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Data driven soft sensor development for complex chemical processes using extreme learning machine



Yan-Lin He^{*a*,*b*}, Zhi-Qiang Geng^{*a*,*b*}, Qun-Xiong Zhu^{*a*,*b*,*}

^a College of Information Science & Technology, Beijing University of Chemical Technology, Beijing 100029, China ^b Engineering Research Center of Intelligent PSE, Ministry of Education in China, Beijing 100029, China

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ABSTRACT

In this paper, a novel double parallel extreme learning machine with Pearson correlation coefficient based independent subnets (PCCIS-DPELM) was proposed for accurately modeling complex chemical processes. Compared with traditional ELM, PCCIS-DPELM has two salient features. One feature is that there are two independent subnets based on the Pearson correlation coefficient (PCC) between the input attributes and output attributes. Another feature is that PCCIS-DPELM has a double parallel structure. The PCCIS-DPELM model can well deal with the highly nonlinear data generating from complex chemical processes. In order to test the performance of PCCIS-DPELM, two complex processes of the Tennessee Eastman (TE) and the purified terephthalic acid (PTA) were selected. Then PCCIS-DPELM based soft sensors were developed for modeling the two complex processes. Compared with double parallel ELM (DPELM) and ELM, the experimental results of the two applications demonstrate that the PCCIS-DPELM model with less number of parameters can achieve smaller predicted relative errors. And the PCCIS-DPELM model can respond faster than the other two models. It is proved that the proposed PCCIS-DPELM is a promising method for accurately modeling complex chemical processes.

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1. Introduction

In modern industry processes, some key variables such as the product quality, the contents of some important components and some other important process parameters should be accurately measured. However, the hard devices for measuring could be very expensive. And the performance of the hard devices is often subject to the large delays and the extreme limitations of the process conditions. Thus, soft sensors, a substitution of the hard device for either the monitoring purpose or the control purpose, have attracted more and more attention (Ge and Song, 2010; Park and Han, 2000). However, the process operations in many industries especially in the chemical and petrochemical industries are more and more complicated, so it is more and more difficult and time consumed to build an accurate soft sensor based on mechanism models. With respect to the mechanism models, data driven based models have attracted more and more interest of researchers (Abbasi et al., 2014; Hosen et al., 2014; Kadlec et al., 2009; Mitra and Ghivari, 2006). Among the data driven technologies, the artificial neural network (ANN), a tool for dealing with the highly nonlinear relationship between the input variables and the output variables, has been successfully applied to developing soft sensors (Zilouchian and Jamshidi, 2001). ANN has some salient features: first of all, ANN has good ability in nonlinear function approximators (Chen et al., 1990;

E-mail address: zhuqx@mail.buct.edu.cn (Q.-X. Zhu).

^{*} Corresponding author at: Beijing University of Chemical Technology, College of Information Science & Technology, 15 Beisanhuan East Road, Chaoyang, Beijing 100029, China. Tel.: +86 10 64426960; fax: +86 10 64437805.

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Cybenko, 1989; Narendra and Parthasarathy, 1990); secondly, ANN has the ability to learn from the known information and then predict the unknown with certain accuracy; lastly, there is no requirements for the knowledge of the related processes when developing the black-box models using the ANN (Almeida, 2002; Minns and Hall, 1996; Mjalli et al., 2007). What is more, the intelligent control capabilities for complex processes can be remarkably improved with the aid of soft sensors based on ANN models (Forouzantabar et al., 2012; Gonzaga et al., 2009; Huang and Lewis, 2003; Tong et al., 2011).

Back propagation (BP) network is one kind of the most widely used neural networks (Chen, 1990; Heermann and Khazenie, 1992). Although BP has been successfully applied in many fields, the performance of BP is limited (Lei et al., 2004). Recently, a novel neural network named extreme learning machine (ELM) was proposed (Huang et al., 2004). The ELM is a single-hidden layer feed-forward neural network. In ELM, the weights between the input layer nodes and the hidden layer nodes are randomly assigned and the weights between the hidden layer nodes and the output layer nodes are obtained by using the least square method (He et al., 2014; Huang et al., 2011a,b, 2004). Compared with the BP network, ELM has an extremely fast learning speed (He et al., 2014; Huang et al., 2011a,b, 2006). In addition, some difficulties in the BP network, like selecting the parameters of the stopping criteria and learning rate, have been avoided in ELM (He et al., 2014; Huang et al., 2004). And it has been proved that ELM can outperform the BP network and the Support Vector Machine (Lan et al., 2013). Due to these salient features, ELM has attracted more and more attention and has been successfully applied to many fields, such as classification (Huang et al., 2011a,b; Rong et al., 2008; Zhang et al., 2007; Zheng et al., 2014), regression (He et al., 2014; Lan et al., 2010; Peng et al., 2013; Qi et al., 2014), recognition (Deng et al., 2014; Minhas et al., 2010; Zong and Huang, 2011), function approximation (Han and Huang, 2006), prediction (Lan et al., 2008; Sun et al., 2008; Wang et al., 2008), and so on.

In the real world applications, the soft sensor should satisfy two special requirements: acceptable precision and fast response. It is meaningful that the measurements form the sensors are accurate and reliable for the purposes of monitoring and control. And a faster response of the sensors can make the control system to better realize real time control. Additionally, the soft sensor models should deal with some particular problems like the highly nonlinear relationship and the different influences between the selected input variables and the output variables. In order to development an effective soft sensor, some improvements for ELM should be made to satisfy the special requirements and well deal with the particular problems. In the traditional ELM model, the relationship between the input attributes and the output attributes is not taken into consideration, and the input attributes with different influences put together in the input layer may weaken the regression accuracy (He et al., 2015a,b). A classification method was used to separate the original input space into several sub-spaces (He et al., 2015a). However, the influences of the input attributes on the output attributes were not taken into account. The different influences of the input attributes on the output attributes were taken into consideration using the Pearson correlation coefficient (He et al., 2015b). However, the learning speed of this model is limited and the model is not easy to build. Additionally, there is also direct information between the inputs and the outputs. However, there are no connections between the input layer nodes and the output layer nodes in ELM. Fortunately, a double parallel structure mentioned in previous work (He et al., 2015a,b; He and Huang, 2005; Yao et al., 2011) can be adopted to solve this problem. The double parallel structure can enable the output layer nodes to not only receive the information from the hidden layer nodes but also receive the direct information from the input nodes, which can enhance the performance of networks (He et al., 2015a,b).

In this paper, a novel double parallel extreme learning machine with Pearson correlation coefficient (PCC) based independent subnets (PCCIS-DPELM) was proposed. Compared with the traditional ELM, PCCIS-DPELM has two salient features. One is that PCCIS-DPELM has two independent subnets based the PCC between the input attributes and the output attributes. According to the PCC, the input attributes can be separated into two groups: input attributes with positive PCC and input attributes with negative PCC. Then the two subnets can be built according to the two attribute groups. The attributes with positive PCC are put together to built a subnet and the attributes with negative PCC are put together to built another subnet. That is to say, the influences of the different input attributes on the output attributes are taken into consideration when developing the subnets. Another feature of PCCIS-DPELM is that PCCIS-DPELM has a parallel structure, in which the output layer nodes not only receive the information from the hidden layer nodes but also receive the direct information from the input layer nodes. The weights between the input layer nodes and the hidden layer nodes are randomly generated, and the weights between the hidden layer nodes and the output layer nodes are analytically determined using the least square method. In this paper, the PCCIS-DPELM is used to develop accurate soft sensors for modeling two complex processes: the Tennessee Eastman (TE) process and the purified terephthalic acid (PTA) process. The TE process and the PTA process are selected due to the fact that there are many factors with high nonlinear effects on them. Additionally, ELM with double parallel structure (DPELM) and ELM are developed for comparisons. In the two illustrated experiments, the results of these two applications demonstrate that PCCIS-DPELM can achieve smaller predicted relative errors than DPELM and ELM. Moreover, PCCIS-DPELM with less number of parameters can obtain the optimal results, which indicates that PCCIS-DPELM with a simpler structure can perform better than ELM and DPELM with a more complicated structure. What is more, the proposed PCCIS-DPELM model can respond fastest among the three models. All the experimental results indicate that PCCIS-DPELM is a promising method for modeling complex chemical processes with comparable accuracy and fast response.

The remaining sections are organized as follows: Section 2 provides some preliminaries about a brief overview of the basic extreme learning machine and the Pearson correlation coefficient; in Section 3, a systematic procedure to construct the novel double parallel extreme learning machine with Pearson correlation coefficient (PCC) based independent subnets (PCCIS-DPELM) is introduced; soft sensors for Tennessee Eastman (TE) process and the purified terephthalic acid (PTA) process are developed using PCCIS-DPELM in Section 4, and the experimental results are demonstrated and also compared with those of DPELM and ELM; Finally, concluding remarks are made in Section 5.

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