Adaptive Soft Sensor Modeling Method for Time-varying and Multi-Dimensional Chemical Processes

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The time-varying and multi-dimensional characteristics are major causes of the low performance of soft sensors in chemical processes. To solve the problem, an improved adaptive soft sensor modeling method is proposed. This method obtains predicted deviation by modular steps of moving window and evaluates deterioration of soft sensors via Itest adaptively. Besides, this paper combines the moving window-autoassociative neural network (AANN) method to update both the modeling auxiliary variable and the auxiliary variable data. Data simulation and result analysis obtained via a continuous stirred tank reactor (CSTR) and a debutanizer column process (DCP) show that the improved adaptive soft sensor modeling method proposed in this paper can evaluate the deterioration of soft sensors and update the soft sensor model adaptively, and improve the predicted performance of soft sensors for time-varying and multi-dimensional chemical processes.

Introduction

In the nearest years, soft sensors have been widely applied to predict dominant variables, which are difficult to measure because of time-delay, hostile environment, and expensive laboratory costs (Corona et al., 2013; Geng et al., 2017). Compared to other modeling methods, soft sensor techniques construct a soft sensor model between easy-measure variables and difficult-measure ones to describe the underlying mapping relationship between the second variable and the primary variable in computer programs (Yuan et al., 2016). With high real-time performance, low cost and easy maintenance, the predictive model used to measure the primary variable arises (Jin et al., 2019). Therefore, a soft sensor is economically preferable and able to reduce the measurement delay significantly. So far, lots of data-driven soft sensor modeling method like principal component regression (Yuan et al., 2014), partial least squares (Li et al., 2018), artificial neural networks (Jana and Banerjee, 2018), support vector regression (Zhang and Liu, 2016) and gaussian process regression (Liu et al., 2015) have been widely used in chemical (Lu and Chiang, 2018), biological (Spann et al., 2018), pharmaceutical (Lauri Pla et al., 2017) and other fields (Liu et al., 2018).

However, industrial processes, especially chemical processes, often embody significant dynamics because of process state variations, degradation of catalyst, raw material changes (Shang et al., 2014). Once a soft sensor has been constructed, the soft sensor models cannot adapt to new conditions and its prediction accuracy will deteriorate. Consequently, soft sensor models should be updated regularly to maintain the accuracy of prediction. Adaptive learning mechanisms mainly include moving window learning, recursive learning, temporal difference modeling, and offset compensation. The methods mentioned above have some disadvantages, such as difficult to choose the size of moving window, unable to track the sudden change of process state, difficult to adapt to the change of functional relationship between the auxiliary variable and dominant variable, and difficult to determine the compensation weight (Kaneko and Funatsu, 2011; Jin et al., 2015, 2019; Fu et al., 2017; Galiasarov et al., 2017).

The moving window method is more suitable for the adaptive learning of chemical processes and its success has been demonstrated in some adaptive learning cases with slower time-varying characteristics (Kaneko and Funatsu, 2013). How to realize the evaluating deterioration of soft sensor model and update the modeling data that the relationship between auxiliary variables and dominant variables has changed are still puzzling researchers. The present adaptive learning methods do not consider the ill-conditioned models caused by overtopping dimension input variables and the poor performances of models caused by high noise.

Through the above discussions, this paper proposes an improved adaptive soft sensor modeling of time-varying, overtrop dimension input variables, and high noise chemical processes. This method applies the moving window-Itest to evaluate the deterioration of the soft sensor model and proposes the moving window-autoassociative neural network to update the modeling sample of soft sensor mode for time-varying, multi-dimensional, and high noise chemical processes. Case studies on the simulated datasets of CSTR demonstrate the effectiveness of the improved adaptive soft
sensor modeling method.

1. Modeling Method of Adaptive Soft Sensor

The adaptive soft sensor modeling method includes three parts: soft sensor modeling based on off-line data, evaluating deterioration of soft sensor model, and updating soft sensor based on on-line data.

1.1 Evaluating deterioration method of soft sensor model based on moving window-test

With the continuous production process of the chemical industry, because of the dynamic variance of chemical processes, equipment status, and production status have changed, leading to the performance deterioration of the established soft sensor model.

To evaluate the deterioration of the soft sensor model adaptively, this paper assumes that the number of samples in a soft sensor model is $m (m \geq 1)$, the number of modeling auxiliary variables is $n (n \geq 1)$, the modeling sample dataset is $S_{\text{prim}} = \{X_{\text{prim}}, Y_{\text{prim}}\}$, the test dataset is $S_{\text{test}} = \{X_{\text{test}}, Y_{\text{test}}\}$, the widths of the test dataset and moving window are $w (w \geq 1)$. The sample dataset is updated by the moving window method which the moving step size is one. The sample data in the current area when the moving window proceeds $l$ steps are $S_{\text{ren}} = \{X_{\text{ren}}, Y_{\text{ren}}\}$.

Because of the popularity of Root Mean Square Error (RMSE) in evaluating the performance of the soft sensor model, the RMSE value is used in this paper as basic data to evaluate soft sensor model deterioration.

The prediction error of the model data is:

$$ R_{\text{pri}} = \sqrt{\frac{1}{w} \sum_{i=1}^{w} [f_{\text{pri}}(x_{\text{pri}}(i)) - y_{\text{pri}}(i)]^2} \quad (1) $$

The prediction error of the current regional data is:

$$ R_{\text{ren}} = \sqrt{\frac{1}{w} \sum_{i=1}^{w} [f_{\text{ren}}(x_{\text{ren}}(i)) - y_{\text{ren}}(i)]^2} \quad (2) $$

If there are no significant differences between $R_{\text{pri}}$ and $R_{\text{ren}}$ then the primary soft sensor model experiences no deterioration and can be used. Otherwise, the primary soft sensor model experiences deterioration, and the soft sensor model should be updated.

The error of the soft sensor model is:

$$ D = | R_{\text{ren}} - R_{\text{pri}} | \quad (3) $$

Based on the Lindburg–Levy theorem and the chemical processes production state, when the moving window proceeds $l$ steps, the data distribution $\{D(l)\}_{l=1}^{L}$ is normal distributions.

The test problem is constructed as:

$$ \begin{align*}
H_0 : (\mu_{\text{pri}} = \mu_{\text{ren}}) & (S_{\text{pri}} = S_{\text{ren}}) \\
H_1 : (\mu_{\text{pri}} \neq \mu_{\text{ren}}) & (S_{\text{pri}} \neq S_{\text{ren}})
\end{align*} \quad (4) $$

The statistical variable is constructed as:

$$ T = \frac{\mu_{\text{ren}} - \mu_{\text{pri}}}{\sqrt{S_{\text{ren}}/L}} \quad (5) $$

where $\mu_{\text{pri}} = 0$ $\mu_{\text{ren}}$ is an average of $\{D(l)\}_{l=1}^{L}$:

$$ \mu_{\text{ren}} = \frac{1}{L} \sum_{l=1}^{L} D(l) \quad (6) $$

$S_{\text{ren}}^2$ is the variance of $\{D(l)\}_{l=1}^{L}$:

$$ S_{\text{ren}}^2 = \frac{1}{L-1} \sum_{l=1}^{L} (D(l) - \mu_{\text{ren}}) \quad (7) $$

From the above, the rejection region of this test problem is:

$$ T > t_{\alpha} \quad (8) $$

When $\mu_{\text{ren}} = \mu_{\text{pri}} = 0$, based on the characteristics of the $t$ distribution, statistical variables $T$ follow the $t$ distribution with $L-1$ degrees of freedom (Shao, 2016):

$$ T \sim t(L-1) \quad (9) $$

Therefore, a suitable threshold $\lambda_i$ can be found by a given confidence interval $\alpha$. If and only if the following condition is true,

$$ T_D > \lambda_i \quad (10) $$

hypothesis $H_1$ is accepted. A significant difference between $R_{\text{pri}}$ and $R_{\text{test}}$ means the soft sensor model has deteriorated. By contrast, hypothesis $H_0$ is accepted. The soft sensor model experiences no deterioration.

Meanwhile, the random abnormal data affects the applicability of evaluating deterioration method, thereby, a constraint condition is proposed as follows:

The value of the statistical variables $T_D$ should exceed the thresholds $\lambda_i$ three times consecutively, only then the performance deterioration of the established soft sensor model can be identified. The formula is as follows:

$$ s.t. \quad T_D > \lambda_i, i = 0, 1, 2 \quad (11) $$

1.2 Updating modeling sample data of soft sensor model based on Moving Window-Autoassociative Neural Network

The influence degree of auxiliary variables on dominant variables has been changed with the productive process in chemical processes. The choice of auxiliary variables affects the accuracy and generalization performances of the soft sensor model (Grbić et al., 2013).

The moving window can achieve a good effect of adaptive update (Rafferty et al., 2016) and obtain the latest data of the current process (Taris et al., 2017). Also, the autoassociative neural network can reduce the dimension of nonlinear processes, filter the redundant information and eliminate the noise (Hamidreza et al., 2014; Bitetto et al., 2016; Nazarko and Ziemianski, 2016). To improve the quality of modeling sample data set, solve the high complexity and incomplete
model structure which is caused by overtop dimension input variables (Cao and Luo, 2013), this paper proposes a Moving Window-Autoassociative Neural Network (MW-AANN) method which can update the modeling sample, filter the redundant information, extract the feature vector and improve the predicted performance of soft sensor model.

To compare the performance of the updated soft sensor model with that of the deteriorated soft sensor model, the width of updated modeling sample data is $m(m \geq 1)$, the number of modeling auxiliary variables is $n(n \geq 1)$.

The sample data in the moving window is:

$$S = \{ y_i(k) | k = 1, 2, \cdots, m \} \cup \{ u_i(k) | k = 1, 2, \cdots, m \}$$

where $y_i(k)$ is the output vector, $u_i(k)$ is the input vector, and $i = 1, 2, \cdots, n$.

The activation function of AANN is:

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

The input layer and the bottleneck layer of the first half are used to compress and decode the input sample information ($R_p = T_{S_p} S_p$). The output layer of the second half completes the decoding of feature information ($S_p = T_{S_p} R_p$). The “Autoassociative” process of nonlinear mapping is completed by $T_{S_p} S_p$ and $T_{S_p} R_p$ (Peng et al., 2012). The sample data which extract from the outputs of the bottleneck layer are used to modeling the soft sensor.

Based on the AANN method, the updated modeling data sample set can be obtained as $S_{\text{ren}} = \{ X_{\text{rew}}, Y_{\text{rew}} \}$. Just like the primary soft sensor model, the number of auxiliary variables in the updated modeling data sample is $n(n \geq 1)$. Moreover, the test data set of the updated soft sensor model is $S_{\text{ren}} = \{ X_{\text{rew}}, Y_{\text{rew}} \}$. The width of the test data set is $w(w \geq 1)$. Through the test data set of updated soft sensor models, the value of $R_{\text{ren}}$ has got. Compared with the values of $R_{\text{pri}}$ and $R_{\text{pri}}$, if the value of $R_{\text{ren}}$ is in the area of Non-deterioration, then the result determines the predicted performance of the soft sensor model has been restored.

### 1.3 Soft sensor modeling based on LSSVM

The least squares support vector machine (LSSVM) is a machine learning method proposed by Suykens (Suykens and Johan, 2012), having excellent computing speed and convergence precision to solve function estimation problems.

The LSSVM model is:

$$y(x) = \omega^T \phi(x) + b$$

where $\phi(g)$ is a nonlinear transformation function, $\omega$ is the adjustable weight vector, and $b$ is the offset value.

The objective function of the LSSVM (Suykens et al., 2012) is:

$$\min J(\omega, \xi) = \frac{1}{2} \omega^T \omega + \frac{C}{2} \sum_{i=1}^{l} \xi_i^2$$

s.t. $y_i = \omega^T \phi(x_i) + b + \xi_i$ $(i = 1, 2, \cdots, l)$

where $x_i \in \mathbb{R}^n$ is the input vector, $y_i \in \mathbb{R}$ is the corresponding output vector, $\xi_i$ is the error between the system output value and the actual value, $C \geq 0$ is the regularization parameter.

Based on the Karush-Kuhn-Tucker (KKT) conditions, the Lagrange polynomial function for the optimization is solved. The LSSVM model for the function estimate is:

$$y' = f(x) = \sum_{i=1}^{l} a_i K(x_i, x) + b'$$

The universal radial basis function is employed in this paper as follows:

$$k(x, x') = \exp \left( -\frac{\|x - x'\|^2}{2\sigma^2} \right), \sigma^2$$ is the kernel radius

### 2. CSTR Simulation Results and Analysis

To verify the proposed sensor modeling method, a non-linear time-varying CSTR is studied. CSTR is an object abstracted from the actual industrial equipment and has a high similarity with industrial equipment, so it has a high reference significance (Mosalanejad and Arefi, 2018). The simulation environment implemented on CSTR simulates the time-varying and nonlinear characteristics to test the effective processing ability of the proposed method to the research problems, which is also a commonly used performance detection method in the industry. CSTR is also
widely used to test the performance of soft sensor models for nonlinear time-varying objects, which has strong persuasion. (Fujiwara et al., 2009; Shao and Tian, 2015)

A schematic diagram of a CSTR (Shao, 2016) is shown in Figure 2.

The definitions and steady-state values of the CSTR parameters are listed in Table 1.

Table 1: Definitions and steady-state values of the CSTR parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAi</td>
<td>Reactant concentration in feed</td>
</tr>
<tr>
<td>k0</td>
<td>Reaction rate</td>
</tr>
<tr>
<td>Fi</td>
<td>Feed flow rate</td>
</tr>
<tr>
<td>Tr</td>
<td>Reactor temperature</td>
</tr>
<tr>
<td>Fc</td>
<td>Cooling water flow rate</td>
</tr>
<tr>
<td>Ti</td>
<td>Feed temperature</td>
</tr>
<tr>
<td>Tci</td>
<td>Temperature at cooling water inlet</td>
</tr>
</tbody>
</table>

The catalyst activity $k_0$ is set in Figure 3.

In this paper, the width of the moving window is 10, $a = 0.01$, and the degree of freedom is 9. That is, when the statistic $T_{DR} > \lambda = 2.8214$, the soft sensor model has deteriorated. Otherwise, the soft sensor model experiences no deterioration.

The $C_A$ is selected as the dominant variable in the soft sensor model. The feed flow rate $F_i$, cooling water flow rate $F_c$ and reactor interior temperature $T_r$ are selected as the auxiliary variables of the soft sensor model.

2.1 CSTR simulation for evaluating deterioration method of the soft sensor model

The sampling cycle of the auxiliary variables and the dominant variable is set to 1 h; the simulation time is set to 90 h. Additionally, gaussian white noise is applied to the simulation data and the simulated data set is then normalized. In the CSTR process, the concentration of raw material $A$ in reactor $C_A$ is selected as the dominant variable in the soft sensor model, and the feed flow rate $F_i$, cooling water flow rate $F_c$ and reactor interior temperature $T_r$ or the reactor interior temperature $T_i$, feed temperature $T_f$ and cooling water temperature $T_{ci}$ are selected as the auxiliary variables of the soft sensor model for the simulation. Moreover, the CSTR process is simulated two times, one is the normal CSTR process, the other is the CSTR process with deterioration problem. The CSTR process data under normal condition is divided into an initial soft sensor model modeling.
and test sample set. The CSTR process data with deterioration problem is divided into a test sample set with deterioration problem, modeling sample data set with updated soft sensor model, and test sample data set.

The LS-SVM parameters $C$ and $\sigma^2$ are optimized by the PSO algorithm.

The training of the soft sensors by the modeling data is illustrated in Figure 4. The training performance of the soft sensor is given in Table 2. From Figure 4 and Table 2, it can be observed that the modeling methods give a good fitting performance. Also, the modeling methods give a good predicted performance, which is shown in Figure 5 and Table 3.

According to the width of the moving window, the test sample sets of the soft sensor model are obtained based on the moving step size. Based on the test sample sets, the values of RMSE are computed. Due to mechanical wear, sensor deterioration of the equipment, values of RMSE increase gradually and the predicted performance of the soft sensor model deteriorate gradually, as shown in Figure 6(a).

The numerical curve of RMSE which is always on the rise shows that the predicted performance of the soft sensor model is deteriorating gradually. According to formulas 3 to 7, the values of $T_D$ can be computed. Additionally, the numerical curve of $T_D$ has been shown in Figure 6(b).

Although there are some abnormal fluctuations, the $T_D$ values are generally in an upward state in Figure 6(b). Based on the $T_D = 2.870572 > \lambda$, to step $l = 7$, it is considered that the deterioration problem may occur in the soft sensor model. However, when the moving window proceeds to step $l = 8$, the value of $T_D$ is 1.595384 less than 2.8214. At this point, it is considered that the data of step 7 are abnormal and the soft sensor model is not deterioration.

Moreover, the values of $T_D$ are 2.846904, 3.4358715, and 3.938894 when the moving window proceeds to step $l = 13$, 14, and 15, respectively. Since the values of $T_D$ are greater than the threshold $\lambda$, on three consecutive steps, the current soft sensor model has deteriorated. This shows the proposed evaluating deterioration method of the soft sensor model can avoid the influence of abnormal data on statistical detection methods with good applicability.

2.2 CSTR simulation for modeling samples updating method of the soft sensor model

Once the soft sensor model deteriorates, the sample data needs to be updated. In this case, the latest sample data of modeling soft sensors in chemical processes are obtained by the moving window method. In order to reduce the number of input variables of the soft sensor model and the complexity of the new soft sensor model, the dimension of variables on the feed flow rate $F_i$, cooling water flow rate $F_c$, reactor interior temperature $T_r$, feed temperature $T_i$ and cooling water temperature $T_{ci}$ should be reduced by AANN.

A 5-3-5 structure is adopted in AANN and the compression ratio of the input layer to the bottleneck layer is $\gamma = 1.67$, as shown in Figure 7.

The training of the updated soft sensor which is established by the data of bottleneck output is illustrated in Figure 8.

The training of the updated soft sensors by the modeling data is illustrated in Figure 8. The training performance of
the updated soft sensor is given in Table 4. From Figure 8 and Table 4, it can be observed that the modeling methods give great fitting performances.

To reflect the predicted performance of the soft sensor model based on the output data of the hidden layer of auto-associative neural network and the generalization performance of the soft sensor model, 4 groups of CSTR process variables are randomly selected for prediction.

The test sample set is modularized by the moving window method. The width is 10, the moving step size is 1, the number of steps is 7. Predicted performances on different test sample sets are shown in Table 4.

The curves of RMSE values for predicted performance on nondeteriorated soft sensor model, deteriorated soft sensor model, and updated soft sensor model are shown in Figure 9. It is worth mentioning that the curves of RMSE value for predicted performance on the updated soft sensor model are based on the 4 groups which are randomly selected from CSTR process variables.

The Error bars of the 4 test groups are shown in Figure 10. As shown in Figure 10, the average values of RMSE for 4 test groups all below the deteriorated value of RMSE, and the average values of RMSE for 4 test groups are closed to the primary value of RMSE. These above suggest that the predicted performance of the soft sensor has been restored.

2.3 Further discussions on modeling samples comparison

To further validate the generalization of the proposed adaptive soft sensor modeling method, serval soft sensor models are built by 4 groups of modeling parameters which are shown in Table 4. Table 5 gives the predicted performances of the soft sensor model.

To analyze the influence of statistical fluctuations, the K-fold cross-validation is used for constructing several experiments. In this paper, 5 parameters of the chemical process are divided into 4 subsets. The model training has been repeated 4 times and 4 subsets are used as the test set. The model prediction results are shown in Table 5. Compared with Table 5 and Table 4, the predicted performances are improved when the training parameters and the test parameters are the same. However, the predicted performances are poor when the training parameters and the test parameters are different. These above indicate that the soft sensor model based on samples of AANN has better generalization. Once the numerical values of model parameters are abnormal, other chemical process parameters can be selected instead of abnormal parameters. It is helpful to guarantee the prediction accuracy of the soft sensor model.

3. DCP Simulation Results and Analysis

In this subsection, the results of the application of the proposed adaptive soft sensor to an actual dataset from a debutanizer column process are presented to further verify the proposed method. The dataset from the DCP can be download from Springer which has become a standard for testing the performance of adaptive soft sensor models.
The definitions of the DCP parameters are listed in Table 6. In this section, 200 samples are selected as the historical database. 150 samples are the modeling dataset, and the other 50 samples are used as the primary test dataset. A total of 100 samples are selected to test the model deterioration and updating effect. The modeling variables of the primary soft sensor model are \( u_1, u_2, u_3, \) and \( u_4 \) selected by experts. Additionally, the parameters of LSSVM are set as \( C = 127.16 \) and \( \sigma^2 = 3.15 \).

Through the modeling dataset and primary test dataset, the performances of the primary soft sensor model are shown in Table 7.

As shown in Table 7, the soft sensor model has a good fitting performance. Notably, the predicted performance of the soft sensor model is not very good due to the noise in the DCP data. Based on the test samples the RMSE and \( T_D \) values change with increasing test samples with the moving window method as shown in Figure 11.

The numerical curve of RMSE which is always on the rise shows that the predicted performance of the soft sensor model is deteriorating gradually. By the threshold of the given confidence range with \( t \)-test which gets from the \( t \)-distribution table, the \( T_D \) values of the RMSE are greater than 2.7764 at steps 9, 10, and 11 as shown in Figure 11(b).

Through the soft sensor model deterioration detection method, deterioration of the primary soft sensor model has been identified. Although the RMSE values exceed 2.7764 at some points in the early steps of the testing process just like step 3, they do not exceed the threshold for three continuous steps, so they do not meet the deterioration criteria which can avoid wrong judgment in \( t \)-test.

Once the deterioration problem occurs, the soft sensor model needs to be updated. The moving window is used to update the DCP samples. Based on the updated DCP samples, an AANN with 7-4-7 structure is used to get the modeling samples of the updating soft sensor model as shown in Figure 12.

According to the AANN method, the modeling samples

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**Table 6** Definitions of the DCP parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( u_1 )</td>
<td>Tower top temperature</td>
</tr>
<tr>
<td>( u_2 )</td>
<td>Tower top pressure</td>
</tr>
<tr>
<td>( u_3 )</td>
<td>Backflow</td>
</tr>
<tr>
<td>( u_4 )</td>
<td>Flow to the next process</td>
</tr>
<tr>
<td>( u_5 )</td>
<td>Layer 6 tray temperature</td>
</tr>
<tr>
<td>( u_6 )</td>
<td>Tower bottom temperature</td>
</tr>
<tr>
<td>( u_7 )</td>
<td>Tower bottom pressure</td>
</tr>
<tr>
<td>( y )</td>
<td>Concentration of butane</td>
</tr>
</tbody>
</table>

**Table 7** Performances of the primary soft sensor model of DCP

<table>
<thead>
<tr>
<th>Performance of soft sensor</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training performance</td>
<td>0.0318</td>
</tr>
<tr>
<td>Predicted performance</td>
<td>0.0748</td>
</tr>
</tbody>
</table>

**Table 8** Performances of the updated soft sensor model of DCP

<table>
<thead>
<tr>
<th>Performance of soft sensor</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training performance</td>
<td>0.0221</td>
</tr>
<tr>
<td>Predicted performance</td>
<td>0.0712</td>
</tr>
</tbody>
</table>

**Table 9** Predicted performances on different test samples of DCP

<table>
<thead>
<tr>
<th>Test samples</th>
<th>Soft sensor model</th>
<th>RMSE Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( u_1, u_2, u_3, u_4 )</td>
<td>Soft sensor model based on MW-AANN method</td>
<td>0.0787</td>
</tr>
<tr>
<td>( u_1, u_2, u_3, u_4 )</td>
<td>Soft sensor model based on MW method</td>
<td>0.0752</td>
</tr>
<tr>
<td>( u_1, u_3, u_6, u_7 )</td>
<td>0.0788</td>
<td></td>
</tr>
<tr>
<td>( u_2, u_4, u_5, u_7 )</td>
<td>0.0784</td>
<td></td>
</tr>
<tr>
<td>( u_3, u_4, u_7 )</td>
<td>0.0787</td>
<td></td>
</tr>
</tbody>
</table>

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Fig. 11 RMSE and \( T_D \) curves of soft sensor model based on test data of DCP

Fig. 12 The 7-4-7 structure of AANN
are got to establish an updated soft sensor model. Also, the parameters of LSSVM are set as $C=125.37$ and $\sigma^2=2.21$ optimized by PSO.

The performances of the updated soft sensor model are shown in Table 8 with the numbers of modeling samples and test samples are 150 and 50, respectively. A comparison of Table 7 and Table 8 shows that the performances of the soft sensor models are similar. The simulation process indicates that the performance of the soft sensor model has been restored.

To further reflect the prediction performance and generalization performance of the soft sensor model based on the AANN, 4 groups of test samples of DCP process variables with the numbers of 50 are randomly selected for prediction as shown in Table 9.

The RMSE values of predicted performances with updated soft sensor models based on 4 different experimental data are 0.0787, 0.0788, 0.0784, and 0.0787, respectively. Comparisons of Table 7 and Table 9 show that the deviations are not more than 10%, and the soft sensor model has similar predicted performances under different test samples. The simulation results show that no matter which 4 process variables are selected, the better predicted performances can be achieved.

Moreover, compared with the basic moving window method, the soft sensor model based on the MW-AANN method has better generalization performance as shown in Table 9.

**Conclusion**

The point at the time-varying and multi-dimensional problems of chemical processes, and adaptive soft sensor modeling method are proposed in this paper. Firstly, an evaluating deterioration method of the soft sensor model is proposed. Based on the RMSE values of the predictive performance evaluation which are obtained by modularizing the test samples set through the moving window, the statistical variable of the statistical hypothesis test is constructed. Through the location of statistical hypothesis test, the soft sensor model has evaluated deterioration adaptively. Second, as the modeling auxiliary variables are difficult to determine, which are caused by the time-varying characteristics of chemical processes, a modeling sample updating method based on moving window-AANN has been proposed. This method filters the noise of sample data sets, reduces the dimension of input vectors, and updates the modeling samples. The soft sensor model based on the updated modeling samples has better predictive accuracy and generalization performance. The above researches are crucial to improving the predicted accuracy in our proposed soft sensor based on simulation results using simulated datasets of CSTR and actual datasets of DCP. Additionally, the simulation results demonstrate the effectiveness of the proposed method.

**Acknowledgement**

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**Literature Cited**


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