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Modeling of hydraulic turbine systems based on a Bayesian-Gaussian neural network driven by sliding window data*

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Abstract: In this paper, a novel Bayesian-Gaussian neural network (BGNN) is proposed and applied to on-line modeling of a hydraulic turbine system (HTS). The new BGNN takes account of the complex nonlinear characteristics of HTS. Two redefined training procedures of the BGNN include the off-line training of the threshold matrix parameters, optimized by swarm optimization algorithms, and the on-line BGNN predictive application driven by the sliding window data method. The characteristics models of an HTS are identified using the new BGNN method and simulation results are presented which show the effectiveness of the BGNN in addressing modeling problems of HTS.

Key words: Bayesian-Gaussian neural network (BGNN), Hydraulic turbine, Modeling, Sliding window data
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1 Introduction

A hydraulic turbine system (HTS) is in essence a complex nonlinear system that involves hydrodynamics, mechanical and electrical dynamics. So the dynamic response characteristics of an HTS are difficult to obtain through mathematical analytical methods. Furthermore, the transfer coefficients of an HTS change with different operating situations, increasing the difficulties involved in on-line modeling.

In research on modeling of nonlinear systems, artificial neural network (ANN) modeling methods are often adopted because they can approximate any nonlinear system (Chen and Chen, 1993) and have been used successfully in many fields (Jung and Ghaboussi, 2006; Caccavale *et al*., 2008; Pei and Mai 2008; Matthias *et al.*, 2008; Yazdan *et al.*, 2008). In research on modeling of HTS, many kinds of ANN have been presented including the multiplayer perception (MLP) network, back-propagation (BP) neural network, radial basis function (RBF) neural network, and fuzzy neural network (FNN) (Sarimveis, 2000; Chang *et al.*, 2003; Chen *et al*., 2003; Wang *et al.*, 2008). The modeling results based on these networks have been reported and show that an ANN can obtain the nonlinear model of an HTS.

Regardless of these inspiring developments in the application of neural networks to nonlinear HTS, there are some intrinsic features of these neural networks which limit their practical application (Ye *et al.*, 1998). First, the topology of BP or RBF neural networks needs to be determined by trial and error. Second, in the training procedures of BP or RBF neural networks, many connection weights need to be adjusted during error function minimization, which inevitably results in a complex error surface and a long training time. Furthermore, the lack of self-tuning ability of these networks limits their practical application in on-line system modeling and in some special processes, such as time-variant systems. To overcome the shortcomings of such neural networks, a kind of Bayesian-Gaussian neural network (BGNN) was proposed by Ye *et al.* (1998) which is an a

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posteriori probability model based on Bayesian theory and the Gaussian hypothesis. The BGNN has many advantages over traditional neural networks, such as easy determination of topological structure and few connection weights to be set when training samples are available. Based on the BGNN structure, in this paper, we propose a novel BGNN in which the off-line training method and on-line application algorithm are redefined using swarm optimization algorithms and a kind of sliding window data driving method. The new BGNN is then applied to the modeling of an HTS to test its effectiveness.

2 Description of the modeling problem of HTS

In our work, an HTS is considered which includes a servomechanism, penstock system, water turbine and generator (Fig. 1) (Shen, 1996; Xiao *et al.*, 2006).

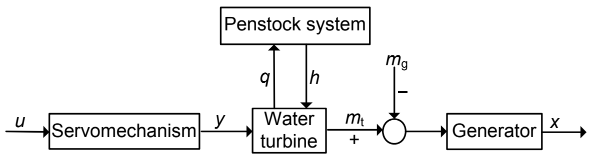

Fig. 1 Illustration of the structure of the hydraulic turbine system (HTS)
u is the output of controller, y denotes the servomechanism output, q is called water flow, h is water head, m_t and m_g are water turbine moment and load moment respectively, and x denotes the frequency of generator

The characteristics of the servomechanism are simple and it can be expressed approximately as a first order system with a translating function model, as described in Eq. (1):

$$y = \frac{1}{1+T_y s}u, \tag{1}$$

where T_y is the inertia time constant of the servomechanism and y denotes its output.

In dynamic process, the running characteristics of the HTS vary with changing operating conditions. For example, the movable Francis turbine is basically nonlinear and its nonlinear characteristics can often be depicted as

$$\begin{cases} m_t = f(y, x, h), \\ q = q(y, x, h), \end{cases} \tag{2}$$

where q is flow, m_t denotes the movable turbine moment, h is the water head, and x is the speed of rotation (generally x is expressed as a frequency). The function relations of f and q are nonlinear and difficult to obtain through mathematical analysis methods. A neural network, as a black modeling technique, can be used to identify nonlinear models. So the BGNN in this work was adopted for modeling of the nonlinear characteristics of the HTS.

The dynamic characteristic of the penstock system is complex and nonlinear between the water head h and the flow q. Because of the difficulty in establishing the precise nonlinear mathematical model, the BGNN is also used to learn the nonlinear relation defined as

$$h = h(q). \tag{3}$$

The dynamic characteristic of a generator, taking account of load characteristics, is often simplified as

$$x = \frac{1}{T_a s + e_n}(m_t - m_g), \tag{4}$$

where T_a is the inertia time constant of the generator, e_n denotes the adjusting coefficient of load, and m_g is described as the changed electrical load moment.

In summary, the modeling problem of the HTS includes mainly the identification of the nonlinear functions in Eqs. (2) and (3).

3 BGNN and training algorithms

The proposed BGNN is an a posteriori probability model based on Bayesian theory and the Gaussian hypothesis (Ye *et al.*, 1998).

Compared with the traditional recurrent and feed-forward neural networks such as BP and RBF, the BGNN can easily determine its topology and weights. The details of the BGNN and some theorem proofs can be found in Ye *et al.* (1998). The structure and redefined training algorithms of the BGNN are illustrated in the following subsections.

3.1 BGNN

The topological structure and connection weights of a BGNN are shown in Fig. 2.

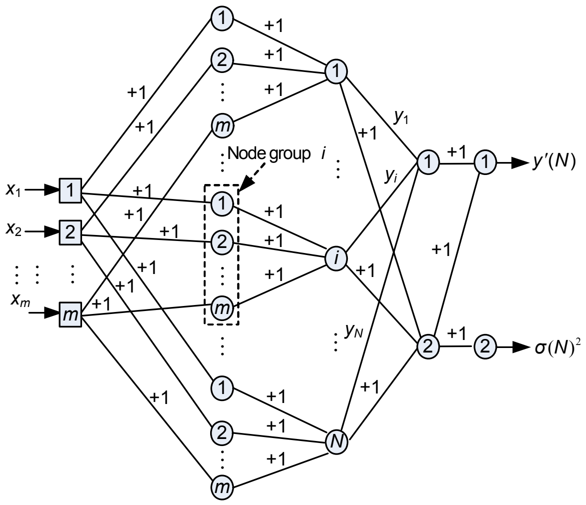

Fig. 2 Topology and connection weights of a BGNN (Ye *et al.*, 1998)

The main structure of the BGNN of Ye *et al.* (1998) is described as follows. Let ($\boldsymbol{X}_i$, y_i) (i=1, 2, …, N) denote the training data set, where N is the number of samples, $\boldsymbol{X}_i$ is the sample input and is represented by an $m\times1$ vector. $\boldsymbol{X}_i=[X_{i1}, X_{i2}, \dots, X_{im}]^{\mathrm{T}}$, and y_i is the sample output. The new output y corresponding to the new input $\boldsymbol{X}$ is generated using the measure of belief view of probability.

Under the Gaussian hypothesis, when the combined samples information ($\boldsymbol{X}_i$, y_i) (i=1, 2, …, N) is known, the probability distribution of $Y(\boldsymbol{X})$ will be approximately (Ye *et al.*, 1998)

$$p(Y\mid Y_1, Y_2, ..., Y_N)=\frac{c}{\sqrt{2\pi}\sigma(N)}\exp\left(-\frac{1}{2}\frac{(Y-y'(N))^2}{\sigma(N)^2}\right), \tag{5}$$

$$y'(N)=\sigma(N)^2\sum_{i=1}^{N}\sigma_i^{-2}y_i, \tag{6}$$

$$\sigma(N)^{-2}=\sum_{i=1}^{N}\sigma_i^{-2}, \tag{7}$$

where in Eq. (5), c is a normalizing constant independent of Y, $y'(N)$ denotes the mean value of Y and $\sigma(N)$ is the variance value.

Assume that

$$\sigma_i^2=\sigma_0^2\exp\left((\boldsymbol{X}-\boldsymbol{X}_i)^{\mathrm{T}}\boldsymbol{D}(\boldsymbol{X}-\boldsymbol{X}_i)\right), \tag{8}$$

where $\boldsymbol{D}$ is defined as the input threshold matrix including the parameters d_{11}, d_{12}, …, d_{mm} which will be evaluated through the network training.

$$\boldsymbol{D}=\begin{bmatrix} d_{11}^{-2} & & \\ & d_{jj}^{-2} & \\ & & d_{mm}^{-2}\end{bmatrix}. \tag{9}$$

The evaluation criterion used in the matrix $\boldsymbol{D}$ parameters training is similar to that of the prediction error method (Ye *et al.*, 1998):

$$V_{N_1}(D)=\frac{1}{2N_1}\sum_{i=1}^{N_1}(y_i-y_i')^2, \tag{10}$$

where N_1 is the net order, and y_i and y_i' are denoted as the desired output and the network output for sample i respectively.

3.2 Redefined training algorithms of the BGNN

The training procedures of the BGNN include the determination of off-line parameters and the application of on-line prediction. The aim of the off-line training of the BGNN is to obtain the desired threshold matrix parameters in $\boldsymbol{D}$. The key problem in the on-line application of the BGNN is to determine the suitable N group history data in the BGNN structure illustrated in Fig. 2. In place of the algorithms presented for the BGNN by Ye *et al.* (1998), in the following subsections we present algorithms redefined to take into account the characteristics of the HTS.

3.3 Off-line optimization of the threshold matrix parameters

The aim of the off-line training of the BGNN is to obtain suitable threshold matrix parameters so as to satisfy the evaluation criterion given in Eq. (10). The above process is in essence an optimization problem. Swarm intelligence algorithms such as genetic algorithms (GA) and particle swarm optimization algorithms (PSO) are powerful tools for optimization applications (Huang and Wang, 2006; Liu *et al.*, 2007). In this paper, an effective and improved *Escherichia coli* foraging optimization algorithm

(IEFOA) developed by Fang and Liu (2008) is applied to the off-line training of the BGNN.

3.4 On-line application of the BGNN driven by sliding window data

Because of its complex characteristics, control of the HTS needs to be on time. Therefore, the modeling of the HTS should also be fast in on-line identification applications. Although a kind of self-adjusting method for the BGNN was proposed by Ye *et al.* (1998), it can incur extra computation time, especially when the input data sample number N is big. So the self-adjusted method has deficiencies for the on-line prediction application of the HTS.

In this study, we use the sliding data window to confirm the input samples of the BGNN in the on-line prediction of the HTS. This is based on the assumption that the data near the present time contribute most to the output of the present system, i.e., a data sample nearer the present time can predict the present output with higher precision.

The aim of adopting the sliding data window is to maintain the prediction data sample scale N unchanged for the BGNN when predicting the output y. The concrete method is shown in Fig. 3.

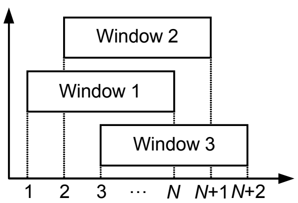

Fig. 3 Work process of sliding window

Fig. 3 shows three windows. The data sample quantity of each sliding window (i.e., the width of the sliding window) is N. In the change from window 1 to window 2, only the data farthest away from the present time of window 1 is eliminated, and window 2 is composed of the data sample nearest to the present time. The change from window 2 to window 3 follows a similar process, and in this way, the sliding window data form.

4 Simulation experiments and results

The above proposed BGNN was applied to the modeling of the HTS described in Eqs. (2) and (3). An HL220 HTS was simulated, with a rotation rate of 300 r/min, water height of 400 m, water flux rate of 36.1307 m^3/s and power rating of 127.6 MW. The water flux inertia time constant was 0.2 s and the generator inertia time constant was 5.9046 s.

To simulate the HTS's characteristics shown in Eq. (2), we constructed the following nonlinear Eq. (11) in the simulation tool of Matlab/Simulink:

$$\begin{cases} m_\mathrm{t} = \int e_y \mathrm{d}y + \int e_x \mathrm{d}x + \int e_h \mathrm{d}h, \\ q = \int e_{\mathrm{q}y} \mathrm{d}y + \int e_{\mathrm{q}x} \mathrm{d}x + \int e_{\mathrm{q}h} \mathrm{d}h, \end{cases} \tag{11}$$

where e_y, $e_{\mathrm{q}y}$, e_x, $e_{\mathrm{q}x}$, e_h and $e_{\mathrm{q}h}$ dentote six transfer coefficients of the HTS, and these parameters changed under a wide range of working conditions. In this study, the coefficients of e_y, $e_{\mathrm{q}y}$, e_x, $e_{\mathrm{q}x}$, e_h and $e_{\mathrm{q}h}$ were obtained using the technology described in detail by Shen (1996) and Li *et al.* (2009).

In an actual HTS, the transfer function of the penstock system nonlinear characteristic shown in Eq. (3) is commonly depicted as Eq. (12) under the condition of elastic water:

$$G_h(s) = \left(H(s)\right) / \left(Q(s)\right) = -2(T_\mathrm{w} / T_\mathrm{r})\mathrm{th}(0.5T_\mathrm{r}s), \tag{12}$$

where T_r is the reflection time of the water pipe, T_w is the inertia time constant of the water flow, and the expression th$(0.5T_\mathrm{r}s)$ denotes a hyperbolic tangent function. It can be seen that the characteristic of the penstock system is basically nonlinear.

4.1 Generation of training and testing data

In simulation experiments, we considered the training and testing samples which were generated by the system under closed-loop control with a reasonable proportion integration differentiation (PID) controller (Fig. 4). Instead of generating random input sequences to the HTS process, training and testing

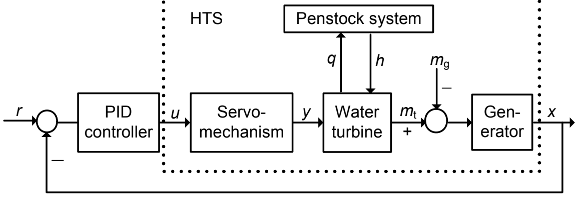

Fig. 4 Generation structure of training set from the control system of the hydraulic turbine generator unit

samples obtained from a closed-loop control system can excite the dynamic characteristics of the HTS as soon as possible, and this is more practical in the application of an HTS control.

In Fig. 4, r is the input exciting signal which takes the normal work situation operating value with random Gaussian white noise of mean 0 and variance 0.02. In the control of the HTS, the training samples u, y, q, h, m_t, m_g, and x are samples in the operation of the HTS with the typical changed work situation which denotes the nonlinear characteristics of the HTS. Therefore, the nonlinear model of the HTS can be obtained based on the BGNN and the training samples.

In the simulation experiments, the training set of the BGNN was obtained under the work situation of a frequency change of 20%, namely from 50 to 60 Hz. But the testing sets of the BGNN were acquired under the work situation of a frequency change from 50 to 40 Hz and with a condition load change of 20%.

4.2 BGNN training and prediction of the HTS models

In the identification of the HTS, the width of the sliding data window N was set as 10. The parameters used in the improved *Escherichia coli* foraging optimization algorithm (Fang and Liu, 2008) were as follows: S=10, Nc=10, Ns=6, w_1=0.2, w_2=0.1, $C(i)$= 0.01.

4.3 Flow BGNN model of the HTS

The input of the flow BGNN model was selected as $y(k)$, $y(k-1)$, $x(k)$, $x(k-1)$, $h(k)$, $h(k-1)$, $q(k-1)$ and $q(k-2)$. The output of the flow BGNN model was $q(k)$. Because the number of the flow BGNN model was 8, 8 threshold matrix parameters in $\boldsymbol{D}$ were to be trained. So the parameter dimension p to be optimized in IEFOA was set as 8.

Following off-line optimization based on the training set, the threshold matrix parameters of the flow BGNN model were obtained as $\boldsymbol{D}$= diag{231.0857, 163.1658, 157.6213, 205.0248, 98.2696, 33.5117, 158.3040, 278.4939}. The identification result is shown in Fig. 5.

The trained flow BGNN model was then applied to the testing sets and the prediction figures are shown in Fig. 6.

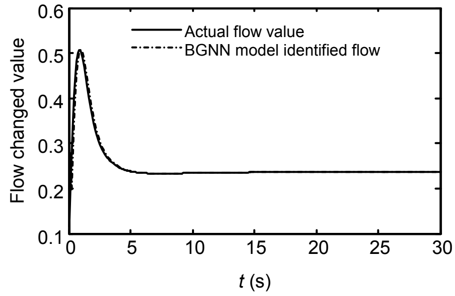

Fig. 5 Flow BGNN model identification with a 20% frequency change

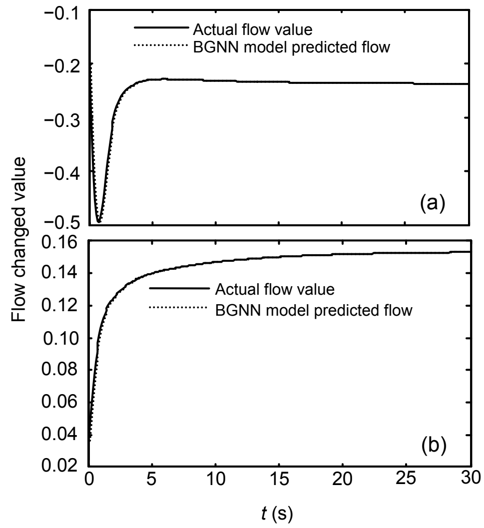

Fig. 6 Flow BGNN model prediction with frequency decreased from 50 to 40 Hz (a) and with a 20% load change (b)

4.4 BGNN moment model of the HTS

In the structure of the hydraulic turbine moment BGNN model, the input was $y(k)$, $y(k-1)$, $x(k)$, $x(k-1)$, $h(k)$, $h(k-1)$, $m_t(k-1)$ and $m_t(k-2)$. The output was $m_t(k)$. The input number of the moment BGNN model was 8 and therefore the number of threshold matrix parameters in $\boldsymbol{D}$ to be trained was 8. Thus, p in the IEFOA was also set as 8.

Following off-line optimization based on the training set, the threshold matrix parameters were obtained as $\boldsymbol{D}$=diag{224.7394, 68.6860, 129.7927, 37.5997, 267.8767, 120.6552, 127.3004, 247.0723}. The identification result is shown in Fig. 7a.

The trained moment BGNN model was then used on the testing sets and the prediction figures are shown in Figs. 7b and 7c.

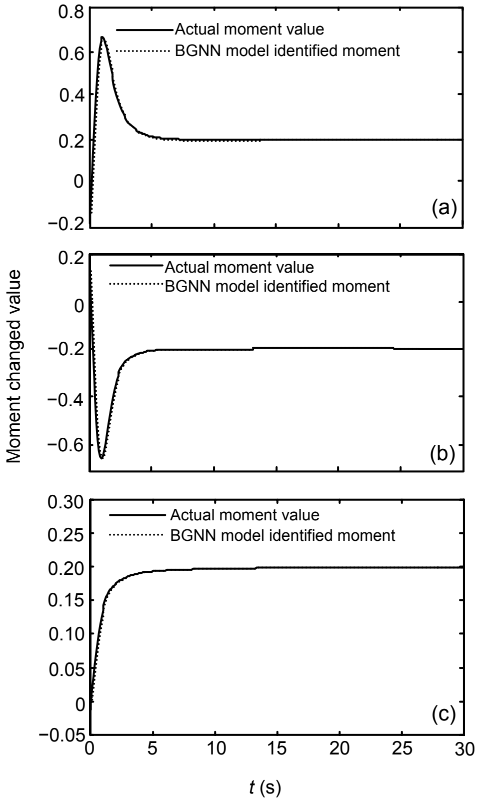

Fig. 7 Moment BGNN model prediction with a 20% frequency change (a), with frequency decreased from 50 to 40 Hz (b), and with a 20% load change (c)

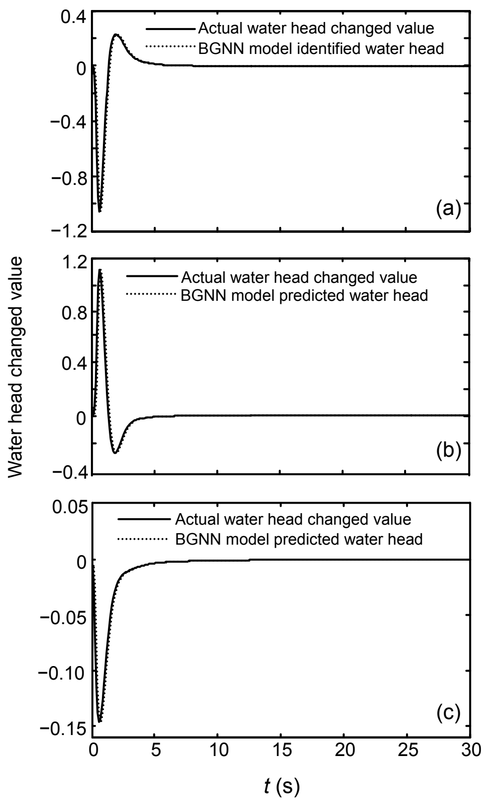

Fig. 8 Water head BGNN model prediction with a 20% frequency change (a), with frequency decreased from 50 to 40 Hz (b), and with a 20% load change (c)

4.5 BGNN water head model of the HTS

The input of the water head BGNN structure was selected as $q(k)$, $q(k-1)$ and $h(k-1)$. The output was $h(k)$. The number of the water head BGNN model was 3 and therefore the number of the threshold matrix parameters in $\boldsymbol{D}$ to be trained was 3. Thus, the dimension p in the IEFOA was 3.

Following off-line optimization based on the training set, the threshold matrix parameters of the water head BGNN model were obtained as $\boldsymbol{D}$= diag{146.9291, 243.4808, 293.7387}.

The identification and prediction results are shown in Fig. 8.

5 Analysis and conclusion

The experimental results show that the proposed BGNN model method can obtain high identification and on-line prediction accuracy for the HTS modeling problem. The reason is that a BGNN based on a sliding data window can fully utilize the window data to realize on-line prediction of the HTS. From the experiments, we can see also that the BGNN can obtain better prediction accuracy of the HTS under different operating conditions. This is because the BGNN model can integrate window data into its structure, sustainably update the structure of the BGNN through the continual sliding of the window, and quickly capture the change in the HTS characteristics. This feature of the BGNN is attractive for a dynamic system in which characteristics often change, and it can be used in the on-line prediction application for a nonlinear dynamic system.

Future work will focus on HTS control applications based on the on-line prediction of the HTS models using the BGNN modeling method.

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