameter input and output of neural network for prediction purpose is proposed. The details of them are presented in section two. It make the neural network possesses more power to map the nonlinearities and dynamical characteristics of a complex system. This architecture is used successfully to predict the rotor vibrational extent of a 200 MW turbo-generator in a power plant and forecast the surging state occurrence of a CO_2 compressor in a chemical plant in China. Results of the prediction coincide with the real situation quite accurately.

2 Architecture of neural networks for fault prognosis

For different purposes, the neural network can be with various kinds of structures and algorithms. Lippman A.S.[5] gave an introduction to software realizations of them which covers a range of most common methods. Among them, a multi-layered feedforward neural network with back propagation algorithm is commonly used in many areas. It is well known that a back propagation neural net with more than three layers can project any arbitrary functional relationship, so it is suitable for time series prediction without any assumption on analyzed data set. It can theoretically represent the nonlinear and dynamical mechanism of a time series. Since the fault prognosis follows the similar way of time series prediction, we also choose the back propagation network for our purpose. The topological architecture of the network is shown in figure 1. The sigmoidal nonlinearities is used as the activation function for each connected node. The formula is listed bellow:

$$f(x) = \frac{1}{1 + e^{-x}} \qquad (2\text{-}1)$$

The relationship between input and output for a single neuron is then represented as following:

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$$y = f\left(\sum_{i=1}^{n} w_i x_i - \theta\right) \tag{2-2}$$

Here W_i : connection weight
X_i : input
y : output
θ : threshold value

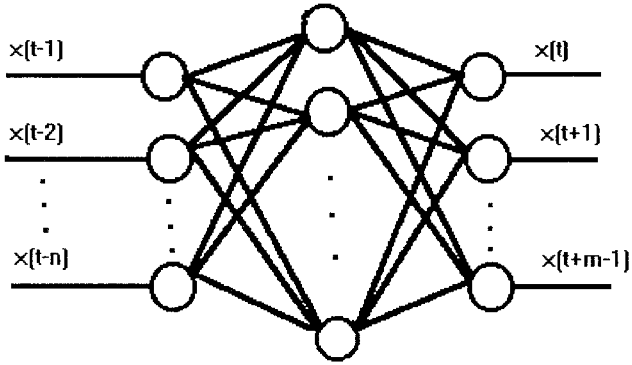

Figure 1 The topological architecture of prediction nueral net

After the decision of neural network structure, we can train it using data samples. The training strategy is that if M step prediction is expected according to past N data, a data window with length of N+M is taken and slides along the data series step by step. The first N data are taken as input and the left M data as output of the prediction neural network. the procedure is clearly shown in table 1.

Table 1 The straegy for training neural network

N input values	M desired output values
X(1), ... , X(N)	X(N+1), ... , X(N+M)
X(2), ... , X(N+1)	X(N+2), ... , X(N+M+1)
X(3), ... , X(N+2)	X(N+3), ... , X(N+M+2)
... ...	... ...
X(K), ... , X(N+K)	X(N+K+1), ... , X(N+M+K)

3 The prediction of rotor vibration using neural net

Before put into practical use, the neural network with the architecture

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mentioned above has been tested to verify its prediction ability. Data samples for simulation were generated by equation (3-1), an autoregressive model with the form of equation (3-2) are obtained by means of Marple Modelling algorithm.

$$P(t+1)=(y1(t)+y2(t)+2*y3(t)+y4(t))/5 \tag{3-1}$$
$$y1(t)=0.004t+1 \qquad y2(t)=\sin(50t)$$
$$y3(t)=\sin(9t+20) \qquad y4(t)=y4(t-1)(1-y4(t-1))*4$$

$$X(t)=-0.678X(t-1)+0.066X(t-2)+0.452X(t-3)+0.5185 \tag{3-2}$$

The waveform of the data samples is shown in figure 2.

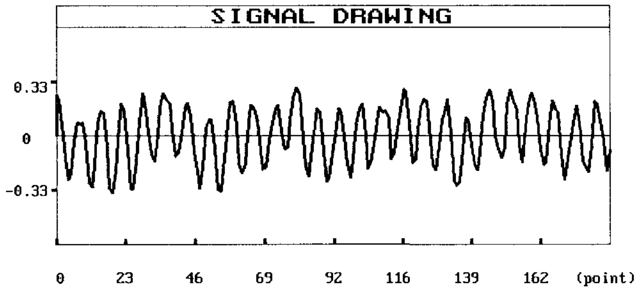

Figure 2 The waveform of simulated data samples

One-step prediction was made using a 7-7-1 neural net, that means it has 7 input neurons, 7 hidden neurons and one output neuron. To compare the effectiveness of both methodsquantitatively, an error function in the sense of variance, as shown in equation (3-3) is quoted here.

$$ERR = \frac{1}{m}\sum_{t=1}^{M}(x_t{'} - x_t)^2 \tag{3-3}$$

M: The number of data samples
X': predicted value
X_t: real value

The prediction error of bothe methods are given bellow and it can be obviously seen that the latter coincids the real value more accurately than the former.

ERR(AR)=0.16289 **ERR(NN)=0.09864**

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Based on this simulation ,We took neural network to predict the peak to peak value of the rotor vibration of a 200 MW turbo-generator. The vibration signal was taken from an eddy current probe mounted in 5th bearing, while the neural network kept the form of 7-15-1. The operation procedure is that when vibration values of seven days earlier are put into the network, then the prediction of the vibration value of one-day latter will be carried out. Thirty groups of vibration historical data were fed into the neural network to train it. After the convergence, the network was put into operation. One-day prediction for peak to peak value of the rotor vibration has been given within fifteen days. Figure 3. shows the results.

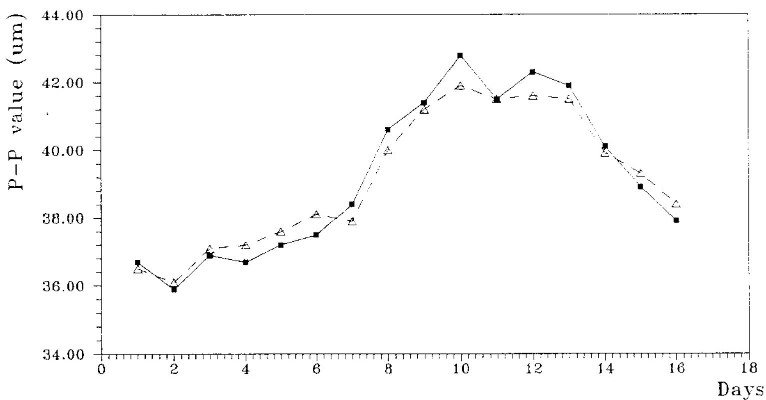

Figure 3 The prediction results of vibration value (peak-peak)

The dashed line indicates the predicted value while the solid line expresses the real value. The satisfied coincidence between them can be seen in the figure though there exists a little amount of random differences.

4 Forecast the surging state of the compressor

Compressors in many chemical plants are often fallen into surging state as the process condition changed even though most of them are equipped with surge proof facilities.

It is harmful for the compressor to be fallen into surging state. The surging state occurrence of the compressor is usually influenced by many process factors jointly to such an extent that even no mathematical model can be found to express them. However, the theory of neural network supply us a possibility to represent this complex and nonlinear relationship by a proper constructed neural network. The same topological architecture was adopted as the one in figure 1. but

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with a multi-parameters input instead of only one. The objective machine is a CO_2 compressor serviced in Luzhou Natural Gas Chemical Industrial Corp. in China. A neural network with the form of 6-3-1 was established and shown in Figure 4. The structure of this nueral net was optimized by Genetic Algorithm and expressed in detail by Z.Y. Han.[6]

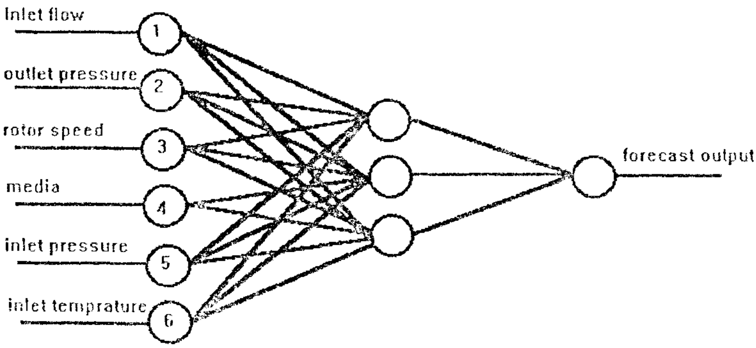

Figure 4 The architecture of the neural net for surge prognosis

According to the surging mechanism, six parameters which are related to the surge occurrence directly were chosen as an input of the network. Only one output neuron gave two kinds of values of 1 or 0. Here 0 stands for normal condition of the compressor and 1 for surging condition. 180 groups of data samples corresponding to both normal condition and surging condition were fed to train this network. After convergence, the weight value between neurons were obtained and is shown in table 2.

Table 2 The weight values between neurons

The weights between input layer and hidden layer						
W_{11}	W_{12}	W_{13}	W_{14}	W_{15}	W_{16}	θ_1
-0.4022	0.1999	-0.4621	0.4134	-0.4479	-0.2811	-0.5603
W_{21}	W_{22}	W_{23}	W_{24}	W_{25}	W_{26}	θ_2
-0.4489	0.1739	-0.1745	-0.3349	-0.3026	-0.0863	-0.7644
W_{31}	W_{32}	W_{33}	W_{34}	W_{35}	W_{36}	θ_3
0.3594	-0.1342	0.3102	0.1250	-0.3789	-0.1970	0.1494

The weights between hidden layer and output layer			
W_1	W_2	W_3	θ
0.2256	0.4705	0.2602	0.4706

The effectiveness was verified in situ by ten groups of normal data and one group of surging data. The right results were given out each time.

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5 Concluding remarks

The research in this paper give rise to a way of fault prognosis for large scale rotating machinery using neural network. The present results both from simulation and practical application in the paper established the feasibility of the way mentioned above. This has been expected by the maintenance engineer for many years. The neural network properly constructed do have the strong ability to represent the complexity and nonlinearities of the large scale rotating machinery. The further work we will do is to make it more applicable in industry.

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