基于时钟循环神经网络的多速率软测量建模

1 INTRODUCTION

Fast and accurate measurement of critical industrial process parameters is crucial in modern industrial processes. However, due to the harsh industrial environment, high sensor maintenance costs, and inadequate measurement technology, it is difficult to achieve real-time reliable measurements of some key parameters using conventional measurement means, and the soft measurement approach provides a viable means to do so.

Soft measurement techniques achieve real-time estimation of dominant variables (quality variables that are difficult to measure) by constructing mathematical relationships between them and auxiliary variables (process variables that are easy to measure) [1,2]. Thus, it is possible to obtain some important process variables that cannot be directly measured by conventional sensors, which is important for the realization of operation status monitoring, and production process optimization. Current research in the field of soft measurement is focused on data-driven models [3]. This approach is based on historical operational data and uses statistical methods or artificial intelligence techniques to develop process models of the quality variables to be measured. Data-driven models do not require a detailed understanding of complex process mechanisms, thus saving time and resources.

In recent years, machine learning such as partial least squares (PLS) [4,5], artificial neural networks(ANN)[6][7], support vector regression (SVR) [8,9], and other methods have been extensively studied and widely used in data-driven modeling. As one of the popular directions of machine learning, deep learning methods achieve the fitting of complex functions by constructing deep nonlinear network structures, which exhibit strong data learning ability and feature extraction ability and draw attention in the field of soft sensing modeling [10]. Sun et al [11] achieved soft sensor model of SO2 emissions in the desulfurization process by constructing a Fully Connected Network (FCN), which is practical and easy to use. Yan et al [12] proposed to use Denoise Autoencoder (DAE) to first extract the key feature information from the input data and then build a multilayer neural network to model the content of oxygen in flue gas based on the extracted features.

Besides, Recurrent Neural Networks (RNNs) are also widely studied and applied in soft sensor modeling because of their special recurrent structure, which is often used to process temporal sequences [13]. However, RNNs suffer from the gradient disappearance problem. So Ke et al [14] used Long-Short Term Memory (LSTM) as a soft sensor model applied in a real sulfur recovery device. LSTM is able to extract both long-term and short-term temporal correlation features, effectively overcoming the shortcomings of RNNs[15]. Yuan et al [16] proposed a supervised LSTM network for soft measurements, which can more purposefully extract nonlinear dynamic features that are strongly correlated with quality variables, and is applicable to the simultaneous temporal and nonlinear characteristics of continuous processes.

However, in actual industrial production, different variables have different importance and measurement difficulty, and different variables will be measured using different measurement periods, or sampling rates [17][18]. For example, variables that are easy to measure may be sampled at higher sampling rates such as seconds and minutes, while quality variables that are difficult to measure may often be sampled once every few hours. A multi-rate scenario is defined when all variables of the whole industrial object contain three and more sampling rates [19]. Currently, for multi-rate soft sensors, up-sampling or down-sampling is usually used to convert multi-rate data to a uniform rate, and then conventional modeling methods can be used. Up-sampling methods usually use interpolation or data filling to transform all data to the fastest sampling frequency [20][21]. Down-sampling methods usually use data lift techniques to fuse all data between adjacent slow sampling points and use them together as inputs to the model [22,23]. Different from the above methods, Chai et al [24] proposed a migration learning based approach. Firstly, the data are divided into different data blocks according to the number of sampled variables, and the data blocks are sequentially migrated into models according to the number of variables owned, from smallest to largest, until a model that can predict the quality variables is finally obtained. Although the above methods can solve the soft sensor modeling problem in multi-rate scenarios to some extent, they do not fully consider the time-series between data and are not universally applicable to industrial processes with time-series. Although the up-sampling method can build a time-series soft measurement model after up-sampling, this method is difficult to apply when multiple sampling rates differ greatly due to the high missing rate, and the soft measurement model based on the filled data has the phenomenon of error accumulation.

Therefore, a multi-rate soft sensor modeling method based on clock recurrent neural networks (CRNNs) is proposed. The method groups the hidden layer neurons corresponding to process variables with different sampling frequencies. According to the process variables collected at each moment, the states of the corresponding hidden layer neurons are updated, while the process variables not collected are not updated. The method is effectively adapted to the data structure of multi-rate scenarios through the idea of clock recurrent neural network, and can fully exploit the process timing characteristics using recurrent neural network structure. At the same time, the hidden layer neurons are grouped and updated, so that the information of process variables with different sampling rates can be stored in different groups of implied layer neurons to avoid the suppression of slow rate variables by fast rate variables. Thus, the method performs soft sensor modeling by mining the timing characteristics of multi-rate data.

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本文的其余部分首先在第二节简要介绍了RNN和CRNN，并给出了提议的方法的的细节。在第三节中，以磨煤机数据集为例，验证了所提方法的有效性。最后，对本文进行总结。

2 METHODOLOGY

2.1 Recurrent Neural Networks

2.2 ClockWork RNN

2.3

3. ILLUSTRATION AND DISCUSSION

3.1 Thermal Power Plant Description

3.2 Modeling and Analysis