Coal blending optimization model for reducing pollutant emission costs based on Support Vector Machine

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Abstract. Factors such as the pollutant formation, pollution emission punishment and pollutant control devices are considered to optimize the coal blending method for a 300 MW boiler unit. The support vector machine (SVM) is used to establish the pollutant formation prediction model for the coal–fired boiler. Moreover, the model built above is trained and verified based on the actual operation data. Then the genetic algorithm is applied to optimize the coal blending method with the coal price to achieve the lowest operation cost. It can be concluded from the results that the precision of the prediction model is relatively high and the ammonia consumption, NOₓ emission punishment, CaCO₃ consumption and desulfurization water consumption have all decreased after optimization, which means both the desulfurization cost and denitrification cost are reduced.

1. Introduction
The main pattern of power generation is coal-firing in China. It is inevitably to lead to pollutants formation and emission such as SO₂ and NOₓ during coal-fired process because of the sulfur and nitrogen element contained in the coal. It has been an urgent problem that how to control the pollution emission of coal-fired power station further as the standard is becoming more and more rigorous.

The key factor of pollutants generation is the coal quality. The common problems existing in coal-fired power station of China are the instability of the coal quality and the use of blended coal. After the coal blending optimization, it can not only decrease the cost of coal, ensure safe and economical operation of the boiler, but also control the pollutants formation and emission effectively, which is significant to protect the environment during the power plant operation [1-3].

In this paper the coal blending optimization model consider the factors such as pollutant formation, pollution discharge punishment and pollutant control devices. Support vector machine (SVM) is applied to establish the pollutant formation prediction model for coal–fired boilers. Moreover, the model built above is trained and verified using actual operation data from a 300 MW boiler. Then, on the basis of the coal cost, removal cost and pollution punishment of NOₓ and SO₂, the genetic algorithm is employed to optimize the coal blending to achieve the minimum operation cost.

2. Algorithm of Support Vector Machine(SVM)
The NOₓ prediction model is established using the algorithm of SVM. N groups of date under different loads are chosen to train the model. Input and output parameters are denoted by \( \{x_i,y_i\}^N \), where \( x_i \) is the...
input parameter of group $i$, $y_i$ is the output parameter of group $i$ and $N$ is the sample size. Radial basis function is chosen to be the kernel function of SVM algorithm:

$$K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j) = \exp\left(\frac{||x_i - x_j||^2}{2\sigma^2}\right)$$  \hspace{1cm} (1)$$

Where $\sigma$ is the kernel parameter and $\phi(x)$ is the mapping function.

The objective function is set as:

$$f(x_i) = \omega \cdot \phi(x_i) + b$$  \hspace{1cm} (2)$$

Where $f(x_i)$ is the model predictive value and $\omega$ is weight coefficient vector. Relaxation factors $\xi_i$ and $\xi_i^*$ and the fitting error $\varepsilon$ are introduced. Constraint conditions are set as: $y_i - \omega \cdot \phi(x_i) - b \leq \varepsilon + \xi_i$; $\omega \cdot \phi(x_i) + b - y_i \leq \varepsilon + \xi_i^*$; $\xi_i \geq 0$, $\xi_i^* \geq 0$, $i = 1, \ldots, N$.

Pollutant formation of coal-fired boiler prediction model is set as follows:

$$R(\omega, \xi, \xi^*) = \frac{1}{2} \omega \cdot \omega + c \sum_{i=1}^{N} (\xi + \xi^*)$$  \hspace{1cm} (3)$$

Where $c$ is penalty coefficient and $c \geq 0$

Lagrange function $L$ is introduced as follows:

$$L(\omega, b, \xi, \xi^*, \alpha, \alpha^*, \gamma, \gamma^*) = \frac{1}{2} \omega \cdot \omega + c \sum_{i=1}^{N} (\xi + \xi^*) - \sum_{i=1}^{N} \alpha_i \left[ y_i - \left( \xi_i + \varepsilon + f(x_i) \right) \right] - \sum_{i=1}^{N} \gamma_i \left[ \xi_i^* - \xi_i \right] - \sum_{i=1}^{N} \gamma_i^* \left[ \xi_i + \xi_i^* \right]$$  \hspace{1cm} (4)$$

Where $\alpha_i$, $\alpha_i^*$, $\gamma_i$, and $\gamma_i^*$ are Lagrange multipliers and they are all above 0.

Minimum value points with respect to $\omega, b, \xi_i$ and $\xi_i^*$ of the function are calculated as below:

$$\frac{\partial}{\partial \omega} L = 0 \Rightarrow w = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) \phi(x_i)$$  $$\frac{\partial}{\partial b} L = 0 \Rightarrow \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) = 0$$  $$\frac{\partial}{\partial \xi_i} L = 0 \Rightarrow C - \alpha_i - \gamma_i = 0$$  $$\frac{\partial}{\partial \xi_i^*} L = 0 \Rightarrow C - \alpha_i^* - \gamma_i^* = 0$$  \hspace{1cm} (5)$$

The Lagrange dual function is obtained as below:
According to the KKT theorem, the relations at the extreme value point are as below:

\[ \alpha_i \left[ \varepsilon + \xi_i - y_i + f(x_i) \right] = 0 \]  
\[ \alpha_i^* \left[ \varepsilon + \xi_i^* + y_i - f(x_i) \right] = 0 \]  

Where \( i = 1, \cdots, N \).

It follows that \( \xi_i y_i = 0, \xi_i^* y_i^* = 0 \) and \( b \) can be calculated based on above equations. Finally the NOx prediction function can be determined.

3. Optimization Model

The research object is a subcritical natural circulation boiler with a rated capacity of 1025t/h. Single furnace, temperature control by tilting burner, balanced ventilation and four corner tangential firing are used in the bituminous coal fired boiler with positive pressure direct blowing coal-pulverizing system and five medium speed mills.

Fourteen operation parameters such as blended coal quality, boiler load, primary and secondary air flow rate and every layer’s secondary air flow rate are set as the input parameters of the coal blending optimization model. Mass concentrations of NOx and SO2 in flue gas are set as model output parameters. The coal blending optimization model consists of NOx prediction model and SO2 prediction model and aims to minimize the coal blending cost. The structure of the coal blending optimization model is shown as Fig1. The NOx prediction model is based on SVM [4]; The SO2 concentration in flue gas is calculated by material balance based on sulfur mass friction in blended coal. The removal costs of NOx and SO2 are fitted calculated using the actual operation data. The pollution punishment is calculated according the pollutant discriminative charge policy in Tianjin.
4. NOx Prediction Model

4.1. Training Samples
Two hundred groups of coal quality and operation condition data of this boiler are chosen and among them 150 groups form the training sample and 50 groups form the testing sample (Table 1). For the precision of the model calculation, the training samples have to be trained in different load ranges as 150-200, 200-250 and 250-300MW, and then normalization processing is carried out.

| No. | P/MW   | Qm1/t·h⁻¹ | Qm2/t·h⁻¹ | S_EAA | S_EAB | S_EBC | S_ECD | S_EDE | S_EEF | S_EOFA | S_EOFAI | S_EOFAII |
|-----|--------|------------|-----------|-------|-------|-------|-------|-------|-------|--------|----------|----------|
| 1   | 150.10 | 197.88     | 747.03    | 64.28 | 19.85 | 28.25 | 19.90 | 20.82 | 10.23 | 0.17   | 0.007    | 0.083    |
| 2   | 151.42 | 171.50     | 832.32    | 64.25 | 19.49 | 27.83 | 19.81 | 20.82 | 9.62  | 0.168  | 0.008    | 0.084    |
|     |        |            |           |       |       |       |       |       |       |        |          |          |
| 155 | 247.47 | 304.46     | 975.63    | 77.35 | 26.90 | 45.77 | 29.95 | 30.83 | 29.97 | 4.69   | 12.07    | 7.326    |
| 156 | 249.12 | 305.89     | 1000.88   | 77.35 | 26.90 | 45.77 | 29.94 | 30.83 | 29.97 | 4.69   | 12.07    | 7.326    |
| 157 | 252.42 | 297.64     | 935.41    | 63.37 | 22.39 | 35.83 | 21.99 | 22.06 | 22.06 | 7.10   | 15.11    | 7.760    |
| 158 | 257.47 | 304.06     | 980.27    | 62.94 | 22.12 | 37.67 | 25.38 | 26.25 | 25.03 | 0.17   | 0        | 0.061    |
| 159 | 257.91 | 279.75     | 987.47    | 62.97 | 22.69 | 29.64 | 28.27 | 25.51 | 15.33 | 15.16  | 5.76     | 9.936    | 7.616    |
| 160 | 260.00 | 324.07     | 733.67    | 62.88 | 26.89 | 34.07 | 19.76 | 21.55 | 19.66 | 0.176  | 0.007    | 0.061    |
|     |        |            |           |       |       |       |       |       |       |        |          |          |
| 195 | 270.55 | 338.58     | 1062.76   | 68.56 | 27.32 | 35.96 | 27.19 | 24.59 | 19.66 | 7.98   | 14.15    | 11.24    |
| 196 | 273.07 | 297.44     | 1047.41   | 68.10 | 22.26 | 39.05 | 24.78 | 25.87 | 24.53 | 8.59   | 19.40    | 13.12    |
| 197 | 278.90 | 324.90     | 1055.25   | 41.97 | 16.88 | 25.74 | 17.64 | 19.02 | 17.62 | 5.98   | 14.45    | 7.73     |
| 198 | 285.27 | 287.91     | 1028.69   | 77.93 | 24.39 | 42.33 | 25.14 | 24.60 | 24.52 | 19.55  | 18.13    | 8.52     |
| 199 | 292.52 | 276.82     | 1059.13   | 78.75 | 24.39 | 42.61 | 24.87 | 24.60 | 24.54 | 19.58  | 18.40    | 8.52     |
| 200 | 297.47 | 282.87     | 1042.58   | 77.93 | 24.39 | 42.33 | 25.15 | 24.60 | 24.52 | 19.57  | 18.38    | 8.51     |

4.2. Model Parameters
The regularization parameters c and the kernel parameter $\sigma$ greatly influence the performance of the model and should be determined first. C is the parameter that weighs fitting curve smoothness and minimize the fitting error. The bigger c is, the more accurately the fitted values of training sample are. Decreasing c can reduce complexity of the model. Increasing $\sigma$ can smooth the fitting curve and decreasing $\sigma$ can reduce complexity of the regression function. The three-step search algorithm is used to make the model more accurate so c is set to 0.5 and $\sigma$ is set to 0.55.

4.3. Model Validation
As illustrated in Fig.2-4, three groups of simulation results and actual results are compared. It can be found that the precision of the NOx prediction model is relatively high. The relative errors of the model training samples are 1.26%, 0.87% and 2.39% respectively. The relative errors of the testing samples are 4.23%, 3.68% and 5.04% respectively.
Figure 2. The predicted and actual measured NO\textsubscript{x} emission at load about 150MV to 200MV.

Figure 3. The predicted and actual measured NO\textsubscript{x} emission at load about 200MV to 250MV.

Figure 4. The predicted and actual measured NO\textsubscript{x} emission at load about 250MV to 300MV.
5. Coal Blending Optimization Model

5.1. Optimization Object Function
The genetic algorithm is selected to optimize. Coal with high nitrogen or sulfur content is of poor quality and low price and burning it will produce acid gas pollutant, cause boiler low temperature corrosion and make lagging more easily. It can influence the safe operation of the boiler, increase the pollutant punishment cost and operation cost. Therefore, the optimization objective of the coal blending optimization model is to reduce the coal blending cost and pollutant emissions while assuring the safe operation of the boiler. The objective function is set as below:

\[
\min: M + m_1 \rho(\text{NOx}) (1-\eta_1) + m_2 \rho(\text{SO2}) (1-\eta_2) + m_3 \rho(\text{NOx}) \eta_1 + m_4 \rho(\text{SO2}) \eta_2 \tag{10}
\]

Where \(M\) is the price of blended coal; \(m_1\) is the pollution punishment of NOx; \(\rho(\text{NOx})\) is the mass concentration of NOx in combustion products; \(m_2\) is the pollution punishment of SO2; \(\rho(\text{SO2})\) is the mass concentration of SO2 in combustion products; \(m_3\) is the total cost of NOx removal per unit mass; \(m_4\) is the total cost of SO2 removal per unit mass; \(\eta_1\) is the NOx removal efficiency and \(\eta_2\) is the SO2 removal efficiency.

5.2. Constraint Conditions
Lower heat value, sulfur mass fraction, nitrogen mass fraction, volatile mass fraction and ash mass fraction in the blended coal are determined as the constraints to ensure the safe operation of the boiler unit. The constraints of coal blending are illustrated as below:

The lower heat value is less than or equal to 21 000kJ/kg. The higher the ash fusion point is, the higher the lower heat value should be. High ash fusion point benefits the safe and economical operation of the boiler.

The sulfur mass fraction is less than or equal to 0.65%. The sulfur mass fraction is the major consideration for coal blending to avoid the low temperature corrosion of the boiler tail heating surfaces and reduce the SO2 mass concentration in exhaust gas.

The nitrogen mass fraction is less than or equal to 0.6%. High nitrogen mass fraction in coal can increase the NOx formation.

The volatile mass concentration is less than or equal to 29.1%. To ensure the stable combustion for the specific boiler unit, the volatile mass fraction in the blended coal is usually higher than the low threshold \(V_{\text{min}}\) and to prevent accidents such as burner nozzle burning out, the volatile mass fraction in the blended coal should be below the high threshold \(V_{\text{max}}\) [5].

The ash mass fraction is less than or equal to 17.1%. To ensure the safe and stable operation, the ash mass fraction should be reduced.

6. Results and Analysis of the Optimization
The calculation results of economic parameters using the coal blending optimization model are illustrated as below:
Table 2. Economic parameters before and after the coal blending optimization (yuan/kW·h)

| Subentry | Ammonia consumption | Denitratio n electric consumpti on | NOx emission punishment | Denitration Cost | CaCO3 consumption | Desulfurizati on electricity consumption | Desulfurizati on water consumption |
|----------|---------------------|-----------------------------------|------------------------|-----------------|------------------|----------------------------------------|----------------------------------|
| Before Optimizati on | 0.01362 | 0.00073 | 0.00066 | 0.01435 | 0.01282 | 0.00521 | 0.00033 |
| After Optimizati on | 0.01361 | 0.00073 | 0.00064 | 0.01434 | 0.01277 | 0.00521 | 0.00032 |

| Subentry | SO2 emission punishmen t | CaSO3 income | Desulfurizati on cost | Denitration electricity compensati on | Desulfurizati on electricity compensatio n | Coal cost | Total cost |
|----------|-------------------------|--------------|----------------------|--------------------------------------|------------------------------------------|----------|-----------|
| Before Optimizati on | 0.00086 | -0.00106 | 0.01730 | -0.01 | -0.015 | 0.2707 | 0.28774 |
| After Optimizati on | 0.00082 | -0.00104 | 0.01727 | -0.01 | -0.015 | 0.2668 | 0.28339 |

As illustrated in Table 2, both the denitration cost and the desulfurization cost have decreased after optimization, because coal blending optimization can reduce the NOx formation and sulfur mass fraction. The coal blending cost consists of blended coal price, pollutant removal cost and emission punishment if not considering electricity compensation and the blended coal price accounts for more than 90%. So reducing the blended coal price can significantly decrease the coal blending cost.

7. Conclusion
In different load ranges as 150-200, 200-250 and 250-300MW, the relative errors of training samples of the NOx prediction model based on SVM algorithm are 1.26%, 0.87% and 2.39% respectively. The relative errors of testing samples of the NOx prediction model based on SVM algorithm are 4.23%, 3.68% and 5.04% respectively.

The ammonia consumption, NOx emission punishment, CaCO3 consumption, desulfurization water consumption and SO2 emission punishment have all decreased after optimization, so the total cost of denitration and desulfurization have decreased.

The blended coal price accounts for more than 90% of the coal blending cost. So reducing the blended coal price can significantly decrease the coal blending cost.

With the increasingly high environment requirement, the pollutant removal cost and emission punishment will account for a higher portion and decreasing them will be the research emphasis in the future.

References
[1] Zhou Hao, Li Yuan, Cen Kefa, Online blend-type identification during co-firing coal and biomass using SVM and flame emission spectrum in a pilot-scale furnace, J. IET RENEWABLE POWER GENERATION. 13 (2019) 253 - 261.
[2] Guerras Lidia S, Martin Mariano, Optimal gas treatment and coal blending for reduced emissions in power plants: A case study in Northwest Spain, J. ENERGY. 169 (2019) 739 - 749.
[3] Zaid M.Z.S.M, Wahid M.A, Mailah M, Mazlan M.A, Coal fired power plant: A review on coal blending and emission issues, 10th International Meeting of Advances in Thermofluids, Bali,
Indonesia, 2018.

[4] Yangping GU, Wenjie ZHAO, Zhangsong WU, Combustion optimization for utility boiler based on least square-support vector machine, J. Proceedings of the CSEF. 30 (2010) 91 - 96.

[5] TAO Peng, By application of volatile combustible base as the base instead of the combustion characteristic discussion, J. Electric Power Technology. 3 (1988) 66 - 68.