Adaptive Nonlinear Model Predictive Control of NOx Emissions under Load Constraints in Power Plant Boilers

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Nitrogen oxide (NOx) emissions are major pollutants of coal-fired boilers. An adaptive nonlinear model-predictive control approach is presented to reduce NOx emissions of power plant boilers. Firstly, the boiler load and the NOx emissions are dynamically predicted by a differential evolution-based least-square support vector machine. Subsequently, based on data-driven prediction modeling, a nonlinear optimization model, with load and capacity constraints, is proposed for NOx emission minimization. Finally, a differential evolution algorithm is used to solve this optimization problem and obtain the optimal control variable settings. Experimental results based on practical data indicate that the proposed approach exhibits a promising performance in the prediction of the boiler load and NOx emissions. Compared with that obtained using the normal control strategy, the proposed approach can reduce NOx emissions by 3.2% and 4.3% under increasing and decreasing loads, respectively.

Introduction

Due to environmental pollution concerns, considerable efforts are made to reduce nitrogen oxide (NOx) emissions (Tan et al., 2016a, 2016b; Tang et al., 2018; Wang et al., 2018) of coal-fired power plants. For example, in China, regulations limit NOx emissions to be within 100 mg/m³ at 6% O2 for coal-fired power plants. To satisfy the aforementioned strict criteria of pollutant emissions, flue gas denitrification (DeNOx) systems are typically setup (Munawer, 2018). However, DeNOx systems exhibit significant limitations including high setup cost and viscous salt byproducts that affect the boiler safety. Alternatively, to address these types of economy and safety concerns, more attention is focused on NOx emission modeling and combustion optimization (Li and Yao, 2017; Zhao et al., 2017; Shi et al., 2019).

Existing NOx emission models are divided into three broad categories as follows: dynamical models, statistical models, and data-driven models. Dynamical models based on laws of fluid flow, heat and mass transport, and chemical processes were proposed. For example, models based on computational fluid dynamics (CFD) were established to estimate NOx emissions. The models accounted for thermal and fuel NOx dynamics with simplifying assumptions (Dal Secco et al., 2015). Li et al. (2004) investigated formation mechanisms and system identification methods for NOx emission modeling. Experimental results indicated the good performance of the models under certain constraints although the dynamical models are typically complex, inefficient, and hardly applicable in modern control systems due to high complexity and uncertainty of combustion processes and parameters.

For statistical models, data collected from supervisor information systems (SIS) is used with statistical algorithms for NOx emission prediction and control. Smrekar et al. (2013) tested the accuracy and robustness of an autoregressive model with exogenous inputs (ARX) for NOx emission prediction. Zhang et al. (2015) established a numerical model to investigate low NOx combustion strategies. Although the statistical models are simple and useful, they are highly sensitive to measurement errors.

Many data-driven models of NOx emissions were proposed. A back-propagation (BP) neural network approach (Bekat et al., 2012) to predict NOx emissions was proposed. However, the approach requires several samples and includes over-fitting problems. Support vector regression (SVR) (Zhou et al., 2012) and regression neural networks (Song et al., 2017) also exhibited reasonable performance. When compared with other modeling methods, least-square support vector machines (LSSVM) exhibit the advantages of demonstrating a simple structure, avoiding overfitting, and showing a high generalization capability. Lv et al. (2013, 2015) utilized a LSSVM based on an ensemble learning paradigm to predict NOx emissions. In the study, a LSSVM is exploited to construct a model for boiler load and NOx emissions of ultra-supercritical coal-fired power generating units. Additionally, LSSVM parameters were optimized for different problems via differential evolution (DE) (Das and Suganthan, 2011).

For the aforementioned prediction models, many optimization approaches are proposed to control NOx emissions.
A particle swarm optimization (PSO) method was employed (Zhou et al., 2010) to regulate model inputs based on support vector regression (SVR). The results indicated that NOx emissions decreased by 32.67% and 16.3% at loads corresponding to 312.08 MW and 288.45 MW, respectively. Wei et al. (2013) employed quantum genetic algorithms (QGA) and simulated annealing genetic algorithms (SAGA) to optimize operating parameters to reduce NOx emissions. The results indicate that the approach achieves low NOx emissions. A micro-genetic algorithm was proposed (Zhou et al., 2004) to obtain the control parameter settings based on an artificial neural network (ANN) prediction model to reduce NOx emissions. An improved artificial bee colony (ABC) algorithm was proposed (Song et al., 2016) to obtain better on-line performance and extreme value extraction for a combustion optimization framework in on-line applications. Adaptive nonlinear model predictive control approaches are successfully applied in numerous industries such as power control (Tang et al., 2017), boiler-turbine control (Liu and Kong, 2013), and steel manufacturing control (Tang and Yang, 2014). In the study, an adaptive nonlinear model predictive control (ANMPC) approach is utilized to reduce NOx emissions.

The main purpose of the study is to model and optimize NOx emission reduction under load constraints. The models of boiler load and NOx emissions are developed based on a differential-evolution-based least-square support vector machine (DELSSVM). Based on the predictive models, we propose a minimization model for NOx emissions under side constraints and boiler load constraints. Subsequently, a DE algorithm is utilized to determine the optimal values of the control parameters.

The remainder of the study is organized as follows. Section 1 briefly reviews the LSSVM regression scheme and DE numerical optimization algorithm. Section 2 presents the proposed adaptive nonlinear model predictive control approach for boiler combustion. Details of the approach include structure of the predictive model, rolling optimization, and feedback correction. Section 3 includes experimental design, results, and analysis. Finally, conclusions are detailed in Conclusions.

1. Methodology

1.1 Least-square support vector machines (LSSVM)

Structural risk minimization corresponds to the underlying principle for both SVM and LSSVM predictors (Suykens and Vandewalle, 1999). For LSSVM, inequality constraints of SVM are converted into equality constraints, and the quadratic programming problem of SVM is transformed into a linear programming problem. Therefore, LSSVM exhibits better computational efficiency.

We assume that $D=\{(x_i, y_i)\}_{i=1}^n$ denotes the training data set, where $x_i \in \mathbb{R}^p$ denotes the training input and $y_i \in \mathbb{R}$ denotes the target output, $P$ denotes the dimension of input, and $n$ denotes the number of samples. To obtain the LSSVM prediction model, we solve the following optimization problem

$$\min_{w,b,e,a} f(w,e) = \frac{1}{2} w^T w + \frac{y}{2} \sum_{i=1}^n e_i^2$$

subject to $y_i = w^T \phi(x_i) + b + e_i, \quad i = 1,2,\ldots,n$ \hspace{1cm} (1)

where $w$ denotes the hyperplane vector, $y$ denotes the regularization parameter, $e_i^2$ denotes the squared error of the $i$th point, $b$ denotes the regressor bias, and $\phi(\cdot)$ denotes a nonlinear function mapping the original input data into a higher dimensional space. The optimization problem Eq. (1) is constructed based on Lagrange function, As shown in Eq. (2):

$$L(w,b,e,a) = f(w,e) - \sum_{i=1}^n a_i[w^T \phi(x_i) + b + e_i - y_i]$$

where $a_i$ denotes the $i$th Lagrange multiplier. The solution is obtained by partially differentiating $L$ with respect to $w, b, e_i, a_i$ as follows:

$$\frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{i=1}^n a_i \phi(x_i)$$
$$\frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^n a_i = 0$$
$$\frac{\partial L}{\partial e_i} = 0 \rightarrow a_i = \gamma e_i$$
$$\frac{\partial L}{\partial a_i} = 0 \rightarrow w^T \phi(x_i) + b + e_i - y_i = 0$$

A positive definite kernel is defined as follows:

$$K(x_i,x_j) = \phi(x_i)^T \phi(x_j)$$

In the study, the kernel function is selected as a Gaussian radial basis function (RBF) as follows:

$$K(x_i,x_j) = \exp(-||x-x_j||^2/\sigma^2)$$

where $\sigma^2$ denotes the kernel width parameter.

We combine Eqs. (1) and (3), and the LSSVM predictive model is obtained as follows:

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

where $K(x_i,x)$ denotes the LSSVM kernel function, and $x$ denotes the independent variable.

The DE is employed to optimize the model parameters, $\sigma^2$ and $y$. This significantly improves the predictive accuracy of the LSSVM model.

1.2 Differential evolution

Differential evolution (DE) denotes a population-based stochastic search algorithm, which is suitable to effectively solve continuous optimization problems. Specifically, DE includes evolutionary processes of mutation, crossover, and selection. Furthermore, DE generates a new population.
through differential mutation and maintains the optimal solution via greedy selection. Thus, DE is widely used in the feature of floating-point encoding, less adjustable parameters. Three crucial control parameters involved in DE include the population size $NP$, scaling factor $F$, and crossover rate $Cr$. The selection of the parameters can significantly influence the optimization performance of the DE algorithm. Storn and Price (1997) suggested that the optimal $NP$ values should be 5–10 times the dimensions of the problem, the initial value of $F$ should be 0.5, and the most effective range should be between 0.4 and 1. Currently, the DE algorithm is widely applied in various fields such as power systems (Sakr et al., 2017), system identification (Mete et al., 2016), and image encryption (Kaur and Kumar, 2018).

2. Adaptive Nonlinear Model Predictive Control of NOx Emissions

2.1 Structure of the proposed model predictive control approach

As shown in Figure 1, the model predictive control scheme is composed of a predictive model, rolling optimization, and feedback correction. The boiler load and NOx emission models are setup to predict the NOx emissions under floating loads. The predictive model is based on historical data and correlated variables and can predict the boiler load and NOx emissions. Subsequently, based on predictive models, an operation optimization problem is constructed under variable constraints. In rolling optimization, the optimization problem is solved to obtain optimal control parameters that can minimize NOx emissions while satisfying the boiler load constraint. Feedback correction is used to improve accuracy of the prediction model.

2.2 Construction of the predictive model

In the study, LSSVM is utilized to construct the predictive model, while the DE algorithm is used to optimize the LSSVM parameters. As shown in Figure 2, the procedure of the proposed algorithm is as follows:

Step 1. Initialize the DE swarm randomly within the search space and set up the DE parameters. Assume that $s_j^g \in \mathbb{R}^p$ ($j = 1, 2, ..., NP$) denotes the $j$th particle in the $g$th iteration. Additionally, $NP$ denotes the size of the population. $s_{j,1}^g$ and $s_{j,2}^g$ denote the regularization parameter and kernel parameter, respectively, and $g$ denotes the iteration counter. Set the maximum iteration count to $G = 100$ and iteration counter to $g = 1$ in this step;

Step 2. Construct the LSSVM model based on the training data and particle information for every particle;

Step 3. Compute the fitness of every particle as the mean absolute prediction error $\varepsilon_j$ of the particle as follows:

$$\varepsilon_j = \frac{1}{n} \sum_{i=1}^{n} |y_i - f(x_i)|$$

where $y_i$ denotes the true value and $f(x_i)$ denotes the predicted value for $x_i$.

Step 4. If the maximum iteration count is reached ($g = G$), then stop the algorithm, and output the predictive model. Otherwise, go to Step 3 after updating the particle parameters as follows:

$$V_j = s_j^g + F \cdot (s_{\text{best},g}^g - s_j^g) + F \cdot (s_j^g - s_{\text{rand},g}^g)$$

$$u_j = \begin{cases} V_j, \text{ rand}(j) \leq Cr \\ s_j^g, \text{ rand}(j) > Cr \end{cases}$$

$$s_j^g = \begin{cases} u_j, \text{ } f(u_j) < f(s_j^g) \\ s_j^g, \text{ } f(u_j) \geq f(s_j^g) \end{cases}$$

where $j$, $r1$, and $r2$ denote distinct random integers between $[1, NP]$, $\text{rand()}$ denotes a random number generating function with a uniform distribution in the interval $[0, 1]$, $F$ denotes a scaling factor, $Cr$ denotes the crossover rate, $V_j$ denotes the donor vector, $u_j$ denotes the trial vector, and $s_{\text{optimal},g}$ denotes the optimal individual in the $g$th generation.

The predictive model of the boiler load and NOx emissions is as follows:
Table 1 Parameters of the boiler load and NOx emission models

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$aa$</td>
<td>Coal mill inlet airflow (A) [t/h]</td>
</tr>
<tr>
<td>$ab$</td>
<td>Coal mill inlet airflow (B) [t/h]</td>
</tr>
<tr>
<td>$ad$</td>
<td>Coal mill inlet airflow (D) [t/h]</td>
</tr>
<tr>
<td>$ae$</td>
<td>Coal mill inlet airflow (E) [t/h]</td>
</tr>
<tr>
<td>$bt$</td>
<td>Boiler load [MW]</td>
</tr>
<tr>
<td>$ff$</td>
<td>Total fuel flow [t/h]</td>
</tr>
<tr>
<td>$fp$</td>
<td>Furnace pressure [Pa]</td>
</tr>
<tr>
<td>$fw$</td>
<td>Main feed-water flow [t/h]</td>
</tr>
<tr>
<td>$ne$</td>
<td>NOx emissions in flue gases [mg/m³]</td>
</tr>
<tr>
<td>$oa$</td>
<td>Flue gas oxygen content (A) [%]</td>
</tr>
<tr>
<td>$ob$</td>
<td>Flue gas oxygen content (B) [%]</td>
</tr>
<tr>
<td>$pa$</td>
<td>Primary air flow [t/h]</td>
</tr>
<tr>
<td>$sa$</td>
<td>Secondary air flow [t/h]</td>
</tr>
<tr>
<td>$ta$</td>
<td>Coal mill inlet temperature (A) [°C]</td>
</tr>
<tr>
<td>$tb$</td>
<td>Coal mill inlet temperature (B) [°C]</td>
</tr>
<tr>
<td>$td$</td>
<td>Coal mill inlet temperature (D) [°C]</td>
</tr>
<tr>
<td>$te$</td>
<td>Coal mill inlet temperature (E) [°C]</td>
</tr>
</tbody>
</table>

\[ Y_s = f_s(\{ff, fw, aa, ab, ad, ae, pa, sa\}) \quad (11) \]

\[ E_j = f_j(\{ff, fw, aa, ab, ad, ae, pa, sa, fp, ta, tb, td, te, oa, ob\}) \quad (12) \]

where $ff, fw, aa, ab, ad, ae, pa, sa, fp, ta, tb, td, te, oa,$ and $ob$ denote the operating parameters (See Table 1 for parameter definitions), while $Y_s$ and $E_j$ denote the predicted values of the boiler load and NOx emissions, respectively.

2.3 Rolling optimization

The aim of rolling optimization is to obtain optimal control parameter settings to minimize NOx emissions while satisfying load constraints. The rolling optimization problem is as follows:

\[ \min_u \sum_{j=1}^{l} |E_j-R_j| \]  
\[ \text{s.t.} \quad Y_L = f_s(\{ff, fw, aa, ab, ad, ae, pa, sa\}); \]
\[ E_j = f_j(\{ff, fw, aa, ab, ad, ae, pa, sa, fp, ta, tb, td, te, oa, ob\}); \]
\[ Y^L \leq Y_L \leq Y^U; \]
\[ u^L \leq u \leq u^U; \]
\[ j = 1, 2, ..., l. \]

where $E_j$ denotes the predicted value of the $j$th predictive mode for the NOx emissions, $R_j$ denotes the target value of the NOx emissions at time $j$, $u$ denotes control variables $ff, fw, aa, ab, ad, ae, pa, sa,$ and $bl$, and $Y_L$ denotes the predicted values of the boiler load. Additionally, $u^L$ and $u^U$ denote the lower and upper bounds of the control variables, respectively, and $u, Y^L,$ and $Y^U$ denote the lower and upper bounds of the boiler load, respectively.

To solve the optimization problem in Eq. (13) and obtain the optimized control variables, a DE algorithm is applied as follows (See Figure 3):

Step 1. Read the data. To satisfy the requirement of rolling optimization, predictive models with $l$ samples are established.

Step 2. Initialize the DE population randomly within the search space. The particle $s_{ia}^j$ represents the $kth$ control variables $ff, fw, aa, ab, ad, ae, pa,$ and $sa$ (See Table 1 for parameter definitions).

Step 3. The boiler load for every particle is calculated by Eq. (11). If the boiler load satisfies the requirement, then go to Step 4. Otherwise, set the relative fitness of the particle to a large value (e.g., 1000) to ensure that the particle does not correspond to the optimal result and go to Step 5.

Step 4. Compute the NOx emissions of every particle and the corresponding fitness as follows:

\[ \epsilon_j = \frac{1}{l} \sum_{j=1}^{l} |E_j-R_j| \quad (14) \]

where $l$ denotes the prediction time length, $E_j$ denotes the predicted value of the $j$th predictive mode for NOx emissions, and $R_j$ denotes the target value of the NOx emissions at time $j$.

Step 5. Find the minimum fitness value of the population.

Step 6. If the minimum fitness value satisfies the emission requirement, then go to Step 9. Otherwise, go to Step 7;

Step 7. If the maximum iteration count is reached (e.g., 10), then go to Step 9. Otherwise, go to Step 8;

Step 8. Update the particles according to Eqs. (8–10), increase the iteration counter $g = g + 1$, and return to Step 3;

Step 9. Output the control parameters and fitness value. Stop the algorithm.

![Fig. 3 Flowchart of the solution of the rolling optimization problem](image-url)
2.4 Feedback correction
The load demand changes follow the power demand, and thus a model reconstruction strategy (shown as Eqs. (15) and (16)) is applied to guarantee the accuracy of the predictive model. Specifically, if each of three consecutive prediction errors of the actual load and NOx emissions is larger than 3%, then the prediction models are reconstructed with the most recent data.

\[
 r_{y,t} = \begin{cases} 1, & \text{if } e_{t-3} > 3\% \text{ and } e_{t-2} > 3\% \text{ and } e_{t-1} > 3\% \\ 0, & \text{if else} \end{cases} \quad (15)
\]

\[
 r_{x,t} = \begin{cases} 1, & \text{if } y_{t-1} > 3\% \text{ and } y_{t-2} > 3\% \text{ and } y_{t-3} > 3\% \\ 0, & \text{if else} \end{cases} \quad (16)
\]

where \( r_{y,t} \) shows whether the NOx emissions model should be reconstructed and \( e_{t-1} \) denotes the prediction errors of the NOx emissions at time \( t-1 \). If \( r_{y,t} = 1 \), then the NOx emissions model should be reconstructed with new training data; and if \( r_{y,t} = 0 \), the NOx emissions model does not change. Thus, \( r_{y,t} \) shows whether the load model should be reconstructed. Additionally, \( y_{t-1} \) denotes the prediction errors of the load at time \( t-1 \). If \( r_{y,t} = 1 \), then the load model should be reconstructed with new training data; if \( r_{y,t} = 0 \), then the load model does not change.

3. Experimental Design, Results, and Analysis
To assess the performance of the proposed model, experiments based on real production data were carried out. Models of multi-layer perceptrons (MLP), partial least squares (PLS) (Wang et al., 2015), and genetic-algorithm back-propagation (GABP) neural networks (Zhang et al., 2015) are compared with DELSSVM in terms of modeling accuracy. A traditional PID control method (Kon and Yamashita, 2012) is also compared with the proposed ANMPC approach in terms of control performance.

The compared algorithms were executed with the LSSVM toolbox in MATLAB on a Core i5 processor with 2-GB RAM and a Windows10 operating system.

3.1 Data description and preprocessing
In the study, data was collected for a super-critical 660-MW tangentially-fired coal boiler (Manufactured by Dong Fang boiler group). The measurement system of the exhaust gas emissions is located in the exhaust gas path at the end of the economizer. The exhaust gas passes through an air pre-heater, four horizontal flues, an electrostatic precipitator, and is then processed by a desulfurizer.

Based on physical analysis, the parameters related to the boiler load and NOx emissions (See Table 2) are collected from the distributed control system (DCS) of the power plant. The parameters exhibit different ranges. Hence, the data are standardized to improve the prediction accuracy. All parameters are linearly denoted as follows:

\[
x^* = \frac{x - \min(x)}{\max(x) - \min(x)}
\]

where \( x^* \) and \( x \) denote the parameters and after and before scaling, and \( \max(x) \) and \( \min(x) \) denote the maximum and minimum parameter values, respectively.

3.2 Performance metrics
To compare the performance of the prediction models, three metrics including the mean absolute error (MAE), mean relative error (MRE), and root-mean-square error (RMSE) were used to measure the average prediction performance of each model on all data points (shown as Eqs. (18) and (20)).

\[
MAE = \frac{1}{N} \sum_{t=1}^{N} |y_t - y_t^*| \quad (18)
\]

\[
MRE = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{y_t - y_t^*}{y_t} \right| \times 100% \quad (19)
\]

\[
RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (y_t - y_t^*)^2} \quad (20)
\]

where \( y_t \) and \( y_t^* \) denote the actual and the predicted values at \( t \), and \( N \) denotes the number of samples in the test data set.

3.3 Parameter settings
Based on Das and Suganthan (2011), the DE population size, \( NP \), is typically set to 20. To select other DE parameters (\( F \) and \( CR \)), we investigated the effect of these control pa-

![Fig. 4 Prediction performance for DE parameter tuning](image-url)
parameters on the prediction MAE metric. As shown in Figure 4, $F$ denotes the scaling factor and is set as 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 1, and $CR$ denotes the crossover rate and is set to 0.5, 0.6, 0.7, 0.8, 0.9, and 1. The results indicate that the algorithm achieves the optimal performance at a crossover rate $CR = 1$ and a scaling factor $F = 0.8$.

### 3.4 Analysis of the NOx emission and boiler load prediction results

The prediction models of the boiler load and NOx emissions were constructed via the algorithm in Section 2.2. The boiler load prediction model includes eight input parameters in Table 1, namely total fuel flow, main feed-water flow, coal mill inlet airflow (A, B, D, E), and total air flow (primary air flow, secondary air flow). The boiler load denotes the output of the model. The model of the NOx emissions includes fifteen input parameters in Table 1 as follows: total fuel flow, main feed-water flow, coal mill inlet airflow (A, B, D, E), total air flow, furnace pressure, coal mill inlet temperature (A, B, D, E), and flue gas oxygen content (A, B). The NOx emissions denotes the output of the model.

Figure 5 shows comparisons between the actual measured values and predicted values for the boiler load for the testing set. The data evidently indicates a good fit with the perfect line where the predicted value corresponds to the actual measured one. This indicate that the prediction model exhibits a promising performance with $R^2 = 0.9773$ for the testing set of the boiler load. The GABP, MLP, and PLS models were compared with those of the proposed model.

The prediction results of the boiler load are shown Figure 6. As shown in the figure, it is realized that all the prediction curves follow the direction of the real data. Hence, all four algorithms can be used to predict the boiler load. However, as shown in Figure 7, the errors of the DELSSVM algorithm evidently vary within a small range of $[-14, 12.5]$ and are more clustered between the values of $-4.5$ and $2.5$. The MLP model exhibits the worst performance with a large error range of $[-13, 22]$ where most errors are between 0 and 10. The prediction errors based on the GABP model are in the range of $\pm 16$, while most values are between $-3$ and $7.5$. The PLS model exhibits an error range of $[-12, 18]$, with most values between $-1$ and 7. Hence, the DELSSVM model exhibits the lowest errors when compared with that of the other models. Table 3 shows the average error metrics of the different prediction algorithms. As shown in Table 3, the DELSSVM model of the boiler load exhibits

![Fig. 6 Prediction results of the boiler load with different algorithms](image)

![Fig. 7 Boxplots of the boiler load prediction errors with different algorithms](image)

<table>
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<tr>
<th>Model</th>
<th>Training error</th>
<th>Testing error</th>
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<tbody>
<tr>
<td></td>
<td>RMSE [mg/m³]</td>
<td>MAE [mg/m³]</td>
</tr>
<tr>
<td>DELSSVM</td>
<td>2.8438</td>
<td>2.1868</td>
</tr>
<tr>
<td>GABP</td>
<td>6.7350</td>
<td>5.8051</td>
</tr>
<tr>
<td>MLP</td>
<td>9.3053</td>
<td>7.5938</td>
</tr>
<tr>
<td>PLS</td>
<td>7.1181</td>
<td>6.5508</td>
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optimal performance with $MAE = 4.3799$, $MRE = 1.14$, and $RMSE = 5.5835$ on the test dataset. The prediction performance of the MLP model on the test data corresponds to the poorest: $MAE = 7.5659$, $MRE = 1.95$, and $RMSE = 9.2899$.

Similarly, Figure 8 shows comparisons between the actual measured values and predicted values for the NOx emissions on the test sets. Specifically, the figure illustrates that the prediction models of NOx emissions generally exhibit better performance with $R^2 = 0.9773$ for the testing set of the NOx emissions. Figure 9 shows the prediction curves of the NOx emissions based on the DELSSVM, GABP, PLS, and MLP models. All the prediction curves follow the direction of the real data. Figure 10 shows that the DELSSVM model of NOx emissions exhibits the lowest prediction errors when compared with the other models. Thus, the DELSSVM model exhibits errors in a small range of $[-21, 23]$, where most values are between $-15$ and $6$. Conversely, the PLS model exhibits the worst errors with a range of $[-15, 90]$ and with most values between $21$ and $60$. The phenomenon is because the PLS mainly solves linear problems and is unable to accurately analyze nonlinear problems.

The results in Table 4 indicate that the proposed DELSSVM model yields a favorable performance for NOx prediction with error metrics of $MAE = 8.8197$, $MRE = 1.56$, and $RMSE = 10.8945$. The PLS model exhibits the worst performance with $MAE = 42.82054$, $MRE = 7.72$, and $RMSE = 47.5385$.

Hence, the DELSSVM-based prediction models of the boiler load and NOx emissions exhibit superior prediction performance, and the prediction results satisfy the requirements of practical operations.

3.5 Analysis of the results of model predictive control

Two different datasets (described in Table 5) were utilized to show the control performance of the proposed approach. The experimental results are given in Figures 11 and 12. In Figure 11, the proposed approach yields lower emissions when compared with those of the canonical PID model when the boiler load becomes larger. Similar results are seen in Figure 12 when the boiler load decreases. Statistical results are provided in Table 6. The proposed approach can decrease NOx emissions by 3.2% when the load increases. Furthermore, the proposed approach can reduce NOx emissions by 4.3% when the load decreases. The results indicate that the proposed approach decreases NOx emissions for changing boiler loads.

A comparison of our ANMPC approach relative to the traditional PID approach suggests that the performance of

<table>
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<th>Testing error</th>
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<td>MRE [%]</td>
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</table>

![Fig. 8 Comparison between actual measured values and predicted values of NOx emissions on test data](image1)

![Fig. 9 Prediction results of NOx emissions with different algorithms](image2)

![Fig. 10 Boxplots of the NOx emission errors with different algorithms](image3)
Conclusions

An adaptive nonlinear model predictive control approach was proposed in the study to minimize NOx emissions under changing loads. A major feature of the proposed approach is that a DE-based LSSVM scheme is proposed to predict NOx emissions and boiler load. The DE was utilized to optimize the parameters of LSSVM to improve model accuracy. Another major feature is that the values of the control variables are set based on the proposed adaptive nonlinear model predictive control (ANMPC) approach. A DE algorithm was used to solve a rolling optimization problem which considered both the NOx emissions and boiler load. Experiments based on practical data were performed to assess the performance of the proposed modeling approach. When compared with the canonical PID approach, the proposed control approach decreased NOx emissions by 3.2% and 4.3% under increasing and decreasing loads, respectively. The results indicated that proposed modeling and control strategies are effective and promising. Future studies will address the inclusion of more data-driven algorithms and evolutionary optimization algorithms in the proposed ANMPC framework and the application of the proposed algorithm in other practical industry problems.

Acknowledgement

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Table 5 Description of the data for control performance evaluation

<table>
<thead>
<tr>
<th>Dataset name</th>
<th>Description</th>
<th>Boiler load range [MW]</th>
<th>Number of samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset 1</td>
<td>Data collected at small boiler loads</td>
<td>371–402</td>
<td>300</td>
</tr>
<tr>
<td>Dataset 2</td>
<td>Data collected at large boiler loads</td>
<td>372–400</td>
<td>300</td>
</tr>
</tbody>
</table>

Table 6 Total NOx emissions with the proposed and PID control approaches

<table>
<thead>
<tr>
<th>Load change [MW]</th>
<th>ANMPC [mg/m³]</th>
<th>PID [mg/m³]</th>
<th>Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drop from 402 to 371</td>
<td>143952</td>
<td>150383</td>
<td>4.3%</td>
</tr>
<tr>
<td>Rise from 372 to 400</td>
<td>162061</td>
<td>167370</td>
<td>3.2%</td>
</tr>
</tbody>
</table>

Fig. 11 NOx emissions with different control approaches for increasing boiler loads

Fig. 12 NOx emissions with different control approaches for decreasing boiler loads

the ANMPC approach is promising and more favorable. Additionally, the proposed ANMPC approach provides effective suggestions to the operator for NOx emission control.

Literature Cited


