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Research Article

Hybrid robust model based on an improved functional link neural network integrating with partial least square (IFLNN-PLS) and its application to predicting key process variables

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ABSTRACT

In this paper, a hybrid robust model based on an improved functional link neural network integrating with partial least square (IFLNN-PLS) is proposed. Firstly, an improved functional link neural network with small norm of expanded weights and high input–output correlation (SNEWHIOC-FLNN) was proposed for enhancing the generalization performance of FLNN. Unlike the traditional FLNN, the expanded variables of the original inputs are not directly used as the inputs in the proposed SNEWHIOC-FLNN model. The original inputs are attached to some small norm of expanded weights. As a result, the correlation coefficient between some of the expanded variables and the outputs is enhanced. The larger the correlation coefficient is, the more relevant the expanded variables tend to be. In the end, the expanded variables with larger correlation coefficient are selected as the inputs to improve the performance of the traditional FLNN. In order to test the proposed SNEWHIOC-FLNN model, three UCI (University of California, Irvine) regression datasets named Housing, Concrete Compressive Strength (CCS), and Yacht Hydro Dynamics (YHD) are selected. Then a hybrid model based on the improved FLNN integrating with partial least square (IFLNN-PLS) was built. In IFLNN-PLS model, the connection weights are calculated using the partial least square method but not the error back propagation algorithm. Lastly, IFLNN-PLS was developed as an intelligent measurement model for accurately predicting the key variables in the Purified Terephthalic Acid (PTA) process and the High Density Polyethylene (HDPE) process. Simulation results illustrated that the IFLNN-PLS could significant improve the prediction performance.

1. Introduction

In the modern industry plants, the implementation of the control system for some key process variables is more and more complicated because of the increasing complexity in the process operators [1]. Thus, an accurate measurement model is quite important for the advanced controller design. Among the methods in the Chemometrics, the partial least square regression (PLSR) has been widely applied [2]. However, the PLSR method fails to deal with the highly nonlinear data of the complex processes [3]. And, the performance of the advanced control systems is subject to the highly nonlinear characteristics and some disturbances, such as the feeding temperature, the feeding quantity, and the fuel amount [4,5]. In order to solve this problem, neural networks (NNs) based modeling strategies have attracted more and more attention. It is well known that NNs have powerful ability in functional approximation and can well handle the highly nonlinear relationship between the input data and the output data. And the NNs based intelligent measurement models have remarkably enhanced the control capabilities for the complex processes [6–8]. Moreover, the distributed control systems (DCS) have been widely applied in most industries so that the process data can be easily collected. Then the data collected from the DCS can be effectively learnt by NNs [9,10].

The back propagation neural network (BPNN) is a typical and widely applied neural network of the NNs [11–13]. A three-layer BPNN has been successfully applied in many fields, such as modeling [14,15], control [16,17], identification [18,19], classification [20,21], etc. However, the proper number of the hidden layer nodes in the BPNN is very difficult to determine. The BPNN with too many hidden layer nodes may be over-fitting. And the BPNN with too few hidden layer nodes cannot well learn the training data. The pruning algorithm is rather efficient to determine the number of the hidden layer nodes. Certain number of hidden layer nodes are added or removed during the pruning phase [22].

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Another method for determining the proper number of the hidden layer nodes is the trial-and-error method [23]. However, the methods of the pruning algorithm and the trial-and-error are much time-consuming. In order to avoid this problem, an alternative neural network named functional link neural network (FLNN) can be adopted. The FLNN was originally proposed by Pao [24]. Different from the BPNN, FLNN is a single-layer neural network. And the FLNN has been developed as a popular method with applications to forecasting, identification, control, classification and modeling [25–29]. As a computationally efficient single-layer neural network, the FLNN's nonlinearity is introduced by the functional expansion of the input patterns by the trigonometric polynomial, the Chebyshev orthogonal polynomial and some other nonlinear functions [24]. FLNN has two main advantages. One advantage is that there is a reduced computational burden by increasing the dimensionality of the input space with a set of linearly independent nonlinear functions. The other advantage is that the difficulty in determining the optimal number of the hidden layer nodes is avoided.

Due to the excellent features, FLNN has attracted more and more attention. However, there are two flaws in the FLNN. One is that the functional expansion of the original inputs is directly put into the network may weak the generalization performance of FLNN. Bartlett's theory on the generalization performance of feedforward neural networks [30] states that the relatively smaller the norm of the weights is, the better generalization performance the networks tend to achieve. What is more, Bartlett [30] and Huang et al. [31] have proved that the training performance can be kept after the input weights are attached with relatively smaller norm. That is to say, the weights with relatively smaller norm have no influence on the convergence during the training phase. In the FLNN, all the expanded inputs are directly put into the network, which means that all the expanded inputs are attached to the weights with the value of 1. According to the theory of Bartlett, the generalization performance can be enhanced by attaching some smaller norm weights to the expanded inputs. The other flaw is that the correlation coefficient analyses between the expanded variables and the outputs are ignored. In the FLNN, the input space is expanded to a nonlinear space for solving the nonlinearity between the original inputs and the outputs. In the regression field, the Pearson correlation coefficient (PCC) is usually used to show the relationship between the inputs and the outputs. If the value of the PCC is closer to 1 or -1, then there is higher correlation between the inputs and the outputs. In our study, the PCC between the expanded inputs with smaller norm weights and the PCC between the original expanded input and the outputs are both calculated out. In order to further improve the performance of the FLNN, only the expanded variables with higher correlation are selected as the inputs.

In this paper, a robust modeling method of an improved functional link neural network integrating with partial least square (IFLNN-PLS) is proposed. First, an improved functional link neural network with small norm of expanded weights and high input–output correlation (SNEWHIOC-FLNN) is proposed to enhance the generalization performance of FLNN. In the SNEWHIOC-FLNN, the expanded inputs are not directly put into the network; the expanded inputs are connected with a group of expanded weights with smaller norm. In the SNEWHIOC-FLNN, the expanded weights can be randomly generated with the range of [0, 1]. Then the Pearson correlation coefficient (PCC) between the expanded variables and the outputs is analyzed. The PCC before the expanded weights is compared with that after the expanded weights. And then the higher related expanded variables are used as the inputs of the network. In this way, the SNEWHIOC-FLNN model has two salient features. On one hand, the SNEWHIOC-FLNN model has a relatively smaller norm of weights attached to the expanded inputs. On the other hand, the expanded variables with higher input–output correlation are selected as the inputs. In order to test the performance of the proposed SNEWHIOC-FLNN model, firstly three UCI (University of California, Irvine) regression datasets named Housing, Concrete Compressive Strength (CCS), and Yacht Hydro Dynamics (YHD) are selected. Compared with the traditional FLNN model, the proposed SNEWHIOC-FLNN model can achieve smaller errors. However, the error back propagation algorithm used in the models usually suffers from the local minimum [31]. In order to achieve a more robust model, the partial least square method is adopted to calculated the connection weights between the input layer and the output layer. Thus, a hybrid robust model based on the improved functional link neural network integrating with partial least square (IFLNN-PLS) was established. Then the IFLNN-PLS model is developed as an intelligent measurement model for predicting the key variables in the Purified Terephthalic Acid (PTA) process and the High Density Polyethylene (HDPE) process. Simulation results illustrated that the IFLNN-PLS could significant improve the prediction performance.

The remaining sections of this paper are organized as follows: Section 2 provides some preliminaries about a brief overview of the basic functional link neural network; in Section 3, a systematic procedure to construct the improved functional link neural network with small norm of expanded weights and high input–output correlation (SNEWHIOC-FLNN) is introduced; the performance of SNEWHIOC-FLNN is tested using three UCI datasets and then a hybrid robust model based on the improved functional link neural network integrating with partial least square (IFLNN-PLS) is developed as an intelligent measurement model for predicting the key variables in the Purified Terephthalic Acid (PTA) process and the High Density Polyethylene (HDPE) process in Section 4, and the simulation results are demonstrated; Finally, concluding remarks are made in Section 5.

2. Preliminaries of FLNN

In our work, the intelligent measurement model is based on the functional link neural network (FLNN) and the partial least square (PLS) technologies. Details of the PLS algorithm can be found in the reference [2]. FLNN is the main subject. So in this section, a brief overview of FLNN is provided.

The FLNN is a kind of feed-forward neural networks. In FLNN, there are a number of enhancement nodes. These enhancement nodes are well known as functional links. The functional links are used as supplementary inputs within FLNN [21]. The supplementary inputs are enhanced by some nonlinear functions. Different types of nonlinear functions have been investigated [21,23]. There is only a single layer in the FLNN. Thus, it becomes very simple and effective to adopt the error back propagation algorithm for adjusting the FLNN parameters.

The structure of traditional FLNN without any hidden layer is shown in Fig. 1. Consider that K arbitrary training samples $\{(\mathbf{x}_i, \boldsymbol{y}_i)\}_{i=1}^{K}$ are available, where there are n elements in $\boldsymbol{x}_i$ and the $\boldsymbol{y}_i$ is a scalar. Each of the input patterns is passed through a functional expansion (FE) block for producing a corresponding m-dimensional expanded vector. The kth input pattern vector is represented by $X_k = [x_1(k), x_2(k), \cdots, x_n(k)]$, where X_k is the kth row vector in the training samples, and $x_n(k)$ is the nth element in X_k. For the kth input pattern, the FE block produces an expanded input vector given by $\hbar(X_k) = [\hbar_1(k), \hbar_2(k), \cdots, \hbar_m(k)]\,(k = 1, 2, \cdots, K)$, where m is the number of the selected nonlinear functions, $\hbar_m(k) = (g_m(x_1(k)), g_m(x_2(k)), \cdots, g_m(x_n(k)))_{1\times n}$ and $g_m(\cdot)$ is the mth selected nonlinear function. The weights vector of the FLNN is represented by $W_k = [w_1, w_2, \cdots, w_{n+m}]$ (for the expanded block, the weights w