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Carbon Monoxide Emission Prediction Based on Concept Drift Detection Using KPCA for Municipal Solid Waste Incineration Processes

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***Abstract*—Municipal solid waste incineration (MSWI) technology has developed rapidly worldwide. Carbon monoxide (CO) is one of the to be controlled key operating index of such processes. CO emission concentration prediction is a challenge problem duo to its large fluctuation range. A new CO emission concentration prediction method based on concept drift detection using kernel principal component analysis (KPCA) is proposed. The proposed approach includes off-line model construction module, on-line concept drift detection prediction and updating module. First, we construct the LSTM-based CO prediction model using historical data and KPCA-based concept drift detection model for calculating the evaluation index. Then, recursive KPCA is used to adaptive monitor the concept drift of the time-varying process. Finally, based on continuous updating of the historical LSTM mode with the concept drift samples, we achieve higher prediction accuracy. The rationality and validity are verified with the actual data of MSWI processes.**

Keywords—municipal solid waste incineration (MSWI), CO emission concentration, concept drift detection, long short-term memory (LSTM), kernel principal component analysis (KPCA), time-varying

I. INTRODUCTION

Due to population growth, prosperity, and urbanization, municipal solid waste (MSW) has increased dramatically [1]. Thus, many cities have appeared "the garbage siege" phenomenon, and the treatment of MSW is imminent [2]. Waste-to-energy (WTE) can be applied to recycle the energy hidden in the MSW [3]. As a typical industrial process, MSW incineration (MSWI) technology can achieve the objective of WTE with characteristics of reduction, harmlessness, and resource utilization [4,5]. It has an important role in the urban renewable energy recycling process [6]. Carbon monoxide (CO), as one of the gases produced in the MSWI process, is colorless and odorless. The people can be poisoned by accidental or intentional contact [7]. CO poisonings account for more than half of fatal poisonings worldwide [8]. In addition, it is directly related to dioxin (DXN), which causes the "NIMBY effect" of MSWI plant construction [9], and is called the "poison of the century" [10]. DXN is very difficult to measure due to the limitations of existing detection techniques [11]. In the actual MSWI process, CO can be detected in real-time by continuous emission monitoring system (CEMS) [12]. It shows that CO has a large fluctuation range duo to the time-varying dynamic characteristics of MSWI processes. Therefore, how to make an accurate prediction of CO emission concentration is an challenge problem. To address this issue, there are at least two problem should be addressed. The first one is how to detect the time-varying, i.e., concept drift detection. The second one is how to make accurate prediction based on such concept drift, i.e., historical prediction model updating based on the samples represented such concept drift.

Most of the concept drift detection methods are based on multivariate statistical methods. Multivariate statistical process control (MSPM) has been widely used, including Principal component analysis (PCA) and Partial least squares (PLS). Normally, PCA-based methods use T^2 and SPE statistics indexes to detect concept drift [13]. However, PCA-based concept drift detection methods are susceptible to external noise. Moreover, it can only build linear latent variable model. In nature, most of the industrial processes have the non-linear characteristics. The statistical analysis model is implicitly developed based on the Gaussian distribution hypothesis. An independent component analysis (ICA) method [14] is also proposed to extract independent components to reduce the data dimension of monitoring variables. In order to solve the nonlinear problems, kernel-based techniques have been successfully developed in recent years [15]. Thus, in order to address the shortcomings of PCA, a Kernel PCA (KPCA) method is proposed. It maps sample data from input space to high-dimensional feature space through nonlinear transformation at first, and then extracts the features in the high-dimensional space.

To the construction method of CO concentration prediction model, Wang et al. [16] used a hybrid framework based on long short-term memory (LSTM) neural networks. It shows that generalization performance is better than auto-regression and moving average (ARIMA), support vector machine, and vector autoregressive. Thus, LSTM has good performance in solving highly nonlinear modeling problem. Zaini et al. [17] used empirical mode decomposition (EMD) and attention-based LSTM to predict CO concentration in urban areas in Selangor. Zhao et al. [18] used BPNN to predict CO concentration field in low-temperature coal oxidation. Suresh et al. [19] used an adaptive neural fuzzy model to predict environmental CO concentration at urban intersections and roads. Yeganeh et al. [20] predicted CO concentration based on the mixed model of PLS and support vector regression. Therefore, the CO emission prediction models for the MSWI process are relatively reported.

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Motivated by the above problems, a new CO emission concentration prediction method based on concept drift detection using KPCA is established.

II. MSWI Process Description for CO Emission

The MSWI process flow is shown in Fig. 1.

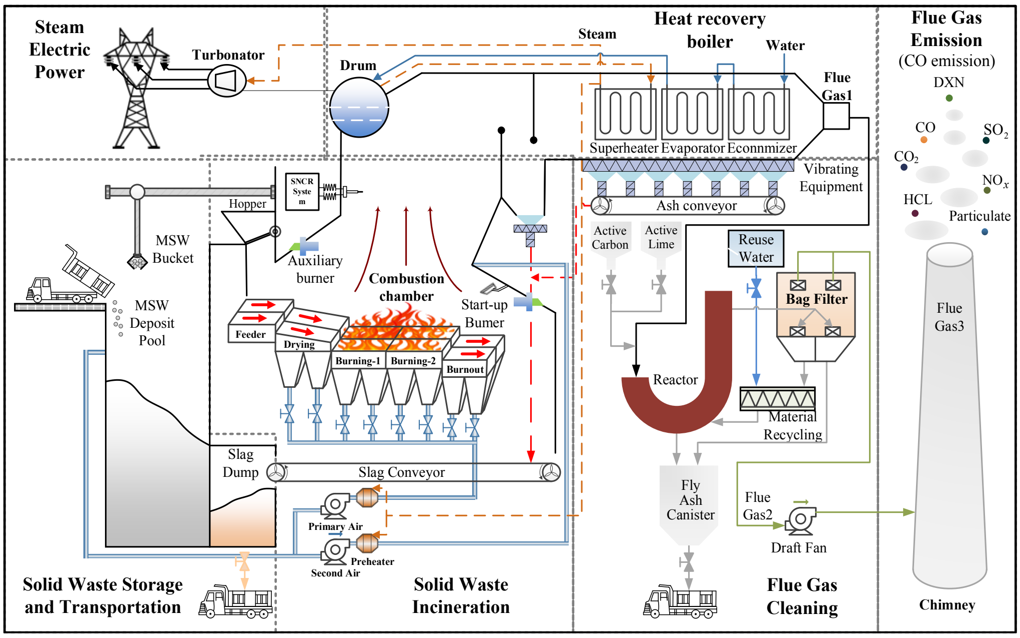


Fig. 1. Process flow of MSWI process

In the process of MSWI, MSW is converted into gas, tar, and coke. Coke and O_2 produce CO, CO_2, and other gases. In the second reaction, MSW volatilized substances in the grate area stay for a long time, and the tar is produced by cracking again to produce CO, CO_2, and coal coke.

The main products of the coke oxidation reaction are CO and CO_2. This article mainly predicts the CO emission concentration in G3 flue gas. It can be seen from the above process that CO is correlated with multiple variables in multiple stages of the MSWI process. It is necessary to carry out feature reduction and select suitable modeling algorithms to achieve higher precision prediction.

III. Modeling Strategy

The proposed modeling structure for CO concentration prediction is shown in Fig. 2, which includes two stages, i.e., offline model construction (historical data) and online prediction (real-time data). In the offline model construction stage based on historical data, LSTM and KPCA model is used to obtain the prediction model based on LSTM and drift index model based on KPCA for calculating the drift index control limit. In the online prediction stage based real-time data, the adaptive monitoring process with moving window recursive KPCA is used to realize drift detection and online measurement as well as LSTM prediction and update prediction.

In offline stage, by using historical data sets $\{\boldsymbol{X}^{\mathrm{His}} \in \mathbb{R}^{N\times M}, \boldsymbol{Y}^{\mathrm{His}} \in \mathbb{R}^{N\times 1}\}$, the prediction model based on LSTM was established and the concept drift index T^2 and SPE control limits were calculated based on KPCA model. In online stage, the process data with fixed window is used to calculate the statistical indicators T^2 and SPE to determine whether the statistical indexes out of the control limits. If they meet the requirements, the older LSTM prediction model are used to make prediction. Otherwise, the historical data set $\left[\boldsymbol{X}^{\mathrm{His}}, \boldsymbol{Y}^{\mathrm{His}}\right]$ and the drift data set $\left[\boldsymbol{X}^{\mathrm{CD}}, \boldsymbol{Y}^{\mathrm{CD}}\right]$ are combined to update the old LSTM model with retraining model. Moreover, the control limit of KPCA is also updated. The updated LSTM model is used for the current and future prediction. The predicted values for each window are combined to output the desired CO emission concentration.

IV. Industrial Application Verification

This article verifies the proposed modeling method based on the MSWI process data set. The first two-thirds of the data sets are used as training sets and the last one-third is used as testing sets. The used estimation indicators are selected as R^2, RMSE and MAE.

A. Experimental Results of Offline Stage (Training Dataset)

TABLE I. Offline Experimental Results

Method	Training dataset			Testing dataset		
	R²	***RMSE***	***MAE***	***R²***	***RMSE***	***MAE***
Offline LSTM	0.9965	2.5529	1.5257	-1.3425	44.7944	37.3119

As can be seen from Table 1, in the training data, R^2, RMSE, and MAE of LSTM are all good, which indicates that LSTM has a good fitting performance to the training data. However, in the testing data, the R^2 of LSTM is negative, the generalization performance is poor, and the prediction effect is poor. These shows that the updating of the historical LSTM model is very necessary.

In this article, LSTM training data is used to calculate concept drift limit. The principal component is determined by the contribution threshold $\delta^{\mathrm{PCA}} = 0.85$. The two historical data and control limits are further obtained, which are 2.7328 and 0.1399 respectively, and the confidence level is 90%.

B. Experimental Results of Online (Testing Dataset)

The moving window size for online monitoring is set to 20. Based on the offline model established in the previous section, the concept drift detection results for testing dataset are shown in Fig. 3 and Table II.

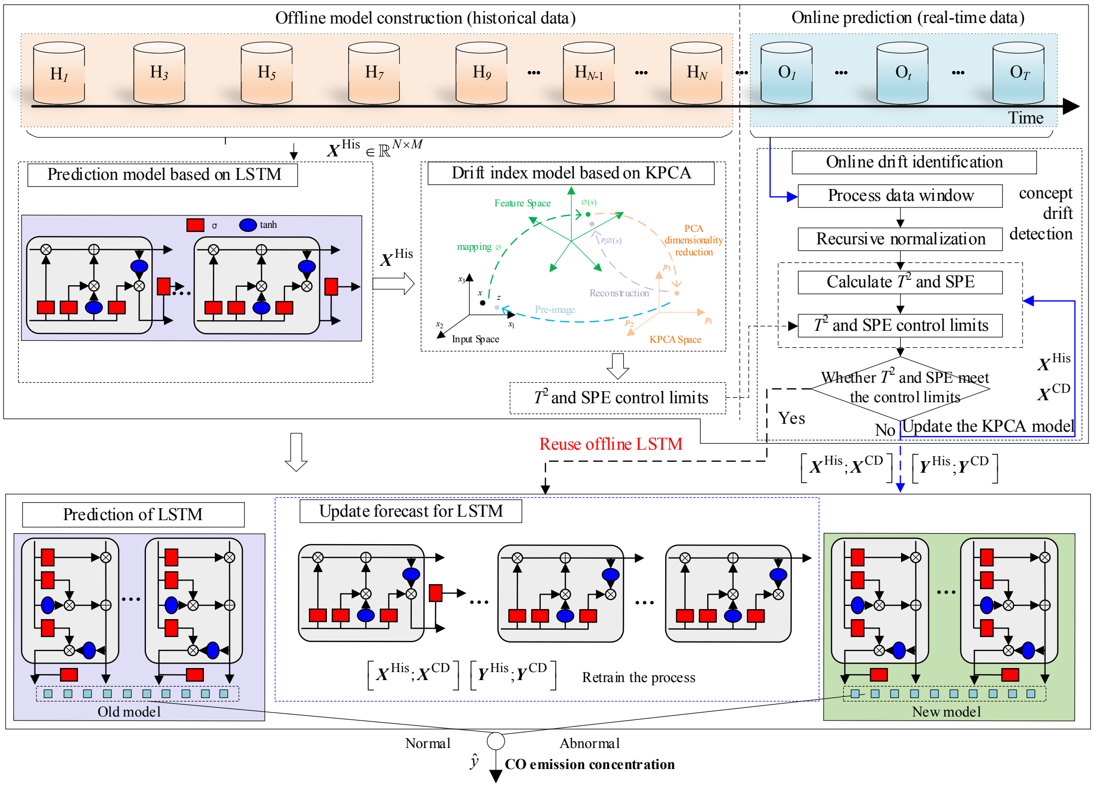
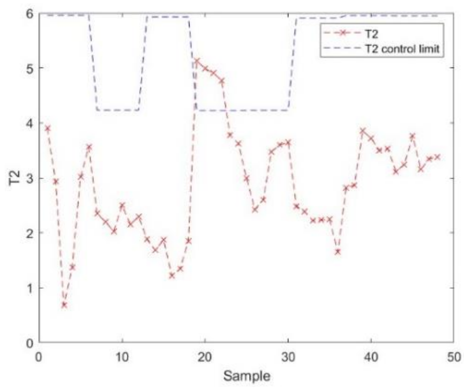
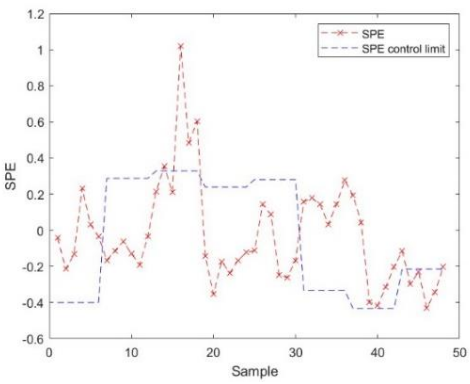


Fig. 2. Soft measurement strategy of CO concentration



(a) T^2



(b) SPE

Fig. 3. T^2 and SPE curves

TABLE II. RESULTS OF THE CONCEPT DRIFT DETECTION

Winsize	Window Sample	Number of drift samples
W1	20	9
W2	20	9
W3	20	19
W4	20	20
W5	20	20
W6	20	20
W7	20	20
W8	20	20
W9	20	20
W10	20	20
W11	20	12
W12	20	5

The concept drift detection results show that there are significant differences between the testing data and training data. When the control limit of historical data is considered, most of the testing data are the drift samples. This article updates the LSTM model and KPCA model with the detected drift samples. The results in Table III show that the LSTM online updating model has high fitting accuracy. The corresponding experimental results are shown in Fig. 4.

TABLE III. STATISTICS OF PREDICTION INDICATORS IN ONLINE STAGES

Stages	R^2	RMSE	MAE
Online	0.9411	7.0990	3.6710

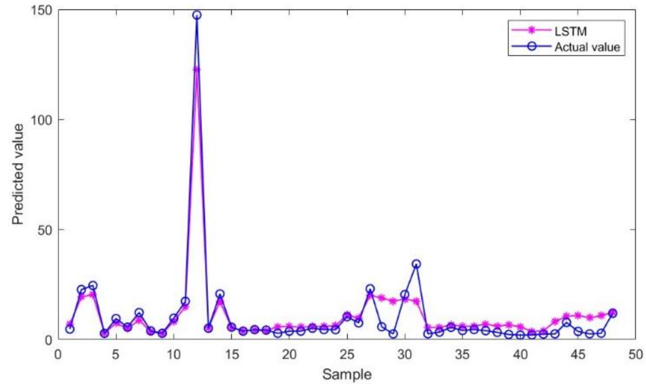


Fig. 4. Prediction results in online stages

As shown in Table III, R^2, RMSE, and MAE of testing data are 0.9411, 7.0990, and 3.6710 respectively. Compared with the offline modeling in Table I, the testing data (online stage) achieves better data fitting and higher modeling accuracy. The results show that the proposed offline modeling and online prediction strategy is effective. It can be seen that for the MSWI process CO data set, the dynamical updated LSTM model is more suitable than the static one.

C. Hyperparameter Analysis

This section analyzes the sensitivity of Hyperparameter "Winsize". Fig. 5 shows that the size of sliding windows have a great impact on the testing process. The model performance is low when it is less than 10. However, it degrades when too large a "Winsize" value is used, such as 30. To improve the accuracy of online measurement, the number of samples in the sliding window is set as 20.

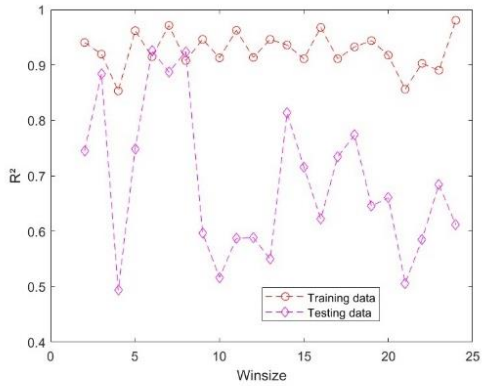


Fig. 5. Relationship Between R^2 and Hyperparameter "Winsize"

V. CONCLUSION

Aiming at the problem of CO emission prediction in the municipal solid waste incineration processes process, this article proposes an CO emission concentration prediction method based on concept drift detection using kernel principal component analysis. The main contributions are as follows: 1) The offline CO emission prediction model based on LSTM and concept drift detection model based on KPCA are constructed; 2) Online concept drift detection are used to obtain the samples that can represent the dynamical change of the time-varying characteristics, which are used to update the historical LSTM model; 3) The validity of the proposed method is verified by actual industrial data. In the future, fast LSTM updating algorithm should be addressed.

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