Applied Thermal Engineering 119 (2017) 553-559

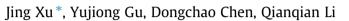
Contents lists available at ScienceDirect

Applied Thermal Engineering

journal homepage: www.elsevier.com/locate/apthermeng

Research Paper

Data mining based plant-level load dispatching strategy for the coal-fired power plant coal-saving: A case study



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HIGHLIGHTS

• A hybrid methodology based on data mining methods for plant-level load dispatching was proposed.

• The model of coal rate was built based on a large amount of actual operating data taken from power plant.

• An actual on-duty coal-fired power plant was adopted as an example and the strategy has been illustrated.

ARTICLE INFO

Article history: Received 5 February 2017 Revised 9 March 2017 Accepted 21 March 2017 Available online 21 March 2017

Keywords: Coal-fired power plant Load dispatching Coal rate Support vector machine

ABSTRACT

One of the most urgent problems facing coal-fired power plants in China today is the coal-waste because several units in one plant experience a partial rated output situation at the same time, which may increase the coal consumption of the power plant. Here we proposed a new hybrid methodology for plant-level load dispatching to minimize coal consumption for the coal-fired power plant. The proposed strategy consists of two parts: A part was to establish the coal consumption model to find the relationship between the coal rate, ambient temperature and load based on PSO- SVM; the other one based on GA to find the load-dispatching optimal solution to minimize the average coal rate of the whole power plant. Additionally, grey correlation analysis was employed to pick up the most relevant input variables to reduce the complexity of the regression model. This work is based on continuously measured supervision information system data from an actual coal-fired power plant with three different types of capacity units in China. Results showed that the proposed strategy performances better than the normal AGC to single unit for power plant energy saving. It is of significant for coal-fired power plant to reduce the coal consumption.

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1. Introduction

The Chinese economy has been in the "new normal" for the recent years. Both of the society total electricity consumption and the unitization hours of power generation devices have dropped sharply in the past five years. Additionally, the development of clean energy resources power generation accelerated for the fossil energy saving and CO_2 emission reduction. At the end of 2015, the installation of wind power and solar power is 128.3 million kilowatts and 41.58 million kilowatts, respectively. Their total installed proportion is 11.3% [1]. Therefore, the coal-fired power plants has to offer less power and keep the output below the rated load to create opportunity for the clean energy resources power generation and to keep the grid power balance. Nowadays,

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http://dx.doi.org/10.1016/j.applthermaleng.2017.03.094 1359-4311/© 2017 Elsevier Ltd. All rights reserved. the coal-fired power units have experienced load transition and partial output situation in most of the time in China.

At present, the majority of coal-fired power units in China are under the control of the power grid called Automatic Generation Control (AGC) [2]. There are two types of AGC modes: plant-level AGC and AGC to single unit. The former refers that power grid gives load instruction to a power plant instead of a unit. The power plant can dispatch load among its own units independently. The latter refers that power grid gives load instruction to a single unit directly which is widely adopted in China which may make all units in one plant stay in partial load situation at the same time without considering the whole coal consumption of the whole power plant. When the load is decreased, the units' running state gradually deviates from the optimal situation and the thermal efficiency of the cycle decreases, and thus, coal consumption rises [2]. Therefore, compared with AGC to single unit mode, the plant-level AGC mode may be more energy-saving when the load dispatches





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reasonably. Therefore, we proposed a plant-level load dispatching strategy to reduce the energy waste for the coal-fired power plant.

The regression model of the coal rate plays an important role to the plant-level load dispatching. The classic solution is to model a linear function between the coal rate and load. However, the coal rate is dynamically time-dependence and of uncertainties especially under the off-designed working conditions and operation boundaries [3,4]. Fortunately, the process supervision entails continuous monitoring of thousands different variables and the historically operation data are recorded in the Supervision Information System (SIS) which can show the actual coal consumption characteristics [5,6]. Therefore, data-mining methods are used to in depth mining the parameter characteristics for power plant by using historically recorded data, such as Support Vector Machine (SVM) [7], Least Squares Support Vector Machine (LS-SVM) [8,9], Artificial Natural Networks (ANN) [10,11]. Autoregressive Integrated Moving Average (ARIMA) [12] and much more. Among them SVM with simple structure was used to establish coal rate regression model in this paper. Additionally, many research works on how to find the optimal solution such as Genetic Algorithm (GA) [13,14], Krill Herd algorithm (KH) [15], and Particle Swarm Optimization (PSO) [16,17]. Among them GA is a relatively easy and widely used method to solve the optimization problem.

The basic idea of the proposed hybrid method is to find a plantlevel load dispatching strategy based on actual operating data. The proposed methodology is divided into two parts. A part based on PSO- SVM algorithm was used to establish the coal consumption model to find the relationship between the coal rate, ambient temperature and load; the other one based on GA was used to find the load-dispatching optimal solution to minimize the average coal rate of the whole power plant. What is more, grey correlation analysis was employed to pick up the most relevant input variables (Key Performance Indicators, KPI) to reduce the complexity of the regression model.

The paper is organized as follows: Section 2 introduced the proposed new hybrid methodology for plant-level load dispatching strategy. An actual coal-fired power plant was employed to be the case power plant in Section 3. Results and discussions were given in Section 4. Finally, some conclusions were drawn in Section 5.

2. Proposed methodology

2.1. KPI selection based on grey correlation analysis

Coal-fired power plant process consists of hundreds of variables while some of the variables directly affect the coal consumption rate of power supply, some of them with minimum influence [12]. Selecting KPI of the coal consumption rate is a demanding subject to reduce the complexity of regression model. Grey correlation analysis (GCA) method was employed to identify the KPI whose variations affect the system functional response mostly, herein.

GCA was proposed by the Ju-long Deng which is used to discover the system behavior and evolution by means of modeling based on the partially known information [18]. The coal rate was selected as decision index d. The correlation coefficient between coal rate d and variable I_i is as follows.

$$\xi_{id}(k) = \frac{\underset{i}{\min(k)} |d(k) - I_i(k)| + \rho \underset{i}{\max(k)} |d(k) - I_i(k)|}{|d(k) - I_i(k)| + \rho \underset{k}{\max(k)} |d(k) - I_i(k)|}$$

$$i = 1, 2, \dots, N; k = 1, 2, \dots, M$$
(1)

where $\xi_{id}(\mathbf{k})$ is the correlation coefficient; $\min_i \min_k |d(\mathbf{k}) - I_i(\mathbf{k})|$ and $\max_{i} \max_{k} |d(k) - I_{i}(k)|$ are the minimum and maximum of decision index d(k) and input variable $I_i(k)$, respectively; N and M represent numbers of input variables and sample, respectively. ρ is the distinguishing coefficient used to adjust the difference of the grey correlation degree calculations which is generally between 0 and 1. Usually, 0.5 is the optimum value of ρ based on a sensitivity analysis of the distinguishing coefficient in literature [19].

The average correlation coefficient degree can calculated as follows.

$$\gamma_i = \frac{1}{N} \sum_{k=1}^{M} \xi_{id}(k) \tag{2}$$

where γ_i is the grey correlation degree between I_i and d. The larger γ_i is, the more powerful I_i associated with it would be. According to the ranking of γ_i , input variables with higher grey correlation degree were selected as inputs of the coal rate regression model.

2.2. Coal rate regression based on SVM tuned by PSO

SVM is a relatively new method for regression problem proposed by. Vapnik and his co-workers [20]. The basic idea of support vector regression is to minimize the structural risk. Assuming the training sample set is $\{(x_i, y_i), i = 1, 2, 3, \dots, n\}$, where x_i is the input vector, and y_i denotes the output vector. It can be described as follows [21]:

$$\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*)$$
s.t. $((w \cdot \varphi(x_i)) + b) - y_i \leq \varepsilon + \xi_i$
 $y_i - ((w \cdot \varphi(x_i)) + b) \leq \varepsilon + \xi_i^*$
 $\xi_i^*, \xi_i \geq 0$

$$(3)$$

where *w* is the weight vector, *C* represents the penalty parameter, ξ_i and ξ_i^* are relaxation parameter for handling inseparable data, $\varphi(x)$ is a nonlinear mapping function, *b* is the partial vector, ε is the insensitive factor.

Lagrange function and duality principle are employed to solve Eq. (3). It turned to be

$$\begin{split} \max_{\alpha,\alpha^*} &-\frac{1}{2}\sum_{i=1}^n\sum_{j=1}^n (\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)K(\mathbf{x}_i, \mathbf{x}_j) - \sum_{i=1}^n \alpha_i(\varepsilon - \mathbf{y}_i) - \sum_{i=1}^n \alpha_i^*(\varepsilon + \mathbf{y}_i) \\ s.t. \quad \sum_{i=1}^n (\alpha_i - \alpha_i^*) &= \mathbf{0} \\ \mathbf{0} &\leqslant \alpha_i, \alpha_i^* \leqslant C\mathbf{i} = 1, \cdots, n \end{split}$$

where α and α∗ are Lagrangian multipliers and $K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$ is kernel function.

By solving Eq. (4), $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_n)^T$ and $\alpha^* = (\alpha_1^*, \alpha_2^*, \dots, \alpha_n^*)^T$ can be obtained. And then regression function can be modeled below:

$$f(\mathbf{x}) = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i) K(\mathbf{x}_i, \mathbf{x}_j) + b$$
(5)

There are three typical kernel functions: Gaussian (Radial basis function, RBF), Polynomial and Linear. RBF was selected herein.

Penalty parameter C and the insensitive factor ε were determined by PSO instead of manual setting to improve the accuracy of regression model. PSO proposed by Kennedy and Ebenhart [22] is a population based stochastic optimization method. It search for the optimal solution using particles. The velocity and position of each particle is determined as follows [23]:

$$\nu_{id}^{t+1} = \beta \nu_{id}^t + c_1 r_1 (p_{id}^t - x_{id}^t) + c_2 r_2 (p_{gd}^t - x_{id}^t)$$
(6)

$$X_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \quad d = 1, 2, \dots, n; i = 1, 2, \dots, m$$
(7)

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