Thermal Power Units' Energy Consuming Speciality Analysis Based on Support Vector Regression (SVR)

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Abstract. There are some characteristics such as multi-borders, nonlinear time-variation of the thermal system of large coal-fired power units, the complex relationships between operating parameters and energy consumption, which affect the operation precision of thermal power units. According to rigorous theoretical analysis key operating parameters are identified and used to determine the standard coal consumption rate. On this basis, features are extracted and used as the inputs to SVR for training and testing. Energy consumption distribution model under full conditions of large coal-fired power units based on aforesaid method achieved a high precision.

Keywords: Energy consumption · Relationship · SVR · Data mining

1 Introduction

Thermal power units provide nearly 80 percent of the electricity in China, and this is a huge consumption of primary energy. More than half of the production of the coal is consumed on this in China. According to this Chinese energy situation, the proportion will not be greatly changed in the near future. The survey from the U.S. EPRI and the electric power industry show that, standard coal consumption [10] of the main generating units, even in the basic load, is higher than the designed value by about 30~40g/kWh. Therefore, energy-saving potential of power plants is huge, and this is closely related to the overall situation of Chinese energy consumption. The correct decision of the units' energy consumption characteristic is not only affecting the decisions for thermal power plants' energy optimization management [3] [13], but also for their practical values.

Plant thermal system is essentially a complex thermal system under multiple boundary conditions [8]. There are high-dimensional non-linear relationships among the operating parameters. The running state of the plant thermal system can be regarded as dynamic characteristics which meet uncontrollable system operating conditions (such as power generation load, ambient temperature, fuel characteristics, etc.), through the adjustment of the controllable parameters and the dynamic characteristics of equipment performance in a specific system environments. It ultimately

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decides the operational status of the units, which show the corresponding energy consumption characteristics. For current large thermal power plants [15] which have complex thermal systems composed of many subsystems, in order to accurately describing the energy consumption characteristics under different operating conditions, and then achieving reasonable optimization to the controllable boundary condition parameters for establishing an optimizing strategies, the analysis of complex system is critical.

For having time [9] variations, nonlinear boundary conditions characteristics of the power plant systems, due to the complexity of the each subsystems' (such as the turbine, the boiler system, regenerative heating system, cold ends system) essential law for the dynamic processes, uncertainty of the physical structural changes (such as the scale of heat transfer equipment, blade variant, etc.) of the actual operation of equipment, complexity of the connections and their interaction rules [4] among the subsystems, the research route to reflect the rules of the relationship between the parameters of each state and then to analyze the units' energy consumption characteristics has been more restricted in practical applications through directly building the traditional mechanism model.

To avoid complex analysis, with the increasing levels of automation and powerful function of real-time database, mining association rules [6] [14] of operating status parameters from massive operating historical data becomes hot in these problems for its advantages such as target specific, units specific etc. Data mining [5] [12], information fusion [3] and other advanced algorithms based on artificial intelligence [7] are emerging.

Analysis of the units' energy consumption characteristics based on ε-SVR is proposed in the paper. The units' energy consumption characteristics model is designed under different loads and boundary conditions. Energy distribution model for large size coal-fired units of full-working-conditions is verified using real data.

2 Characterization of the Thermal Power Units' Energy Consumption

2.1 Analysis of the Thermal Systems' Boundary Conditions

Plant system is a complex thermal system [11] composed of many subsystems (equipment), and these are connected by specific way, which works under multi-boundary conditions, completes the process of energy conversion from thermal energy to mechanical energy and ultimately to electricity.

The composition of unit process and the scope of the study is shown in Figure 1.

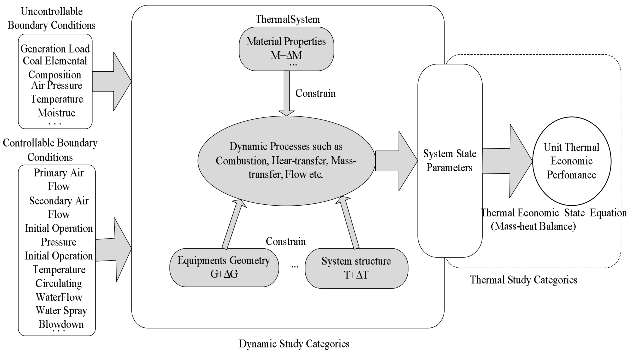


Fig. 1. Thermal unit process and scope of the study diagram

As shown above, thermal system with the certain device structures, material properties and system structures conducts the process of combustion, heat transfer, mass transfer and flow through each device inside, and this shows corresponding running state parameters in the constrained conditions such as uncontrollable boundary conditions (such as power generation load, the local meteorological conditions, coal quality, etc.), controllable boundary conditions (such as the turbine initial operating parameter, circulating water flow, boiler primary or second air flow, etc.) and system structures and device characteristics. These state parameters are ultimately expressed as the thermal and economic performance indicators of the unit's thermal efficiency or power supply coal consumption rate.

2.2 Description of Unit Energy Consumption

The most fundamental indicators of energy performance of thermal power units usually expressed as power supply coal consumption rate b_{sn} as follow:

$$b_{sn} = \frac{123}{\eta_b \eta_i \eta_m \eta_g \eta_p (1-\sum \xi_i)} \tag{1}$$

Where, $\eta_b, \eta_i, \eta_m, \eta_g, \eta_p, \sum \xi_i$ are respectively the boiler efficiency, cycle thermal efficiency, mechanical efficiency, generator efficiency, pipeline efficiency and auxiliaries electricity consumption rate.

To certain unit, equipment structure, material properties and system structure, even specific defects have been fixed. So b_{sn} can be expressed by function of system boundary conditions:

$$b_{sn} = f(N_g, T_{xrw}, D_w, P_0, T_0, T_{rh}, C_{coal}) \tag{2}$$

where, $N_g, T_{xrw}, D_w, P_0, T_0, T_{rh}, C_{coal}$ are respectively the load, circulating water inlet temperature (determined by the cooling tower performance and the ambient temperature), the circulating water flow, main steam pressure, main steam temperature, reheat steam temperature, coal characteristics.

3 Energy Consumption Distribution Model Based on ε-SVR

As a new technology in data mining, support vector machine (SVM) [1] was originally proposed in the 1990s by Vapnik, which is a new tool with the optimization method to solve machine learning problems. SVM is based on the statistical learning theory — VC dimension theory and structural risk minimization principle. Then the traditional empirical risk minimization principle has been changed. SVM has theoretical foundation and rigorous deduction process. Support vector regression (SVR) has advantages such as uniqueness of solution, global optimality, etc. It has unique advantage on the pattern recognition problems of small sample, nonlinear and high dimensionality, and so it was successfully applied in fields of industrial process control, non-linear classification, pattern recognition, and time-sequence prediction.

The concept of the feature space was proposed in SVM. The nonlinear problem in the original number field will be transformed into a linear problem in the feature space. And the kernel function was proposed. Then a linear problem in the feature space can be transformed into the nonlinear problem in the original number field. The feature space and the concrete form of nonlinear mapping are not mentioned, in order to obtain the best generalization ability.

For a given training set:

$$T = \{(x_1, y_1),(x_2, y_2)\cdots(x_l, y_l)\} \in (X,Y)^l,$$

$$x_i \in X = R^n, \; y_i \in Y = R, \; i = 1,2,l.$$

Where x_i is the input variable, y_i is the corresponding target value, l is the number of samples. The target is to look for a real-valued function $f(x)$ within the scope of R^n, using $y = f(x)$ to infer the arbitrary pattern x corresponding y values.

For linear regression problem, it is to seek the classification hyperplane $f(x) = \omega \cdot x + b$, for all samples, that is:

$$|f(x_i) - y_i| \le \varepsilon \tag{3}$$

Where $f(x)$ is as smooth as possible. It's so-called optimal regression hyperplane for the maximum interval regression classification hyperplane. Among them, ω is the adjustable weight vector, b is the bias. Regression hyperplane is called the best regression hyperplane when interval is $2/\|\omega\|_2$. The regression problem is a typical quadratic programming problems:

$$\begin{aligned} &\min \frac{1}{2}\|\omega\|_2 \\ &s.t. \left|f(x_i) - y_i\right| \le \varepsilon \left(i = 1, ..., l\right) \end{aligned} \tag{4}$$

A nonlinear function $\Phi(\cdot)$ is used to map the input space R^n to a higher dimensional feature space Z. The optimal regression hyperplane $f(x)$ will be found in the feature space Z.

For the given training set:

$$T=\{(x_1,\ y_1),(x_2,y_2)\cdots(x_l,y_l)\}\in(X,Y)^l\ ,$$

Where $x_i\in X=R^n$, $y_i\in Y=R$, $i=1,2,l$ .As $\varepsilon>0$,the $\varepsilon-SVR$ algorithm can be expressed as the following optimization problem:

$$\begin{aligned}&\min_{\omega,\xi,\xi^*,b}\frac{1}{2}\omega^T\cdot\omega+C\sum_{i=1}^{n}\left(\xi+\xi^*\right)\\ \text{s.t.}\quad & y_i-\omega^T\cdot\Phi(x_i)-b\le\varepsilon+\xi_i\\ &\omega^T\cdot\Phi(x_i)+b-y_i\le\varepsilon+\xi^*\\ &\xi,\xi^*\ge 0\end{aligned}\tag{5}$$

C is the penalty factor, which is used for regulating the smoothness and training accuracy of the function $f(x)$; $\xi^*=(\xi_1,\xi_1^*,\cdots,\xi_l,\xi_l^*)^T$ is the slack variable, which is used for relaxation the constraints of SVM with hard boundary, ε is used to control the model fitting accuracy. The above optimization problem is solved by converting to dual problem through Lagrange method:

$$\begin{aligned}&\min_{\alpha,\alpha^*}\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\alpha_i-\alpha_i^*\right)\left(\alpha_j-\alpha_j^*\right)K\left(x_i,x_j\right)+\varepsilon\sum_{i=1}^{n}\left(\alpha_i+\alpha_i^*\right)-\sum_{i=1}^{n}y_i\left(\alpha_i-\alpha_i^*\right)\\ \text{s.t.}\quad&\sum_{i=1}^{n}\left(\alpha_i+\alpha_i^*\right)=0\\ &0\le\alpha_i\le C\ ,\ 0\le\alpha_i^*\le C\end{aligned}\tag{6}$$

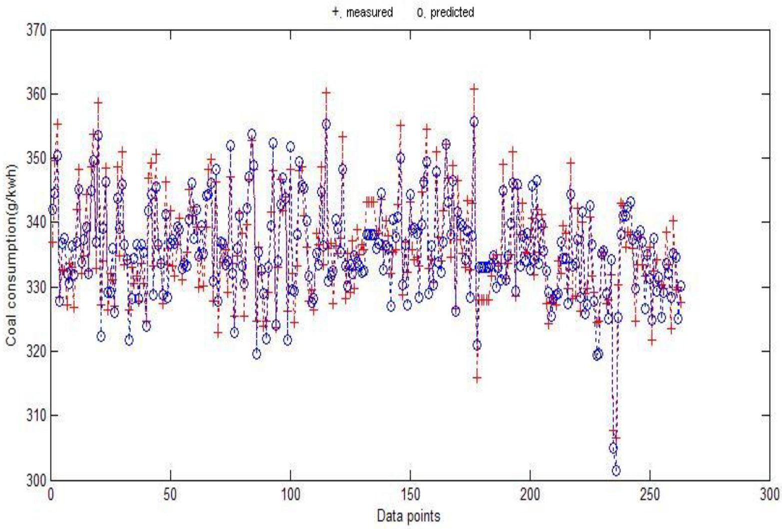
K is the kernel matrix, $\langle\cdot,\cdot\rangle$ is the vector inner product. $K(x_i,x_j)=\langle\Phi(x_i),\Phi(x_j)\rangle$.

The model (4) has been solved to obtain the optimal solution $\bar{\alpha}=(\bar{\alpha}_1,\bar{\alpha}_1^*,\cdots,\bar{\alpha}_l,\bar{\alpha}_l^*)^T$, the resulting distribution model of the supply coal consumption:

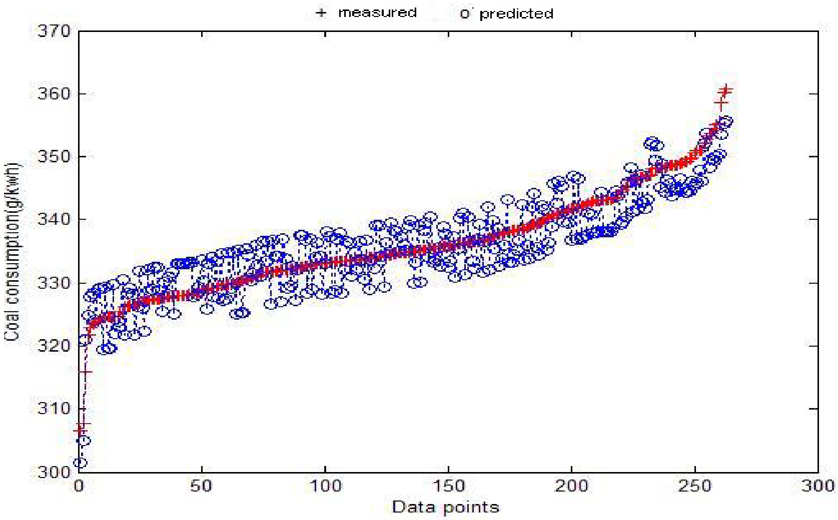
$$f(x)=\sum_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)K\left(x,x_i\right)+b\tag{7}$$

4 Example

The data in the paper was collected from a certain power plant unit No. 3, a total of 3250 data points from March 2006 to May 2006. The 2260 controllable sample points were obtained though quasi-steady-state test, error and redundant data elimination, and other data de-noising and cleaning process. The data was used as input of ε-SVR for training and testing. The unit energy consumption characteristics model under different loads and boundary conditions has been obtained with high precision validated by actual data. The results are shown in Figure 2.



(a)



(b)

Fig. 2. Supply coal consumption distribution based on the ε-SVR

In the process, the radial basis function (RBF) [2] was chosen as the kernel function. The nonlinear sample can be processed by RBF in an effective manner.

Table 1. The features of the parameters σ and C in the model (ε = 0.05)

C	σ	Number of support vectors	The proportion	MSE (g)	*Modeling time (s)*
Inf	0.1	255	97.0%	3.8994e-002	*22*
Inf	1	75	28.5%	1.8442e-002	*20*
Inf	3	59	22.4%	1.7120e-002	*20*
Inf	5	70	26.6%	1.7449e-002	*21*
1	1	86	32.7%	2.4146e-002	*20*
5	1	76	28.9%	1.9186e-002	*22*
100	1	75	28.5%	1.8442e-002	23

As shown in Table 1, the value of σ and the C has a great significance for the model. The number of support vectors obtained by the model, modeling time and accuracy of the model were different with different values of the σ and C. In general, the size of the approximation error pipeline was controlled by the parameter ε in loss function, and then the number of support vectors and generalization ability were controlled by it. If the value was greater, then the accuracy was lower. Commonly, the range of ε was 0. 000 1～0. 1. Penalty factor C is used for the compromise of controlling model complexity and approximation errors. It is found that the smaller the C, the greater the training error of the sample. It resulted in a larger risk for the structure of the model. Also, the larger the C, it will have a higher degree of data fitting. This will weaken the model generalization ability.

For RBF kernel function, the parameter σ has important impact on prediction accuracy. With σ increasing, the forecast performance of the model continuously improves, but when it rises to a certain value, over-fitting phenomenon appears, and the generalization ability degrades. The range was from 0.1 to 3.8generally.

5 Conclusions

After a careful investigation on the many conditions about thermal power unit, a model that can prevent the phenomenon of "over-learning" is to fix C to 100 as the optimal parameter. When the support vectors are less, the minimum mean square error (MSE) and MSE average are 0.017g/kwh and 0.022g/kwh respectively. This shows that the proposed model has a high precision rate.

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