Hierarchical Quality-Relevant Feature Representation for Soft Sensor Modeling: A Novel Deep Learning Strategy

Xiaofeng Yuan, *Member, IEEE*, Jiao Zhou, Biao Huang, *Fellow, IEEE*, Yalin Wang, *Member, IEEE*, Chunhua Yang, *Member, IEEE*, and Weihua Gui, *Member, IEEE*

***Abstract*—Deep learning is a recently developed feature representation technique for data with complicated structures, which has great potential for soft sensing of industrial processes. However, most deep networks mainly focus on hierarchical feature learning for the raw observed input data. For soft sensor applications, it is important to reduce irrelevant information and extract quality-relevant features from the raw input data for quality prediction. To deal with this problem, a novel deep learning network is proposed for quality-relevant feature representation in this article, which is based on stacked quality-driven autoencoder (SQAE). First, a quality-driven autoencoder (QAE) is designed by exploiting the quality data to guide feature extraction with the constraint that the potential features should largely reconstruct the input layer data and the quality data at the output layer. In this way, quality-relevant features can be captured by QAE. Then, by stacking multiple QAEs to construct the deep SQAE network, SQAE can gradually reduce irrelevant features and learn hierarchical quality-relevant features. Finally, the high-level quality-relevant features can be directly applied for soft sensing of the quality variables. The effectiveness and flexibility of the proposed deep learning model are validated on an industrial debutanizer column process.**

***Index Terms*—Artificial neural network (ANN), deep learning, quality-driven autoencoder (QAE), soft sensor, stacked QAE (SQAE).**

Manuscript received April 21, 2019; revised June 17, 2019 and August 3, 2019; accepted August 30, 2019. Date of publication September 2, 2019; date of current version February 28, 2020. This work was supported in part by the National Key R&D Program of China under Grant 2018YFB1701100, in part by the National Natural Science Foundation of China under Grant 61590921, Grant 61703440, Grant 61860206014, and Grant 61621062, in part by the 111 Project under Grant B17048, in part by the Natural Science Foundation of Hunan Province of China under Grant 2018JJ3687, and in part by Innovation-driven Plan in Central South University under Grant 2018CX011. Paper no. TII-19-1483. (*Corresponding author: Yalin Wang.*)

X. Yuan, J. Zhou, Y. Wang, C. Yang, and W. Gui are with the School of Automation, Central South University, Changsha 410083, China (e-mail: yuanxf@csu.edu.cn; 754712094@qq.com; ylwang@csu.edu.cn; ychh@csu.edu.cn; gwh@csu.edu.cn).

B. Huang is with the Department of Chemical and Materials Engineering, University of Alberta, AB T6G2G6, Edmonton, Canada (e-mail: biao.huang@ualberta.ca).

Color versions of one or more of the figures in this article are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TII.2019.2938890

I. Introduction

With the fast development of data measuring and storing techniques, as well as the wide use of distributed control systems (DCS), vast amounts of data are collected in modern industrial processes. For effective process monitoring, control, and optimization, they largely depend on the real-time identification of process key quality variables, most of which are often difficult to measure online [1]–[5]. Therefore, it is imperative to develop data-driven soft sensor models to estimate these quality variables by those routinely measured process variables based on massive data within the industrial processes [6]–[8]. Up to now, a number of data-driven methods have been successfully developed for soft sensor applications, like principal component analysis (PCA) [9], partial least squares (PLS) [10], artificial neural networks (ANN) [11], and support vector machine (SVM) [12], to name just a few.

Generally, there are complex correlations, nonlinearities, and redundancies in the massive high-dimensional process data. They can easily lead to poor robustness, instability, and even failure of the soft sensor models. To better model the complicated real-world process data, it is necessary to carry out feature representation for them, which can capture useful information for soft sensor modeling. However, it is often labor-intensive, time-consuming, and expensive to design domain-specific handcrafted features for complex data patterns. Alternatively, many different feature extractors, like PCA and PLS, have been designed to capture the underlying features from observed data automatically [13], [14].

Although the aforementioned methods can be utilized to learn different features for data modeling tasks, their expressive ability is still insufficient to describe the complex data patterns in large-scale processes due to the shallow network architectures. Recently, deep learning [15], [16] has been developed for hierarchical feature representation of complex data patterns, which has made impressive progress in many fields, such as natural language processing, image recognition, and computer vision [17]–[19]. Especially, it became a milestone that AlexNet (a large deep learning model) won the champion in the famous ImageNet Large Scale Visual Recognition Challenge contest, which showed considerable breakthrough improvement in image recognition accuracy in 2012. Since then, deep learning has drawn more and more attention and become a mainstream of machine learning. Up to now, many different deep networks like deep belief network (DBN) [20], [21], stacked autoencoder (SAE) [22], and convolutional neural network (CNN) [23] have been designed and applied in industry extensively. Moreover, they can outperform traditional state-of-the-art machine learning models, such as SVM on different real-world problems [24]–[26].

Deep learning can learn hierarchical features from the raw observed data progressively with the greedy layer-wise unsupervised pretraining technique. These features can be easily utilized for different tasks like classification and regression problems, which can usually achieve more effective results. Recently, deep learning has been introduced for process data modeling, such as fault classification and soft sensor in industrial plants [20], [27]–[35]. Jiang *et al.* proposed a dynamic sparse SAE network to extract discriminative features for fault classification in dynamic processes [32]. Shang *et al.* applied DBN to predict the 95% cut point of the heavy diesel in a crude distillation unit, which showed impressive advantages of deep learning for soft sensor modeling [20]. Yao *et al.* developed a semisupervised deep learning framework for inferential modeling, which was based on the hierarchical extreme learning machine [28].

As can be seen, most of the aforementioned deep networks focus on learning features for the raw data by stacking basic modules, which reconstructs the input by feature representation while constrains the representation to have certain desirable properties. For example, regular autoencoder seeks to keep the reconstruction input error as small as possible. However, AE is usually not stable and robust to the corruption of the inputs. Denoising autoencoder was developed to recover the original undistorted input from partially corrupted one. Features learned in this way are more robust to noises than the ordinary autoencoder [22]. When there are more hidden neurons than the inputs, sparse autoencoder can be adopted to make sure that only a small number of hidden neurons are active at the same time [36]. The learned features are good representation for the raw observed input data since these networks are unsupervised autoencoders. However, it may not be a good way of feature learning for soft sensor modeling, in which it is necessary and important to learn quality-relevant features from the raw observed input data with the guidance of the quality data. This idea has attracted a lot of attention in traditional shallow learning methods [37]–[39]. For example, PLS is just such a counterpart of PCA for quality-related feature learning. In the work by Yuan *et al.* [27], a deep learning model was first proposed for quality-related feature representation based on variable-wise weighted stacked autoencoder (VWSAE) network. In each autoencoder of the VWSAE, a variable weighted objective function is designed to learn more abstract features by prior reconstruction for important quality-related input/feature variables of its input layer. However, there are two main limitations of the VWSAE. First, it needs to measure the pair-wise Pearson correlation between each dimension of the input variables and the quality variable for each autoencoder, which may be inefficient and cumbersome. More importantly, the Pearson relationship is only a linear correlation measure, which does not take the important nonlinear relationships into consideration. As the nonlinear variable correlation is not measure sufficiently, it may still miss important quality-related information in the VWSAE.

To alleviate the aforementioned problems, a new deep learning model is proposed to learn hierarchical quality-relevant features, which is based on stacked quality-driven autoencoder (SQAE). Different from the VWSAE, SQAE directly utilizes the quality variables to construct a new deep learning network, which consists of multiple stacked quality-driven autoencoders (QAE). In each QAE, the output layer is composed of two parts: the hidden variables from its low layer and the quality variables. Therefore, high-level features are learned from their low-level ones by the objective that the learned features can simultaneously reconstruct their previous low-level features and predict the quality variables as good as possible. In this way, the learned features should not only try to represent its input representations but also largely predict the quality variables. Therefore, quality-relevant features can be effectively learned since they should largely predict the quality data. In a hierarchical stacked way, irrelevant information can be gradually reduced, and quality-relevant features can be progressively focused from the raw input data. After that, regression models can be constructed between the quality variables and the learned features for prediction. Therefore, SQAE network is more capable of improving the performance of soft sensors. The main contribution of this article lies in the following aspects. First, a novel QAE network is proposed for quality-relevant feature learning, which is very different from other unsupervised self-learning autoencoders. Then, multiple QAEs are layer-wise stacked to construct a deep network for learning of hierarchical features that are largely relevant to the quality variables. At last, the deep quality-relevant features are used to build predictive regression models for accurate prediction. In this stage, traditional regression methods like least squares regression and support vector machine can be directly used. Alternatively, an additional output layer for quality variables can be added to the top layer of SQAE for fine-tuning and prediction of the quality variables.

The rest of this article is structured as follows. In Section II, the basic stacked autoencoder is briefly revisited. Section III introduces the novel SQAE and its soft sensor application. Then, a case study is carried out to validate the effectiveness of the proposed method in Section IV. Section V concludes this article.

Some important notations that are used throughout this article are first given as follows.

x:	raw input variable vector.
y:	quality output variable vector.
z,h:	general notations for the input and hidden variable vectors of an autoencoder, respectively. Here, z can be the raw input variable vector or extracted feature vector at a certain layer.
h^k:	hidden variable vector at the kth hidden layer of deep networks.

II. Stacked Autoencoder

SAE is a deep learning neural network with multiple autoencoders hierarchically. An autoencoder is a three-layer unsupervised feature learning network with one input layer, a hidden layer, and one output layer. The hidden layer transfers the input

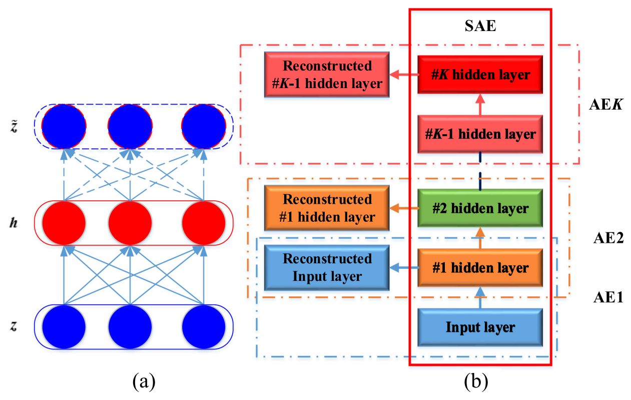


Fig. 1. Structure for AE and SAE. (a) AE network. (b) SAE network with K autoencoders.

vector into hidden feature representation by nonlinear mapping. In the output layer, AE aims to reconstruct its input data by the hidden features. Fig. 1(a) shows a network illustration of AE.

Generally, the input and hidden variable vectors of the AE can be denoted as $z \in R^{d_z}$ and $h \in R^{d_h}$, respectively. The reconstructed input variable vector at the output layer can then be denoted as $\tilde{z}$. At the hidden layer, z is transformed to obtain the hidden feature representation h by an encoder as

$$h = f(Wz + b) \tag{1}$$

where W and b are the weight and bias parameters, respectively. And f is the activation function like sigmoid function. Then, the hidden feature variable vector h is decoded to the reconstructed input vector at the output layer as

$$\tilde{z} = \tilde{f}(\tilde{W}h + \tilde{b}) \tag{2}$$

where $\tilde{W}$, $\tilde{b}$, and $\tilde{f}$ are the weight matrix, bias vector, and activation function at the output layer, respectively. To obtain feature representation for its inputs, AE tries to ensure that the reconstructed $\tilde{z}$ can be mostly identical to the real value z. Given a dataset of N training samples $z_i \in \{z_1, z_2, \ldots, z_N\}$, the corresponding transformed features and reconstructed input data are denoted as $h_i \in \{h_1, h_2, \ldots, h_N\}$ and $\tilde{z}_i \in \{\tilde{z}_1, \tilde{z}_2, \ldots, \tilde{z}_N\}$, respectively. To train the model parameters and obtain the feature data, the following objective function of a mean squared error term is minimized on the training data by the backpropagation algorithm.

$$\begin{aligned} J(W, \tilde{W}, b, \tilde{b}) &= \frac{1}{2N}\sum_{i=1}^{N} \|\tilde{z}_i - z_i\|^2 \\ &= \frac{1}{2N}\sum_{i=1}^{N} \left\| g(z_i, W, b, \tilde{W}, \tilde{b}) - z_i \right\|^2. \end{aligned} \tag{3}$$

SAE is a deep network consisting of multiple autoencoders with a hierarchically stacked structure. The basic structure of the SAE is illustrated in Fig. 1(b). For an SAE with K autoencoders, the raw input vector $x \in R^{d_x}$ is fed to the input layer of the first AE (AE1) to train its parameter set $\{W_1, b_1\}$ and obtain the first-layer features by minimizing the reconstruction error for x on the training samples. Then, the first-layer feature vector h^1 is used as the input vector for AE2. Also, the parameter set $\{W_2, b_2\}$ and the second-level feature h^2 vector can be obtained by minimizing the reconstruction error for h^1 on the training samples. In a successive way, the whole SAE can be pretrained layer by layer until AEK is pretrained for its parameter set $\{W_K, b_K\}$ and feature data h^K.

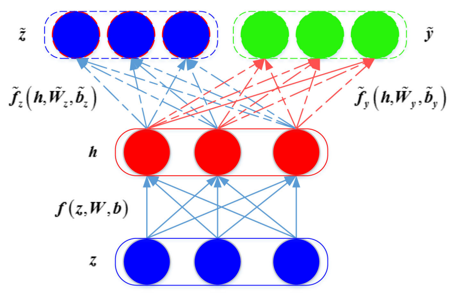

$\tilde{z}$
$\tilde{y}$
$\tilde{f}_z(h, \tilde{W}_z, \tilde{b}_z)$
$\tilde{f}_y(h, \tilde{W}_y, \tilde{b}_y)$
h
$f(z, W, b)$
z

Fig. 2. Illustration of quality-driven autoencoder.

III. Stacked Quality-Driven Autoencoder

As can be seen, the original SAE-based deep network learns hierarchical features that can represent the raw input data as good as possible. Moreover, high-level abstract features are progressively obtained from low-level ones layer by layer. Such features may be a good representation for the raw input data. However, they may not be good representation for prediction of the quality variables since irrelevant information may be retained in the obtained features. To handle this problem, an SQAE is designed to learn hierarchical quality-relevant features in this section. In each QAE, the quality variables are also used to guide the feature learning by adding them to the output layer. Each QAE generates new features from its inputs, then reconstructs the quality data and its input data simultaneously. In this way, the features are learned with the constraint that they can predict the output as good as possible. Hence, QAE can learn quality-relevant features for output prediction. By constructing deep network with stacked QAEs, hierarchical quality-relevant features can be consecutively extracted from the raw input data.

A. Quality-Driven Autoencoder

QAE is also a three-layered network structure with the input, hidden, and output layers. Still, z and h are used to denote the input and hidden variable vectors, respectively. The quality variable vector is denoted as $y \in R^{d_y}$. In the original AE, the output is just the reconstructed input $\tilde{z}$. Differently, QAE intends to reconstruct both its input data and the quality data simultaneously, which are denoted as $\tilde{z}$ and $\tilde{y}$, respectively. Fig. 2 shows the network illustration of QAE. For the sake of simplicity, $\{W, b\}$ and $\{\tilde{W}, \tilde{b}\}$ are still used to represent the parameter sets of the encoder and decoder, respectively. f and $\tilde{f}$ are the corresponding activation functions. As the decoder consists of two parts, its parameter sets and activation function can be decomposed to two parts with regard to the input layer data and quality data. That is to say, its parameters can be decomposed as

$$\tilde{W} = \begin{bmatrix} \tilde{W}_z \\ \tilde{W}_y \end{bmatrix}, \quad \tilde{b} = \begin{bmatrix} \tilde{b}_z \\ \tilde{b}_y \end{bmatrix}, \quad \tilde{f} = \begin{bmatrix} \tilde{f}_z \\ \tilde{f}_y \end{bmatrix}. \tag{4}$$

Thus, the reconstructed input and quality data of QAE can be written as

$$\begin{bmatrix} \tilde{z} \\ \tilde{y} \end{bmatrix} = \tilde{f}(f(z)) = \begin{bmatrix} \tilde{f}_z\left(f(z, W, b), \tilde{W}_z, \tilde{b}_z\right) \\ \tilde{f}_y\left(f(z, W, b), \tilde{W}_y, \tilde{b}_y\right) \end{bmatrix}. \tag{5}$$

Then, given the training dataset of the input layer data $z_i \in \{z_1, z_2, \ldots, z_N\}$ and the corresponding quality data $\{y_1, y_2, \ldots, y_N\}$, QAE can be trained to minimize the reconstruction error at the output layer, which is

$$J(W, \tilde{W}, b, \tilde{b}) = \frac{1}{2N}\left(\sum_{i=1}^{N}\left\|\left(\begin{bmatrix} \tilde{z}_i \\ \tilde{y}_i \end{bmatrix} - \begin{bmatrix} z_i \\ y_i \end{bmatrix}\right)\right\|^2\right)$$
$$= \frac{1}{2N}\sum_{i=1}^{N}\left(\|\tilde{z}_i - z_i\|^2 + \|\tilde{y}_i - y_i\|^2\right). \tag{6}$$

The objective function of QAE comprises of two parts. The first one is the reconstruction error for the data at its input layer. This is used to ensure that the learned feature can capture the main input data patterns. The second one is the prediction error for the quality data. With this constraint, it ensures that the hidden features can largely predict the quality variables. With this constraint, quality-relevant features can be extracted in QAE.

Compared to the original AE, QAE does not increase the computational complexity too much. Taking the forward propagation stage, for example, it totally computes $d_z * d_h + d_h * d_z$ times of multiplications in one iteration for a sample. While for QAE, the number of multiplications is $d_z * d_h + d_h * (d_z + d_y)$. As the dimension d_y of the quality variable vector is usually much smaller than d_z, the computational complexity of AE and QAE is comparable for the forward propagation. In a similar way, it can be evaluated for the computational complexity for the backpropagation stage.

As can be seen, the original AE and the proposed QAE are different from each other. AE is an unsupervised feature learning network, which just reconstructs its input variable vector. Different from AE, the output layer of QAE consists of not only its input variables but also the quality variables. Hence, it is partly a supervised learning network to some degree. The relationship between AE and QAE is very similar to that of PCA and PLS. Although both QAE and VWAE [27] try to learn quality-relevant features from the input data, they are different from each other. VWAE has the same network structure as the original AE, in which the output layer is just the input variable vector. The improvement of VWAE lies in that the output layer reconstructs important quality-related input variables with large weights. However, QAE directly utilizes the quality variables to construct a different new network, in which the output layer consists of not only its input variables but also the quality variables.

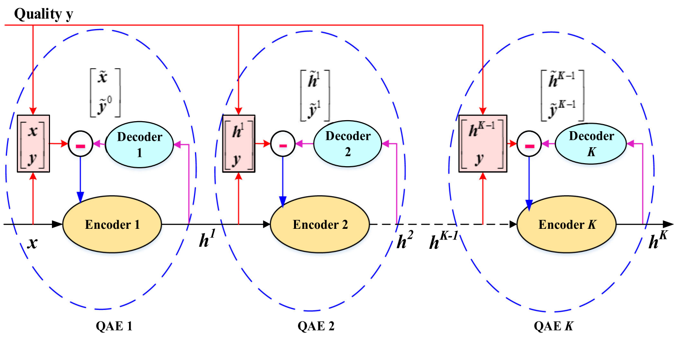


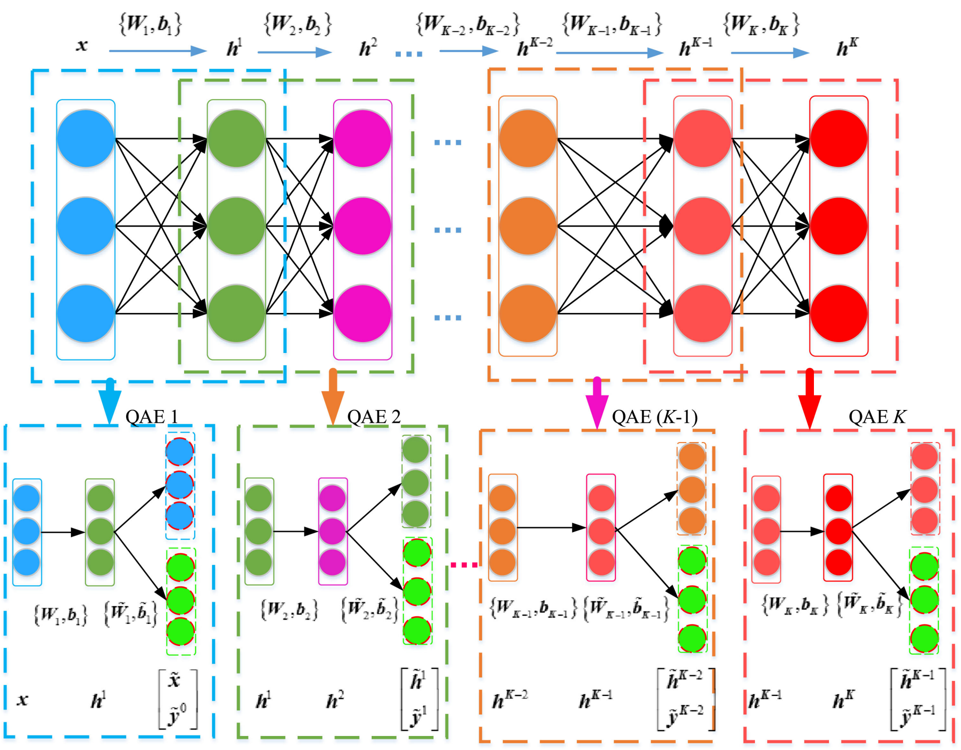
Fig. 3. Stacking flowchart of SQAE.

B. Deep SQAE

The deep SQAE network is constructed by hierarchically stacking multiple QAEs. In SQAE, the hierarchical quality-relevant features are layer-wise learned from the raw observed input data. At first, the raw observed input data are fed to the input layer of the SQAE. By nonlinear transformation, the first-level features are generated at the first hidden layer of the SQAE. In a successive way, high-level features can be obtained from its adjacent low-level ones with nonlinear transformation. However, this cannot be directly computed since the connecting weight and bias parameters are unknown. Hence, layerwise pretraining is carried out for the SQAE network. Fig. 3 shows the stacking flowchart of the SQAE. At first, QAE1 is designed for the first hidden layer. The input of QAE1 is just the raw input data. In order to obtain the first-layer quality-relevant feature, the raw input data and the quality data are simultaneously reconstructed at its output layer. By minimizing the reconstruction error for both the raw input data and the quality data, the first QAE can be pretrained by the gradient-descent back-propagation algorithm. After that, the first-layer feature vector is connected to the input layer of QAE2 to obtain the second-layer feature. At the output layer of QAE2, the first-level feature data and the quality data are also reconstructed by the second-level features. Then, BP algorithm can be utilized to pretrain QAE2. In this way, all the K QAEs are progressively constructed and pretrained one after another until the top layer of SQAE is reached.

Hence, given the raw observed input dataset $\{x_1, x_2, \ldots, x_N\}$ and the corresponding quality dataset $\{y_1, y_2, \ldots, y_N\}$, SQAE can be pretrained to obtain hierarchical quality-relevant features. The detailed pretraining procedure for the SQAE can be illustrated in Fig. 4, which is described as follows.

At first, $\{x_1, x_2, \ldots, x_N\}$ are transmitted to the input layer of SQAE to generate the corresponding first-level feature data $\{h_1^1, h_2^1, \ldots, h_N^1\}$ by nonlinear activation function f with parameter set $\{W_1, b_1\}$ at the first hidden layer. As $\{h_1^1, h_2^1, \ldots, h_N^1\}$ and $\{W_1, b_1\}$ are unknown, this cannot be calculated directly. Hence, QAE1 is designed to reconstruct the raw input data and the quality data simultaneously at its output layer. The



x
$\{W_1, b_1\}$
h^1
$\{W_2, b_2\}$
h^2
$\{W_{K-2}, b_{K-2}\}$
h^{K-2}
$\{W_{K-1}, b_{K-1}\}$
h^{K-1}
$\{W_K, b_K\}$
h^K
QAE 1
QAE 2
QAE (K-1)
QAE K
$\{W_1, b_1\}$ $\{\tilde{W}_1, \tilde{b}_1\}$
x h^1 $\begin{bmatrix}\tilde{x}\\ \tilde{y}^0\end{bmatrix}$
$\{W_2, b_2\}$ $\{\tilde{W}_2, \tilde{b}_2\}$
h^1 h^2 $\begin{bmatrix}\tilde{h}^1\\ \tilde{y}^1\end{bmatrix}$
$\{W_{K-1}, b_{K-1}\}$ $\{\tilde{W}_{K-1}, \tilde{b}_{K-1}\}$
h^{K-2} h^{K-1} $\begin{bmatrix}\tilde{h}^{K-2}\\ \tilde{y}^{K-2}\end{bmatrix}$
$\{W_K, b_K\}$ $\{\tilde{W}_K, \tilde{b}_K\}$
h^{K-1} h^K $\begin{bmatrix}\tilde{h}^{K-1}\\ \tilde{y}^{K-1}\end{bmatrix}$

Fig. 4. Pretraining procedure of deep SQAE.

pretraining of QAE1 is carried out by minimizing the reconstruction error on the training data as

$$J_1(W_1, b_1, \tilde{W}_1, \tilde{b}_1) = \frac{1}{2N}\sum_{i=1}^{N}\left(\|\tilde{x}_i - x_i\|^2 + \left\|\tilde{y}_i^0 - y_i\right\|^2\right). \tag{7}$$

After QAE1 is pretrained, its encoder part is kept in the whole QEAE network and $\{h_1^1, h_2^1, \ldots, h_N^1\}$ can be calculated. Moreover, they are then utilized to extract the second-level feature data $\{h_1^2, h_2^2, \ldots, h_N^2\}$. For the remaining levels of features, they can be progressively obtained by following a similar way. Here, assume the kth ($k = 1,2,\ldots, K - 1$) layer of feature data $\{h_1^k, h_2^k, \ldots, h_N^k\}$ has already been learned. They will be utilized to obtain the $(k + 1)$th-level feature data $\{h_1^{k+1}, h_2^{k+1}, \ldots, h_N^{k+1}\}$ by nonlinear activation function f with parameter set $\{W_{k+1}, b_{k+1}\}$. To this end, QAE(k+1) is built to reconstruct both the kth-level feature data and the quality data at its output layer, which can be denoted as $\{\tilde{h}_1^k, \tilde{h}_2^k, \ldots, \tilde{h}_N^k\}$ and $\{\tilde{y}_1^k, \tilde{y}_2^k, \ldots, \tilde{y}_N^k\}$, respectively. Similarly, this QAE is trained by minimizing the reconstruction error for the kth-level feature data and the quality data as

$$\begin{aligned}&J_{k+1}(W_{k+1}, b_{k+1}, \tilde{W}_{k+1}, \tilde{b}_{k+1})\\ &\quad= \frac{1}{2N}\sum_{i=1}^{N}\left(\left\|\tilde{h}_i^k - h_i^k\right\|^2 + \left\|\tilde{y}_i^k - y_i\right\|^2\right)\\ &k = 2, 3, \ldots, K - 1.\end{aligned} \tag{8}$$

In this way, SQAE is pretrained from the bottom to the top hidden layers. In each layer, the features are learned from their adjacent low-level ones with the additional constraint that the learned features can largely predict the quality variables. Hence, the irrelevant features are gradually reduced and quality-relevant features are progressively learned layer by layer.

C. SQAE for Soft Sensor Modeling

With the SQAE network, it is much more effective and efficient to utilize the deep quality-relevant features for soft sensor modeling. For soft sensing, regression models can be directly constructed between the quality variables and the learned quality-relevant features. To build the regression models, the least square regression (LSR), the two-layered neural network (NN) [27], and a least square support vector machine (LSSVM) [40] are utilized as three classical regression algorithms. Given the raw training input data $X = \{x_1, x_2, \ldots, x_N\}$ and the quality data $Y = \{y_1, y_2, \ldots, y_N\}$, as well as the testing input data $X_t = \{x_{1_t}, x_{2_t}, \ldots, x_{N_t}\}$, the detailed SQAE-based feature learning and soft sensor modeling procedures are listed in Table I as follows.

To assess the performance of the soft sensor model, the root-mean-squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination R^2 are calculated on the testing dataset, the definition of which can be found in [27] and [41].

IV. Case Study

To assess the performance of the SQAE network, it is applied to an industrial debutanizer column process in this section [42]. First, a general description is given for the debutanizer column.

TABLE I
TRAINING AND TESTING PROCEDURE OF SQAE-BASED SOFT SENSOR MODELING

```
Training stage:
  >Determine the number of feature layers $K$ in SQAE.
  >Train QAE1 with $X$ and $Y$ by BP algorithm to obtain its encoder network parameter $\{W_1,b_1\}$ and the first-level quality-related feature data $H^1=\{h_1^1,h_2^1,...,h_N^1\}$.
  > set $k$=2;
  >Main loop:
    While k≤K, repeat:
      -Train QAE $k$ with $H^{k-1}$ and $Y$. After that, the weight parameter of its encoder part is $\{W_k,b_k\}$. Meanwhile, the $k$th-level feature data are $H^k=\{h_1^k,h_2^k,...,h_N^k\}$.
      -Set $k$=$k$+1;
  > After SQAE is layer-wise pretrained, the top-layer features $H^K=\{h_1^K,h_2^K,...,h_N^K\}$ are used to predict the quality data.
  > Build and train LSR, NN and LSSVM regression models between Y and $H^K$, respectively.
Testing stage:
  > Substitute the testing input data into the input layer of the SQAE network. Then, obtain its top-layer feature data $H_t^K=\{h_{1_t}^K,h_{2_t}^K,...,h_{N_t}^K\}$ by forward propagation.
  > The quality variable can be predicted as $\hat{Y}_t=\{\hat{y}_{1_t},\hat{y}_{2_t},...,\hat{y}_{N_t}\}$ for the testing dataset with the trained LSR, NN and LSSVM models.
```

Then, deep SQAE-based soft sensors are utilized to predict the butane content.

A. Debutanizer Column

The petrochemical industry, especially the refining process, is a production facility that composes a number of connected chemical processing units and operations to produce specific materials or convert raw materials into valuable products. It is often characterized as a highly complex process equipped with modern control systems. The debutanizer column is one important part of the industrial refinery process, which is designed for desulfuration and naphtha split [42]. The flowchart of the debutanizer column is shown in Fig. 5. The debutanizer column mainly consists of six devices, which are the heat exchanger, bottom reboiler, overhead condenser, feed pump to the LPG splitter, head reflux pump, and reflux accumulator. To keep stable production and ensure product quality, it is required to maximize the stabilized gasoline content (C5) in the overheads and minimize the butane content (C4) in the debutanizer bottoms, which are the feeds of the subsequent light pressure gas splitter and naptha spilliter, respectively.

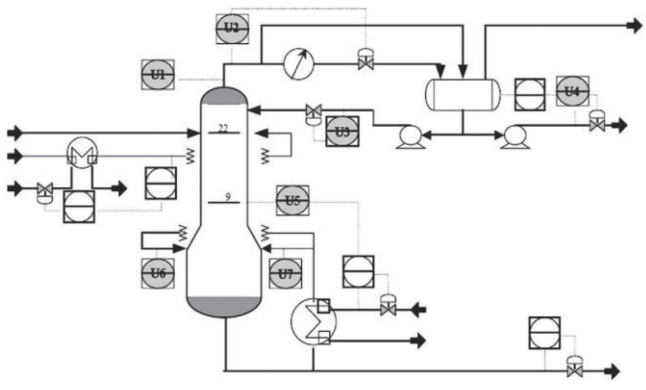


Fig. 5. Schematic flowchart of the debutanizer column [43].

TABLE II
VARIABLE DESCRIPTION FOR THE DEBUTANIZER COLUMN

Input variables	Variable description
u_1	Top temperature
u_2	Top pressure
u_3	Reflux flow
u_4	Flow to next process
u_5	6th tray temperature
u_6	Bottom temperature A
u_7	Bottom temperature B

Hence, it is necessary to identify the C4 content online for effective control. Nevertheless, C4 concentration is actually not measured at the bottom flow of the debutanizer column directly, but on the overheads of the subsequent deisopentanizer column by gas chromatograph, which often results in large time delay.

Usually, the measurement technique with gas chromatograph cannot ensure the real-time control and optimization of the debutanizer column. Moreover, the measuring devices also suffer from offline examination and maintenance. To alleviate these problems, soft sensor strategies are adopted to predict the C4 concentration at the bottom. Thus, seven routinely measured process variables are selected for data modeling, which are given in Table II for their descriptions.

B. Results and Discussion

To deal with complex nonlinearities, deep learning is adopted for hierarchical feature learning. To take process dynamics into consideration, the augmented variables

$$\begin{bmatrix} u_1(k), u_2(k), u_3(k), u_4(k), u_5(k), u_5(k-1), u_5(k-2), \\ u_5(k-3), (u_6(k)+u_7(k))/2, y(k-1), y(k-2), \\ y(k-3), y(k-4) \end{bmatrix}^T$$

are used as the raw observed input variables of the deep SQAE network at the kth sampling instant [42]. A total of 2390 data samples are collected in this process. For model training and testing, 1000 samples are used as the training dataset and the remaining ones are for the testing dataset.

To construct the SQAE-based soft sensor model, it is necessary to first configure the network structure, which is determined

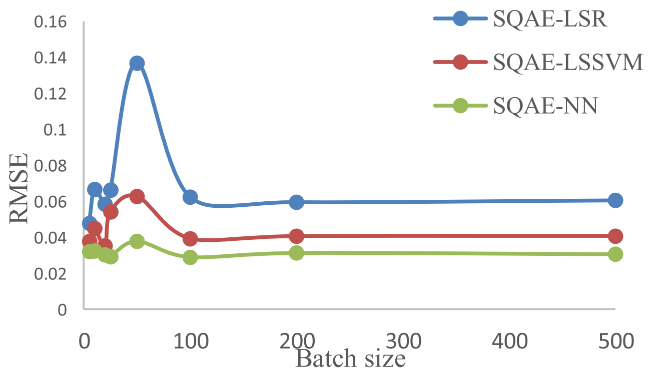


Fig. 6. Prediction RMSE for the three SQAE-based models on the testing dataset with different pretraining batch size.

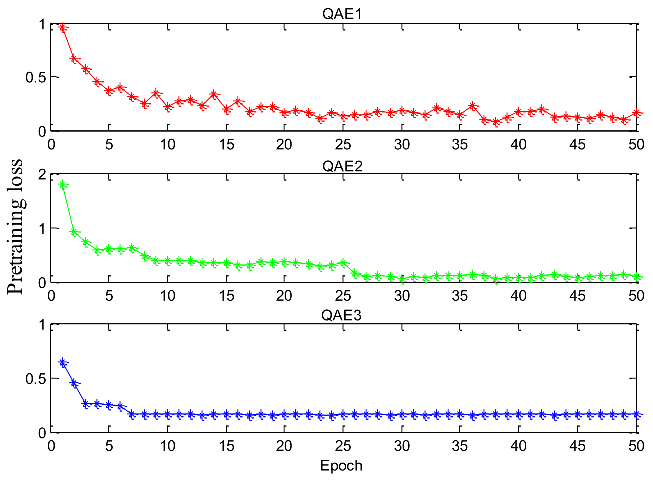


Fig. 7. Convergence analysis for pretraining of SQAE.

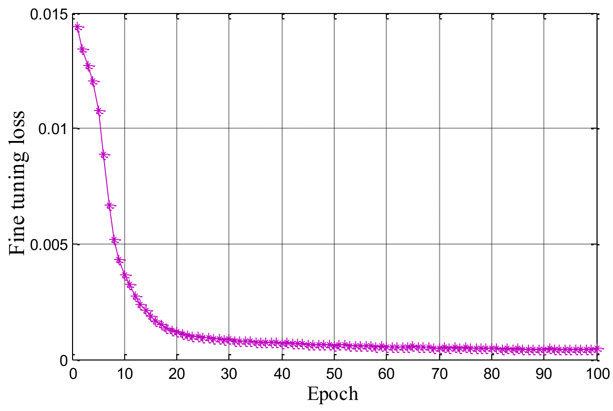


Fig. 8. Learning loss curve of fine-tuning for SQAE.

TABLE III
COMPARISON OF PREDICTION PERFORMANCE WITH NINE DIFFERENT MODELING METHODS

Method	RMSE	MAE	MAPE	R^2
SAE-LSR	0.1105	0.0767	0.4401	0.5287
VWSAE-LSR	0.0597	0.0471	0.3261	0.8622
SQAE-LSR	0.0584	0.0435	0.3221	0.8682
SAE-NN [27]	0.0438	0.0304	0.3154	0.9260
VWSAE-NN [27]	0.0379	0.0277	0.2680	0.9444
SQAE-NN	0.0303	0.0220	0.2331	0.9646
SAE-LSSVM	0.0573	0.0419	0.3209	0.8734
VWSAE-LSSVM	0.0396	0.0342	0.2764	0.9395
SQAE-LSSVM	0.0352	0.0284	0.2552	0.9521

as [13 10 7 4] from [27]. The number of neurons in the input layer of SQAE is 13 since there are 13 variables in the augmented variable vector. The practical guide of Bengio [44] is a good way to determine some commonly used hyperparameters. For example, the sigmoid function is used as the activation function for the neurons. The learning rate is set to 1. For some other important parameters, such as the batch size of pretraining, the trial and error technique is exploited to set proper parameter values. Here, different batch sizes from the range [5 10 20 25 50 100 200] in the pretraining stage are taken for example to show the trend of performance changes of the three SQAE-based soft sensor models, which is shown in Fig. 6. As can be seen, the general trend of the prediction RMSE first gets large with the increase of the batch size. When the batch size is 50, the performance is the worst for all the three methods. After that, the performance will decrease and then keep at a relatively stable level. From this, a proper batch size is better to set in a range from five to 25. In this article, it is set to 20.

With this batch size, convergence analysis is first carried out for the pretraining procedure of SQAE. Fig. 7 gives the learning loss in the layer-wise pretraining of each QAE within 50 epochs. As can be seen, the three QAEs can converge very fast in the pretraining stage. For QAE1 and QAE2, they can reach the convergent state after about 25 iterations. While for QAE3, it converges within ten iterations. Furthermore, convergence performance is analyzed for the fine tuning procedure after pretraining is finished. Fig. 8 shows the learning training error for the SQAE, in which the whole network can converge very fast after about 50 epochs.

After feature learning, the quality values can be predicted by substituting the features to the trained LSR, NN, and LSSVM models. For performance comparison, the original SAE and VWSAE [27] are also adopted for the feature representation of the raw observed input data, followed by LSR, NN, and LSSVM regression models. Denote the nine approaches as SAE-LSR, SAE-NN, SAE-LSSVM, VWSAE-LSR, VWSAE-NN, VWSAE-LSSVM, SQAE-LSR, SQAE-NN, and SQAE-LSSVM. Table III lists the prediction performance of the nine methods on the testing dataset.

From the comparative results of RMSE, MAPE, MAE, and R^2 indices, it can be easily seen that SQAE-LSR can achieve the best prediction accuracy among the first three models in Table III. Also, when the same NN regression model is used, SQAE-NN achieves better performance than VWSAE-NN and SAE-NN. Moreover, SQAE-LSSVM outperforms SAE-LSSVM and VWSAE-LSSVM in the four prediction indices. As for SAE, it only focuses on feature representation for the raw observed input data itself. The learned feature may contain a lot of irrelevant information with the quality variable,

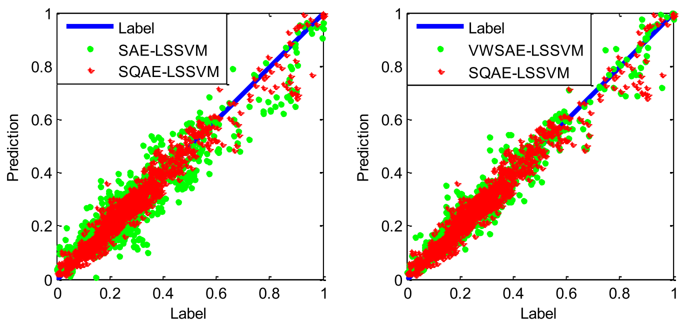


Fig. 9. Scatterplots of predicted and labeled values for the quality variable with SAE-LSSVM, VWSAE-LSSVM, and SQAE-LSSVM.

which can deteriorate the prediction performance of regression models. By taking the variable correlations with the quality variable into account, the weighted reconstruction objective is designed to pretrain each autoencoder in VWSAE. Thus, VWSAE can reduce irrelevant features by giving small weights to less important variables in the reconstruction objective. In this way, VWSAE-based models can provide much better prediction performance than the corresponding SAE-based approaches when the same regression model is used. However, VWSAE only measures the Pearson linear variable correlations, the nonlinear correlations are not fully considered in the variable-wise weighted reconstruction objective. Hence, it is not sufficient for the learning of deep quality-relevant features that typically have nonlinear relation with the quality variable. Differently, SQAE learns the features directly with the reference of the quality data by predicting it at the output layer of each QAE. It does not need to measure the variable correlations at each layer. Hence, the quality-relevant features are extracted more sufficiently. In a stacking way, the learned hierarchical features are more suitable for prediction of the quality variable. Therefore, when the same regression method is used, the SQAE-based methods can provide better predictions than the corresponding SAE-based and VWSAE-based ones. Also, one can easily conclude that for the same feature extraction network, LSSVM and NN can achieve much better prediction accuracy than LSR since they can deal with more complex nonlinear data relationships.

Furthermore, the detailed prediction results of SAE-LSSVM, VWSAE-LSSVM, and SQAE-LSSVM are taken as examples to investigate the prediction performance on the testing dataset. Fig. 9 shows the scatterplots of the predicted and labeled values for the three methods. In this figure, each data point represents a testing sample. The point values of horizontal and vertical axes represent the corresponding labeled and predicted values of the quality variable, respectively. From Fig. 9, it is easily seen that the prediction points of SQAE-LSSVM lie much tighter alongside the diagonal line than these of SAE-LSSVM and VWSAE-LSSVM. Thus, SQAE is more capable of learning quality-relevant features for soft sensor regression.

Also, the computational performance is analyzed for the pretraining of SAE, VWSAE, and SQAE. Here, the batch gradient descent algorithm is used to pretraining each layer of the deep networks. The batch size is set to 20. For the pretraining of each layer, different epochs are adopted to investigate the computational cost. Table IV lists the pretraining running time for the three deep networks with different epochs. As can be seen, for different epochs, SAE has the smallest pretraining time. VWSAE and SQAE have comparable running time. This may be because VWSAE needs to carry out pair-wise variable correlation analysis in the pretraining of each layer. While for SQAE, the quality variable is additionally utilized to guide feature learning. It enlarges the network structure and increases the number of parameters at the decoder part in the pretraining, which may also result in the increase of computational cost. Moreover, the total pretraining time is almost in proportion to the epochs in pretraining stage.

TABLE IV
PRETRAINING TIME OF THE THREE DIFFERENT DEEP NETWORKS

Epochs	SAE	VWSAE	SQAE
1	0.0062	0.0789	0.0785
10	0.0591	0.6722	0.7435
20	0.1103	1.3338	1.2857
50	0.2664	2.8775	3.2128
100	0.6325	6.1196	6.2972
200	1.3372	11.5767	13.2530

TABLE V
RMSE PERFORMANCE COMPARISON OF SQAE WITH TRADITIONAL AE-BASED DEEP NETWORKS

Method	SAE	SDAE	SSAE	SQAE
RMSE	0.0438	0.0427	0.0412	0.0303

As can be seen, QAE is a very different model from the widely used regular AE, denoising AE, and sparse AE, etc. For these traditional AE-based models, they have the same network structure of basic autoencoder, in which the output layer tries to reconstruct its input data with certain desirable properties, such as robustness or sparsity. Hence, they are unsupervised learning networks, in which they cannot ensure the features are quality-relevant. Different from them, QAE directly utilizes the quality variables to construct a new partially supervised network, as shown in Fig. 4. In QAE, the output layer consists of not only its input variables but also the quality variables. With such a structure, the learned features should not only represent their input data but also largely predict the quality variables. In this way, QAE can learn quality-relevant features due to its partially supervised characteristic. Therefore, it can obtain different performance when QAE is used to construct a deep SQAE network. Here, the performance of SQAE is further compared with the traditional SAE, stacked denoising AE (SDAE), and stacked sparse AE (SSAE).

Taking the RMSE index, for example, Table V gives the prediction performance on the testing dataset with the four different methods. For SDAE, the performance achieves the best with 20% zero marking noise for the inputs. For SSAE, the sparsity parameter is set to 0.05. As can be seen, the RMSE performance is very similar for SAE, SDAE, and SSAE. This is because they are constructed in an unsupervised way at the pretraining stage. They cannot learn features that are related to the quality information. Differently, SQAE can improve the performance effectively since it utilizes the quality data to guide the layer-wise feature learning in each layer. Thus, hierarchical quality-relevant features can be properly learned for better quality prediction.

V. Conclusion

In this article, a novel deep network was developed for the quality-relevant feature learning and soft sensor model development, which was based on the stacked quality-driven autoencoder. As most existing deep learning networks mainly focus on the feature representation for the raw observed input data, it may contain irrelevant information and cannot discover quality-relevant features for soft sensor modeling. To handle this problem, SQAE aimed to utilize the quality data to guide the learning of potential features with a constraint that the features can reconstruct both the quality data and the input-layer data as good as possible at each QAE. Thus, quality-relevant features could be well preserved and irrelevant information was gradually reduced with the hierarchically stacked structure of SQAE. Then, the learned quality-relevant deep features could be directly used to build regression models for quality prediction. The industrial application of the SQAE-based soft sensor showed its effectiveness and flexibility over the original SAE-based and VWSAE-based ones. In real implementation, since the dimension of the quality variables may be much smaller than that of the input variables in each QAE, the second part of the prediction error often had less influence on the total pretraining objective function in (6). To enhance the importance of the quality prediction error, an adjustable weight could be added to the second part of the loss function in order to learn quality-relevant features.

References

[1] Z. Ge, “Review on data-driven modeling and monitoring for plant-wide industrial processes,” *Chemometr. Intell. Lab. Syst.*, vol. 175, pp. 16–25, 2017.

[2] X. Yuan, Y. Wang, C. Yang, Z. Ge, Z. Song, and W. Gui, “Weighted linear dynamic system for feature representation and soft sensor application in nonlinear dynamic industrial processes,” *IEEE. Trans. Ind. Electron.*, vol. 65, no. 2, pp. 1508–1517, Feb. 2018.

[3] X. Wang, B. Huang, and T. Chen, “Multirate minimum variance control design and control performance assessment: A data-driven subspace approach,” *IEEE. Trans. Control Syst. Technol.*, vol. 15, no. 1, pp. 65–74, Jan. 2006.

[4] L. Zhou, J. Zheng, Z. Ge, Z. Song, and S. Shan, “Multimode process monitoring based on switching autoregressive dynamic latent variable model,” *IEEE. Trans. Ind. Electron.*, vol. 65, no. 10, pp. 8184–8194, Oct. 2018.

[5] Z. Chen, S. X. Ding, T. Peng, C. Yang, and W. Gui, “Fault detection for non-Gaussian processes using generalized canonical correlation analysis and randomized algorithms,” *IEEE. Trans. Ind. Electron.*, vol. 65, no. 2, pp. 1559–1567, Feb. 2018.

[6] S. Khatibisepehr, B. Huang, and S. Khare, “Design of inferential sensors in the process industry: A review of Bayesian methods,” *J. Process Control*, vol. 23, no. 10, pp. 1575–1596, 2013.

[7] J. Dai, N. Chen, X. Yuan, W. Gui, and L. Luo, “Temperature prediction for roller kiln based on hybrid first-principle model and data-driven MW-DLWKPCR model,” *ISA T.*, to be published, doi: 10.1016/j.isatra.2019.08.023.

[8] P. Kadlec, R. Grbić, and B. Gabrys, “Review of adaptation mechanisms for data-driven soft sensors,” *Comput. Chem. Eng.*, vol. 35, no. 1, pp. 1–24, 2011.

[9] Y. Wang, K. Sun, X. Yuan, Y. Cao, L. Li, and H. N. Koivo, “A novel sliding window PCA-IPF based steady-state detection framework and its industrial application,” *IEEE Access*, vol. 6, pp. 20995–21004, 2018.

[10] X. Yuan, J. Zhou, Y. Wang, and C. Yang, “Multi-similarity measurement driven ensemble just-in-time learning for soft sensing of industrial processes,” *J. Chemometr.*, vol. 32, no. 9, 2018, Art. no. e340.

[11] L. Fortuna, P. Giannone, S. Graziani, and M. G. Xibilia, “Virtual instruments based on stacked neural networks to improve product quality monitoring in a refinery,” *IEEE Trans. Instrum. Meas.*, vol. 56, no. 1, pp. 95–101, Feb. 2007.

[12] Y. Wang, D. Wu, and X. Yuan, “A two-layer ensemble learning framework for data-driven soft sensor of the diesel attributes in an industrial hydrocracking process,” *J. Chemometr.*, to be published, doi: 10.1002/cem.3185.

[13] N. Chen, J. Dai, X. Yuan, W. Gui, W. Ren, and H. N. Koivo, “Temperature prediction model for roller kiln by ALD-based double locally weighted kernel principal component regression,” *IEEE Trans. Instrum. Meas.*, vol. 67, no. 8, pp. 2001–2010, Aug. 2018.

[14] W. Shao, Z. Ge, and Z. Song, “Quality variable prediction for chemical processes based on semisupervised Dirichlet process mixture of Gaussians,” *Chem. Eng. Sci.*, vol. 193, pp. 394–410, 2019.

[15] G. E. Hinton, S. Osindero, and Y.-W. Teh, “A fast learning algorithm for deep belief nets,” *Neural Comput.*, vol. 18, no. 7, pp. 1527–1554, 2006.

[16] G. E. Hinton and R. R. Salakhutdinov, “Reducing the dimensionality of data with neural networks,” *Science*, vol. 313, no. 5786, pp. 504–507, Jul. 2006.

[17] Y. Bengio, A. Courville, and P. Vincent, “Unsupervised feature learning and deep learning: A review and new perspectives,” 2012, *arXiv:1206.5538v1*.

[18] P. N. Druzhkov and V. D. Kustikova, “A survey of deep learning methods and software tools for image classification and object detection,” *Pattern Recognit. Image Anal.*, vol. 26, no. 1, pp. 9–15, 2016.

[19] R. Sarikaya, G. E. Hinton, and A. Deoras, “Application of deep belief networks for natural language understanding,” *IEEE/ACM Trans. Audio Speech Lang. Process.*, vol. 22, no. 4, pp. 778–784, Apr. 2014.

[20] C. Shang, F. Yang, D. Huang, and W. Lyu, “Data-driven soft sensor development based on deep learning technique,” *J. Process Control*, vol. 24, no. 3, pp. 223–233, 2014.

[21] Y. Wang, Z. Pan, X. Yuan, C. Yang, and W. Gui, “A novel deep learning based fault diagnosis approach for chemical process with extended deep belief network,” *ISA Trans.*, to be published, doi: 10.1016/j.isatra.2019.07.001.

[22] X. Yuan, C. Ou, Y. Wang, C. Yang, and W. Gui, “Deep quality-related feature extraction for soft sensing modeling: A deep learning approach with hybrid VW-SAE,” *Neurocomputing*, to be published, doi: 10.1016/j.neucom.2018.11.107.

[23] L. O. Chua and T. Roska, “The CNN paradigm,” *IEEE Trans. Circuits Syst. I, Fundam. Theory Appl.*, vol. 40, no. 3, pp. 147–156, Mar. 1993.

[24] Y. Sun, X. Wang, and X. Tang, “Deep learning face representation by joint identification-verification,” in *Proc. 27th Int. Conf. Neural Inf. Process. Syst.*, 2014, vol. 27, pp. 1988–1996.

[25] K. Noda, Y. Yamaguchi, K. Nakadai, H. G. Okuno, and T. Ogata, “Audio-visual speech recognition using deep learning,” *Appl. Intell.*, vol. 42, no. 4, pp. 722–737, 2015.

[26] D. Yu, G. Hinton, N. Morgan, and J. T. Chien, “Introduction to the special section on deep learning for speech and language processing,” *IEEE Trans. Audio Speech Lang. Process.*, vol. 20, no. 1, pp. 4–6, Jan. 2012.

[27] X. Yuan, B. Huang, Y. Wang, C. Yang, and W. Gui, “Deep learning based feature representation and its application for soft sensor modeling with variable-wise weighted SAE,” *IEEE. Trans. Ind. Inform.*, vol. 14, no. 7, pp. 3235–3243, Jul. 2018.

[28] L. Yao and Z. Ge, “Deep learning of semi-supervised process data with hierarchical extreme learning machine and soft sensor application,” *IEEE. Trans. Ind. Electron.*, vol. 65, no. 2, pp. 1490–1498, Feb. 2018.

[29] W. Yan, D. Tang, and Y. Lin, “A data-driven soft sensor modeling method based on deep learning and its application,” *IEEE. Trans. Ind. Electron.*, vol. 64, no. 5, pp. 4237–4245, May 2017.

[30] X. Yuan, L. Li, and Y. Wang, “Nonlinear dynamic soft sensor modeling with supervised long short-term memory network,” *IEEE. Trans. Ind. Inform.*, to be published, doi: 10.1109/TII.2019.2902129.

[31] Y. Liu, C. Yang, Z. Gao, and Y. Yao, “Ensemble deep kernel learning with application to quality prediction in industrial polymerization processes,” *Chemometr. Intell. Lab. Syst.*, vol. 174, pp. 15–21, 2018.

[32] L. Jiang, Z. Ge, and Z. Song, “Semi-supervised fault classification based on dynamic Sparse Stacked auto-encoders model,” *Chemometr. Intell. Lab. Syst.*, vol. 168, pp. 72–83, 2017.
[33] H. Wu and J. Zhao, “Deep convolutional neural network model based chemical process fault diagnosis,” *Comput. Chem. Eng.*, vol. 115, pp. 185–197, 2018.
[34] V. Gopakumar, S. Tiwari, and I. Rahman, “A deep learning based data driven soft sensor for bioprocesses,” *Biochem. Eng. J.*, vol. 136, pp. 28–39, 2018.
[35] B. Andò, S. Graziani, and M. G. Xibilia, “Low-order nonlinear finite-impulse response soft sensors for ionic electroactive actuators based on deep learning ” *IEEE Trans. Instrum. Meas.*, vol. 68, no. 5, pp. 1637–1646, May 2019.
[36] A. Sankaran, M. Vatsa, R. Singh, and A. Majumdar, “Group sparse autoencoder,” *Image Vision. Comput.*, vol. 60, pp. 64–74, 2017.
[37] Z. Ge, “Supervised latent factor analysis for process data regression modeling and soft sensor application,” *IEEE. Trans. Control Syst. Technol.*, vol. 24, no. 3, pp. 1004–1011, May 2016.
[38] Z. Ge and X. Chen, “Supervised linear dynamic system model for quality related fault detection in dynamic processes,” *J. Process Control*, vol. 44, pp. 224–235, 2016.
[39] L. Zhou, J. Chen, Z. Song, Z. Ge, and A. Miao, “Probabilistic latent variable regression model for process-quality monitoring,” *Chem. Eng. Sci.*, vol. 116, pp. 296–305, 2014.
[40] H. Q. Wang, F. C. Sun, Y. N. Cai, L. G. Ding, and N. Chen, “An unbiased LSSVM model for classification and regression,” *Soft Comput.*, vol. 14, no. 2, pp. 171–180, 2010.
[41] Y. Xu, W. Yang, and J. Wang, “Air quality early-warning system for cities in China,” *Atmos. Environ.*, vol. 148, pp. 239–257, 2017.
[42] L. Fortuna, S. Graziani, and M. G. Xibilia, “Soft sensors for product quality monitoring in debutanizer distillation columns,” *Control Eng. Pract.*, vol. 13, no. 4, pp. 499–508, 2005.
[43] L. Fortuna, S. Graziani, A. Rizzo, and M. G. Xibilia, *Soft Sensors for Monitoring and Control of Industrial Processes*. Berlin, Germany: Springer, 2007.
[44] Y. Bengio, “Practical recommendations for gradient-based training of deep architectures,” in *Neural Networks: Tricks of the Trade*. Berlin, Germany: Springer, 2012.

Xiaofeng Yuan (M’17) received the B.Eng. and Ph.D. degrees in control science and engineering from the Department of Control Science and Engineering, Zhejiang University, Hangzhou, China, in 2011 and 2016, respectively.

He was a Visiting Scholar with the Department of Chemical and Materials Engineering, University of Alberta, Edmonton, AB, Canada, from November 2014 to May 2015. He is currently an Associate Professor with the Department of Automation, School of Automation, Central South University, Changsha, China. His research interests include deep learning and artificial intelligence, machine learning and pattern recognition, industrial process soft sensor modeling, process data analysis, etc.

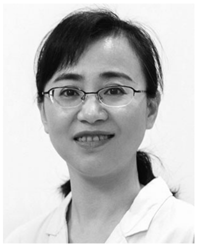
Jiao Zhou received the B.Eng. degree in control science and engineering from the School of Electrical Engineering, Nanhua University, Hengyang, China, in 2017. She is currently working toward a postgraduate degree with the School of Automation, Central South University, Changsha, China.

Her research interests include machine learning, soft sensor modeling, process data mining, etc.

Biao Huang (M’97–SM’11–F’17) received the B.Sc. and M.Sc. degrees in automation from the Beijing University of Aeronautics and Astronautics, Beijing, China, in 1983 and 1986, respectively, and the Ph.D. degree in process control from the University of Alberta, Edmonton, AB, Canada, in 1997.

He is currently a Professor with the Department of Chemical and Materials Engineering, University of Alberta. His research interests include the areas of process control, state estimation, soft sensors, system identification, control performance assessment, fuel cell, and biomedical modeling.

Dr. Huang is an Editor-in-Chief for *Control Engineering Practice*, and an Associate Editor for the *Journal of Process Control* and *Canadian Journal of Chemical Engineering*. He is a Fellow of the Canadian Academy of Engineering.



Yalin Wang (M’17) received the B.Eng. and Ph.D. degrees in control science and engineering from the Department of Control Science and Engineering, Central South University, Changsha, China, in 1995 and 2001, respectively.

Since 2003, she has been with the School of Information Science and Engineering, Central South University, where she was at first an Associate Professor and is currently a Professor with the Department of Automation, School of Automation, Central South University. Her research interests include the modeling, optimization, and control for complex industrial processes, intelligent control, and process simulation.

Chunhua Yang (M’09) received the M.Eng. degree in automatic control engineering and the Ph.D. degree in control science and engineering from Central South University, Changsha, China, in 1988 and 2002, respectively.

She was with the Department of Electrical Engineering, Katholieke Universiteit Leuven, Leuven, Belgium, from 1999 to 2001. She is currently a Full Professor with the Department of Automation, School of Automation, Central South University. Her current research interests include modeling and optimal control of the complex industrial processes, intelligent control system, and fault-tolerant computing of real-time systems.

Weihua Gui (M’09) received the B.Eng. and M.Eng. degrees in control science and engineering from Central South University, Changsha, China, in 1976 and 1981, respectively.

From 1986 to 1988, he was a Visiting Scholar with the University Duisburg-Essen, Duisburg, Germany. He is currently a Full Professor with the Department of Automation, Shool of Automation, Central South University. His main research interests include the modeling and optimal control of complex industrial processes, distributed robust control, and fault diagnoses.