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Special Focus on Optimization for Cyber-Physical Energy Systems

Energy consumption diagnosis in the iron and steel industry via the Kalman filtering algorithm with a data-driven model

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Dear editor,

In the iron and steel enterprises, the energy cost (electricity, gas, among others) accounts for 20%–30% of the total production cost. Real-time perceiving and monitoring energy consumption data through cyber-physical energy system is extremely important for saving energy. The purpose of this research is to analyze energy consumption data to identify any abnormalities.

With respect to energy analysis across industries, Gopalakrishnan et al. [1] examined the energy utilization in the wood manufacturing industry. Usón et al. [2] proposed a thermoeconomic diagnosis method to determine fuel consumption variation and improve energy efficiency of a coal-fired power plant. Saidur and Mekhilef [3] analyzed the energy use data and presented energy-savings strategies in Malaysian rubber-producing industries.

Most results in literature focus on the qualitative analysis of energy use. This study aims at providing a quantitative indicator of energy consumption via the Kalman filter algorithm proposed by Kalman [4]. The traditional Kalman filter algorithm is based on the physical model of a particular system. For energy consumption diagnosis in iron and steel plant, the expression of energy consumption is unknown. Therefore, a data model-based Kalman filtering method is proposed. In literature, the statistical characteristics of the sample data are used to describe the system using the mean and the variance of the state variables when it is difficult to obtain the exact mathematical model. Yan et al. [5] studies the optimal fusion of sensors data by taking linear transformations to establish a new measurement model to decouple noises. Sohlberg [6] dealt with condition monitoring and failure diagnosis for a steel strip rinsing process based on a priori knowledge and data. Cao et al. [7] researched wind turbine fault diagnostics using the unscented Kalman filter approach. Wen et al. [8] investigated the fault estimation of non-uniformly sampled-data systems.

This research uses least square support vector machine (LSSVM) to express the input and output relationship of the studied system. In the model, the consumption of one or more types of energy is set as the input variables, and the energy needed to be diagnosed is set as the output variable.

LSSVM-based Kalman filtering algorithm. SVM maps inseparable data set in a low-dimension space to the high-dimension space and constructs an optimal decision function

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

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The obtained model of the training sample set (x_i, y_i) is used as the physical model in the Kalman filtering algorithm. Suppose the discrete system equations are as follows [9]:

$$x_k = F_{k-1}x_{k-1} + G_{k-1}u_{k-1} + w_{k-1}, \quad (2)$$

$$y_k = H_k x_k + v_k. \quad (3)$$

Assuming that the mean values are zero, and the covariance matrix P is known, then the time update equation is

$$x_k^- = F_{k-1}x_{k-1}^+ + G_{k-1}u_{k-1}, \quad (4)$$

$$P_k^- = F_{k-1}P_{k-1}^+ F_{k-1}^{\mathrm{T}} + Q_{k-1}. \quad (5)$$

The state update equation is

$$K_k = P_k^- H_k^{\mathrm{T}} (H_k P_k^- H_k^{\mathrm{T}} + R_k)^{-1}, \quad (6)$$

$$x_k^+ = x_k^- + K_k(y_k - H_k x_k^-), \quad (7)$$

$$P_k^+ = (I - K_k H_k)P_k^-. \quad (8)$$

Eqs. (4) and (7) are the update equations of estimated covariance. Substitute (5) into (6) to get

$$x_k^+ = \left(1 - \frac{P_k^+ H_k^{\mathrm{T}} H_k}{R_k}\right) x_k^- + \frac{P_k^+ H_k^{\mathrm{T}}}{R_k} y_k. \quad (9)$$

Assuming that the observation matrices H are unit matrices, then

$$x_k^+ = \left(1 - \frac{P_k^+}{R_k}\right) x_k^- + \frac{P_k^+}{R_k} y_k, \quad (10)$$

where R_k is the noise of the observation. From (4) and (7), the covariance matrix of the estimated error P_k^+ is propagated by Q_k. The state of each period is what we concern about, that is x_k in (1). For the energy consumption process, here u_k is equal to zero, then Eq. (1) can be written as

$$x_k = F_{k-1}x_{k-1} + w_{k-1}. \quad (11)$$

By now, we have established an LSSVM-based energy consumption model. A priori estimate is directly obtained from the LSSVM model as follows:

$$x_k^- = f_{ls}(\cdot). \quad (12)$$

x_k^- is used as the priori estimate of the Kalman algorithm at time k. With x_k^-, we assume that the system state is linearly propagated along time as follows:

$$F_{k-1} = x_k^- (x_{k-1}^+)^{-1}, \quad (13)$$

where x_{k-1}^+ is the posteriori estimate of state variables of the system at time $k-1$. F_{k-1} is the simulation matrix calculated by LSSVM at time $k-1$; the optimal estimate is obtained using (5)–(7). Then, the prediction equation of the mean square error is as follows:

$$P_k^- = F_{k-1}P_{k-1}^+ F_{k-1}^{\mathrm{T}} + Q_{k-1}, \quad (14)$$

where Q_{k-1} is the covariance of process excitation noise of the system at time $k-1$. The Kalman filter gain equation is

$$K_k = P_k^- H_k^{\mathrm{T}} (H_k P_k^- H_k^{\mathrm{T}} + R_k)^{-1} = P_k^+ H_k^{\mathrm{T}} R_k^{-1}, \quad (15)$$

where the unit matrices H_k and H_k^{T} are the observation matrix and the transpose matrix of the observation matrix of the system at time k, respectively. R_k is the covariance matrix of the observation noise of the system at time k. Then, the posteriori estimate equation is as follows:

$$x_k^+ = x_k^- + K_k(y_k - H_k x_k^-), \quad (16)$$

where y_k is the observation value of the system at time k. In the iron and steel enterprises, the most efficient way to assess the time-varying consumption ratio of energy is to analyze the statistical characteristics of the data. Assuming that the measured value is subject to a normal distribution, the probability density function is

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma_s} \exp\left\{-\frac{(x - E_s)^2}{2{\sigma_s}^2}\right\}. \quad (17)$$

The following definition of abnormal function is adopted,

$$\alpha(x) = \exp\left\{\frac{(x - E_s)^2}{2\sigma_s^2}\right\}. \quad (18)$$

A time window is selected and the mean outliers of the estimated value in the time window Δt is calculated as

$$\beta = \frac{1}{\Delta t}\sum_{i=t}^{t+\Delta t} \alpha(x_i). \quad (19)$$

Then, β is used as the evaluation indicator of the operating state during the time period $t + \Delta t$. If the time window is too small, the results will be affected by one or two measurement points. Otherwise, the sensitivity of the algorithm will be decreased. Then the standard deviation of the measured values of the dynamic system is defined as

$$S = \sqrt{\sum_{k=t}^{t+\Delta t} \left(f(k) - y_k^{(\mathrm{obs})}\right)^2 / N}. \quad (20)$$

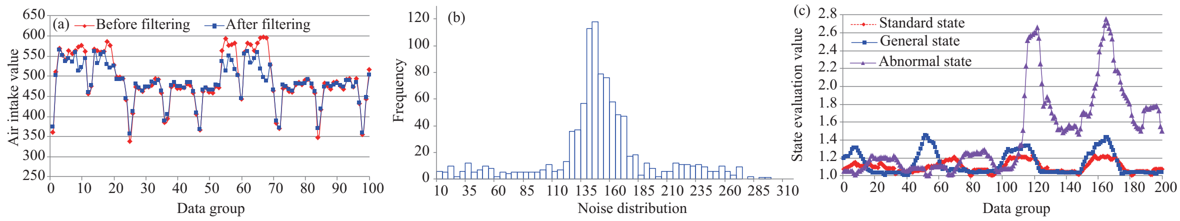

Figure 1 (Color online) Diagnosis of energy consumption in hot blast stove system. (a) Filtering results; (b) noise distribution; (c) diagnosis results.

After obtaining the evaluation criteria, each time the time window is moved, the sum of the anomalous factors corresponding to the time window is calculated to provide the state evaluation results.

Experimental results of the hot blast stove system. In the process of iron smelting, the hot air blown from the bottom of the furnace is the important combustion improver. With the running of the blast furnace, the amount of air intake gradually deviates from the normal value till damping down. The measurement data after maintenance are selected as the standard data. 100 groups of such data are shown to Figure 1(a).

The statistical results of the noise of 1000 groups of such data are shown to Figure 1(b), indicating that the noise of air intake data is in line with the normal distribution hypothesis. Then the corresponding probability distribution function and abnormal function are

$$f(x) = 0.0026 \exp\left\{-\frac{(x-485.8997)^2}{47112.27}\right\}, \quad (21)$$

$$\alpha(x) = \exp\left\{\frac{(x-485.8997)^2}{477112.27}\right\}. \quad (22)$$

The changing curves with respect to different operating states are shown to Figure 1(c), where β of standard operating state can be set as the diagnosis reference. The general operating state refers to the state in which the fluctuations of the measured data of air intake appear. The abnormal operating state refers to the state in which the air intake of the blast furnace appears to have a greater degree of fluctuations, which is an indicator that the system is going to be down. With the diagnosis results, the operators could determine whether and when to arrange maintenance for the system.

Conclusion. This research studies the energy consumption diagnosis problem in iron and steel plants. An LSSVM-based data driven model is designed, combined with the Kalman filtering algorithm for energy diagnosis. Based on the statistical properties of the standard data, the diagnostic model of energy consumption is designed and used to evaluate the state of the hot blast stove system in a blast furnace. Our research provides a feasible idea of combing a statistical model with the Kalman filtering algorithm for solving problems without a physical model.

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