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Research Article

A Modeling and Optimizing Method for Electricity Current Intensity of Coal Mills

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Coal mills consume a huge amount of station service electricity power of a coal-fired power plant. Meanwhile, the operation of coal mills also has a large influence on boiler combustion. Among all the operating factors, the electricity current intensity of coal mills reflects the electricity power consumption as well as operating status of coal mills. If the electricity current intensity of coal mills can be predicted by giving a set of operation parameters, the operating status can be adjusted accordingly. The electricity current intensity of coal mills can be reduced or minimized subject to the coal type parameters and the load of the boiler through optimizing the coal mill operations. This paper builds a model to predict the electricity current intensity of coal mills using a Support Vector Machine based on a set of practical sensing data. Via optimizing the hyperparameters of the model, a reasonable prediction ability is achieved. Under a given production running condition, the electricity current intensity of the coal mill decreases from 47.9 AM to 46.5 AM, which is a remarkable achievement for the coal mill running process. This method may provide a feasible online solution for coal mill optimization.

1. Introduction

Coal mill is an important auxiliary device for coal-fired boilers since it directly influences the boiler combustion. The coal mill grinds the raw coal to a certain fineness, and then, the coal powder is carried to the burners by first air of boiler combustion. During this grinding process, a large quantity of electricity power (generally one-third) is consumed. On the other hand, this grinding process also affects the combustion efficiency by coal fineness. Smaller coal fineness means consuming more electricity power as well as more complete combustion. It is very difficult to find the equilibrium or Pareto optimality of the running state which is expected towards the minimum electricity consumption and maximum combustion efficiency for a given type of coal and load [1]. If the current intensity of a coal mill can be predicted with a given set of operation parameters, it is of significant help for optimizing operations of the coal mill running state. The current intensity of the coal mill may be reduced or minimized subject to coal type parameters and the load of the boiler via optimizing the coal mill operations.

A coal mill is a multivariable system. Many coal mill operator parameters have influences on running state and energy consumption, such as coal feeding rate and rotational speed of the separator. Coal-fired power plants usually need to handle a variety of coal types and accommodate load changes which dramatically influence coal mill operation. To date, no precise mathematical model has been obtained for a coal mill operating process due to the nonlinear nature, strong-coupling character of variables, and complex processes occurring inside the mill. Consequently, the control of mills remains a rough way with some large granular tune-up in most of the existing power plants [2]. It is very difficult to keep the mill running at a good state in such simple control. Therefore, a well-designed optimization scheme is required.

A precise prediction of the electricity current intensity of a coal mill is the basement for optimizing the mill operation. Electricity energy savings can be obtained through the prediction of the current electricity intensity of the coal mill

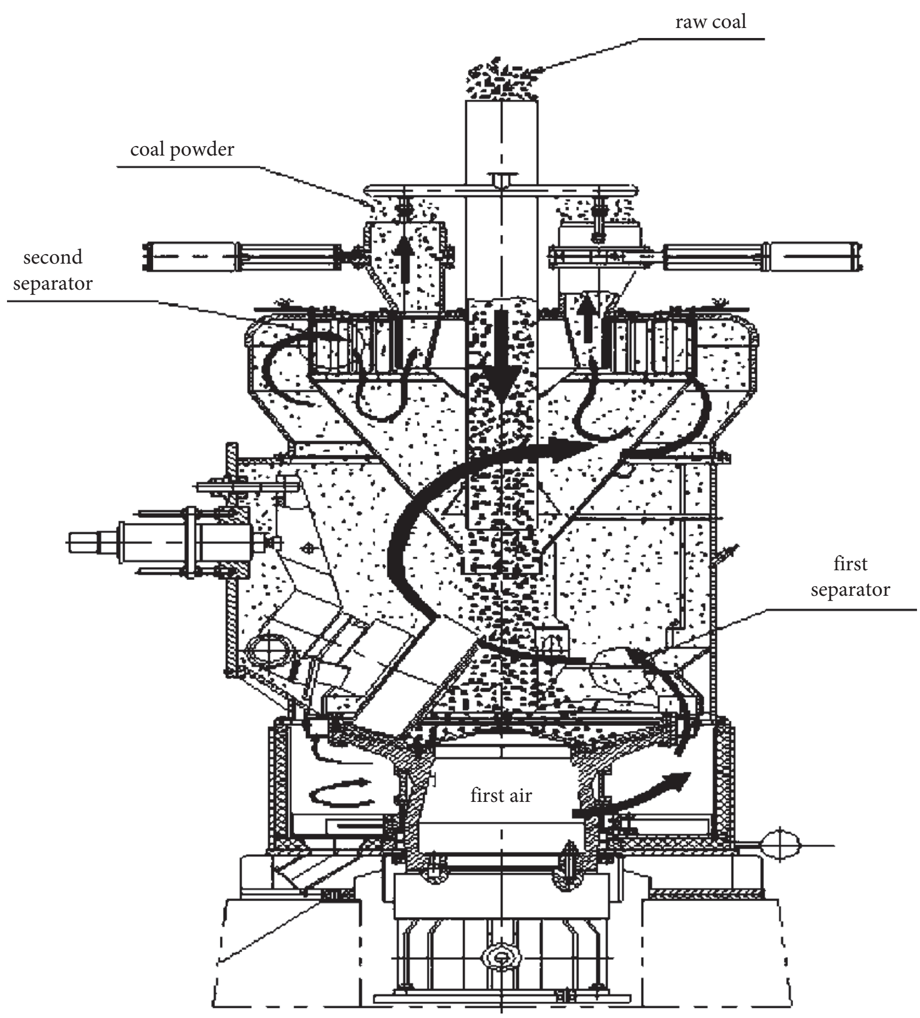

Figure 1: The construction of medium-speed mills.

and optimizing mill operations [3]. Hence, coal mill optimization has become one of the most active coal-fired related research for many years. Wang et al. [4] optimized the coal mill by minimizing the energy consumption using a neural-network model and genetic algorithm. They built a radial basis function (RBF) neural network model, which used the main factors that affected the power consumption as input variables, for determining the energy consumption. Using this model, a reduction in electricity consumption was achieved. Gao et al. [5] built a coal mill mathematical model based on the analysis of mass flow, heat exchange, and energy balance. The simulation results illustrated that this model could be used to estimate some operational parameters and be induced into the monitoring and optimization of coal mills.

Aforementioned research studies infer that predicting coal mill operation variables and adjusting them is a feasible way for coal mill optimization. The electricity current intensity of coal generally represents the energy consumption, so the objective of optimizing goal is to reduce the energy consumption. In this process, building a model to predict the electricity current intensity of a coal mill is the key step for coal mill optimization.

With the aim of improving performance and reducing the energy consumption of coal mills, this paper contributes to proposing a data-driven model for the prediction of the electricity current intensity of coal mills. The simulated results show that the prediction performance of this model is remarkable, and the optimization method can significantly save energy.

2. Multidata Collection

Medium-speed coal mills are widely used in thermal power plants and play an irreplaceable role in the pulverizing process. This paper focuses on a positive pressure direct firing type of medium-speed coal mill, which is equipped with a dynamic separator. Figure 1 illustrates the construction of the coal mill. The raw coal falls down from the top center pipe and is dried by the primary air. The powder is blown into the top of the mill. After that, fine particles are sent to the burner, while coarse coal particles are separated by the upper separator and returned to the coal mill for further grinding. During the whole grinding process, a mass of electricity energy is consumed.

For modeling the coal mill production process in order to predict the electricity current density, we first studied and analyzed factors that influenced the electricity current density. These data include all parameters that have influences on the electricity current density, such as quantity of primary air at the inlet, mixed primary air temperature at the inlet, air pressure at the inlet, coal feeder speed, and dynamic separator rotation speed. Operational parameters and corresponding electricity current density of this coal mill are collected from the distributed control system (DCS). 24 sets of single-factor experiments to collect different possible operation conditions data have been done in almost four months in a local power plant. Three different types of coal are separately used in these experiments. The raw coal has been sampled from the feed-belt conveyer. All the properties of coal samples including volatile content, moisture content, ash content, and heating value are analyzed in the laboratory.

3. Methodology

3.1. Support Vector Machines. With the widespread deployment of data services in some traditional industries, multifarious industrial applications, for example, soft sensors [6], process control [7], and robotic systems [8], are successfully updated with data-driven methods. Among the developed data mining technologies, Support Vector Machines (SVMs) have absorbed much attention because of their high accuracy prediction performance for small data samples and computational simplicity for decades. SVM has become a widely used regression algorithm, which was invented by Vladimir Vapnik in 1979 [9]. SVM has been proved to be useful and powerful for regression in power plant fields, such as the boiler combustion process [7]. Detailed descriptions and solution steps of nonlinear regressions are given by Cristianini and Shawe-Taylor [10] and Vapnik [11]. Likewise, in this article, SVM shows good regression ability, especially for small sample problems, as well as the generalization of the SVM model. Especially because our work is to realize an online system including online training due to the inconstant situation and online optimization with the second-level response for real-time control, some complex learning frameworks are not suitable in practice. Thus, we decided to use SVM in modeling coal mill production process. This paper is determined to use SVM for modeling the electricity current density of a coal mill.

3.2. Genetic Algorithm. Genetic algorithm (GA) is a popular evolutionary algorithm for optimization problems. The inspiration of GA is derived from biological evolution and genetics theory that leaves the fittest to survive. Selection, crossover, and mutation are three main operations. GA has the ability to solve complex and nonlinear problems and is often used in the combinational optimization and artificial intelligence. It can consider many points in the search space simultaneously to reduce the chance of encountering a local optimum and enhance operational efficiency. The details of the usage of GA are referred in [12].

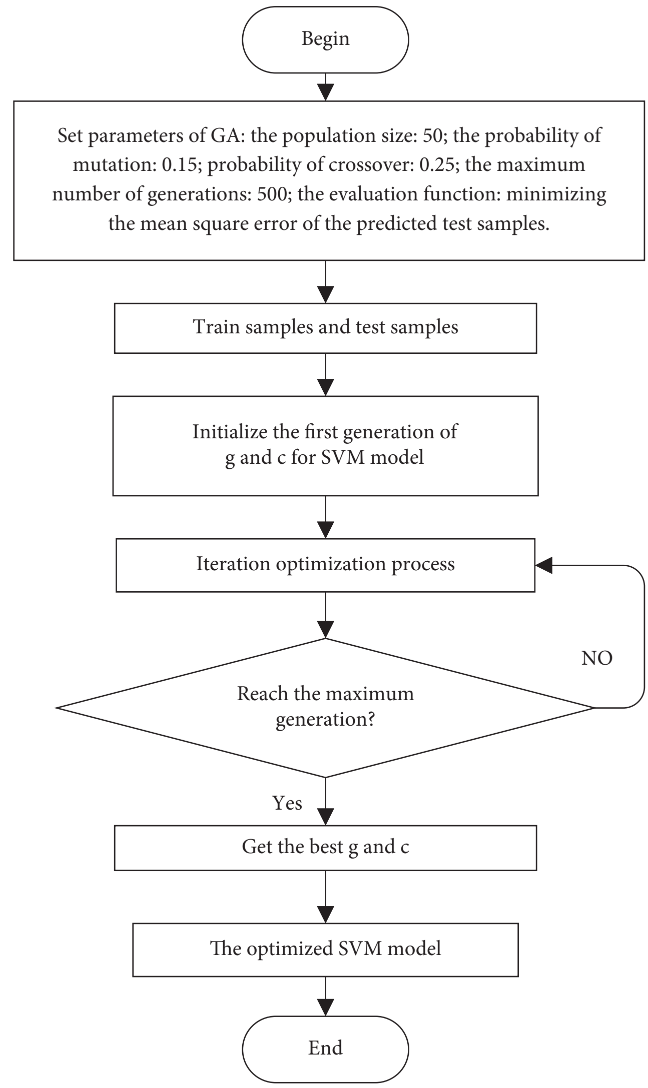

Figure 2: The SVM model optimization process.

3.3. Modeling. This section discusses building a nonlinear SVM model to predict the electricity current density within a given coal mill using operational parameters and coal properties. The radial basis function (RBF) was selected as the kernel function for modeling coal mills, because some related works by Keerthi and Lin [13] and Lin and Lin [14] have shown that the RBF has a better model prediction performance than other often used functions. The RBF function is given by $\exp(g \times |x_i - x_j|^2)$, where g is a coefficient and x_i and x_j are data vectors.

After theoretically analyzing the factors influencing the electricity current density during the coal mill system production process and communicating with experts, we selected the input values of the model as follows: quantity flow of first air of the inlet, mixed primary air temperature at the inlet, air pressure at the inlet, coal feeder speed, dynamic separator rotation speed, and coal properties, which fully

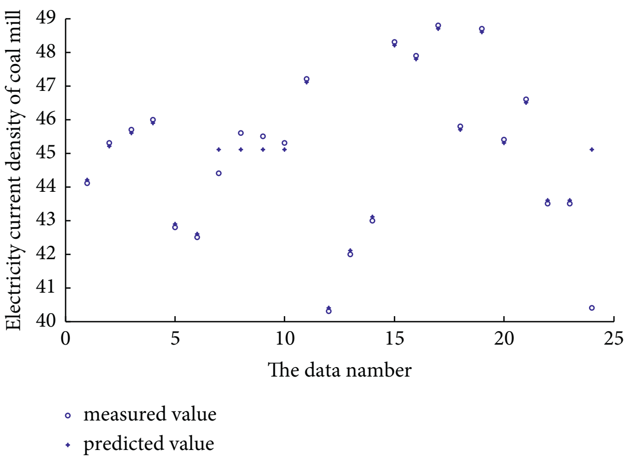

Figure 3: Prediction of the SVM model for all data.

include moisture content, violent content, ash content, and lower heating value. The electricity current density is defined as the only output.

Besides the kernel function, the parameters g (a parameter in the RBF function) and C (penalty factor) are needed to be determined. These two parameters have prime influence on SVM model prediction performance. However, how to determine them has not been theoretically solved. In this paper, GA is not only used in optimizing control systems but is also used in optimizing these two parameters. The optimization region of g and C is set (0,500) and (0,800), respectively. These optimization regions were empirically selected based on our previous research [15]. The other parameters of the GA framework are set as follows: population size is 50, probability of crossover is 0.25, probability of mutation is 0.15, the maximum number of generations is 500, and the evaluation function is calculated by minimizing the mean square error of the predicted test samples. When the evaluation function reaches the minimum value, the best values of g and C are obtained. The optimization process of g and C in generating the SVM model is shown in Figure 2. A terminal criterion (the acceptable mean square error) can also be set to stop the iteration process before the maximum generation is reached.

4. Experiments

4.1. Prediction Results. A sixfold cross-validation (6 CV) is applied on the 24 sets of data to build the SVM models for predicting electricity current density. The relationship between measured data and predicted data for all the 24 sets of data is shown in Figure 3. And, a reasonable prediction ability is achieved by our proposed model, also seen in Figure 3.

The mean comparative error for all data is 0.77%, and the highest comparative error is 10.4%. The highest error is obtained from training data, which reflects good generalization of the model. We utilized this model to predict another new 30 sets of data that are collected in normal production process. In these data sets, some operational parameters of many data sets are quite similar, even the same. The prediction result is shown in Figure 4. The mean comparative error is 0.9%, and the highest comparative error is 2.6%, which means that the proposed model also achieves a good prediction ability for new data generated by this coal mill.

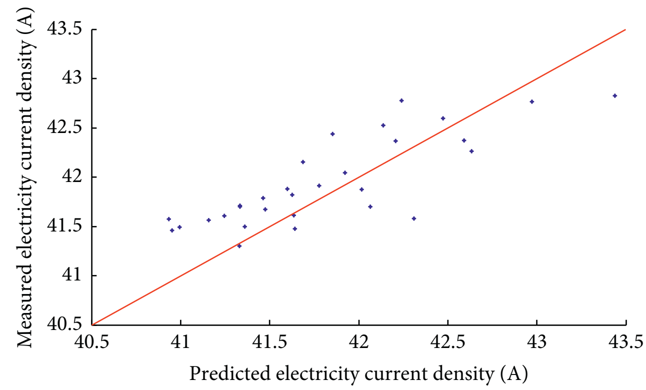

Figure 4: Prediction for test data.

4.2. Optimizing Results. With the predicted electricity current density from the data-driven model, the coal mill can be optimized to reduce energy consumption via adjusting operation parameters. For a given coal mill production state, the coal feeder speed (represent load of the boiler) and the type of coal are not adjustable. The parameters that can be tuned are as follows: the quantity of first air of the inlet, the air pressure of the inlet, the air temperature of the inlet, and the dynamic separator speed. Based on the prediction of electricity current density from the model, we try to optimize these adjustable parameters (operational plan) to tune down the electricity current density for reducing the energy consumption. Table 1 displays the optimization results. The parameters of Case 1 are the parameters of the normal production process. The parameters of Case 2 are the optimized result of Case 1 using the SVM model. The coal feeder speed and the coal parameters are kept unadjusted. Case 3 is the implemented result according to Case 2. The electricity current density of Case 1 and Case 3 is collected from DCS. The electricity current density of Case 2 is predicted using the SVM model. The electricity current density is reduced by 1.4 Ampere under the conditions of a given type of coal and load with the optimized operational parameters. This optimization reduces electricity energy consumption by about 3%. The changes of operational parameters are in accordance with the historical operational experience of the operators.

This optimization only focuses on energy consumption and does not consider the coal fineness that also has influence on combustion. This optimization may result in coarse coal fineness that may increase the carbon content in fly ash. Extra work building models for coal fineness and optimizing the coal mill for both sides of energy consumption and combustion efficiency is ongoing in future processes.

Table 1: Optimization result for reducing energy consumption.

Case	Electricity current density	Quantity of first air at the inlet (t/h)	Pressure of the inlet (kPa)	Air temperature of the inlet (°C)	Dynamic separator speed (rpm)
1	47.9	111.3	6.78	261.5	672
2	46.1	98.1	5.98	291.63	630
3	46.5	98.3	5.74	289.8	638

5. Conclusion

This paper uses the Support Vector Machine and genetic algorithm (GA) to model the relationship between electricity current density and coal mill operational parameters. The results show that a reasonable prediction ability has been achieved. This model in conjunction with GA is utilized to optimize coal mill operation for energy reduction. We conclude that, for a given load and coal type, the electricity current density of coal mill is reduced and thus electricity energy consumption of coal mill can be reduced through precise operations which are guided with optimization results. This method may be a feasible way for optimizing the coal mill operation for reducing the energy consumption online due to its simplicity in the training data step.

In this research, due to production limits, the amount of data for modeling is collected as only 24 sets. If more data can be used in this method, the optimization result may have been more accurate. The optimization only focuses on the electricity current density of the coal mill and does not consider the coal fineness of the coal mill. In our future work, we will try to enrich the data for applying them to more production processes and build the coal fineness model to give the coal mill operation a multi-objective optimization that considers both sides of the electricity current density and the coal fineness.

Data Availability

Raw data were generated at a Chinese power plant. Derived data supporting the findings of this study are available from the corresponding author on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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