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A Fuzzy Sequential Pattern Mining Algorithm Based on Independent Pruning Strategy for Parameters Optimization of Ball Mill Pulverizing System

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Abstract. This paper presents a fuzzy sequential pattern mining algorithm based on independent pruning strategy for parameters optimization of ball mill pulverizing system. Based on the Apriori-alike process, the proposed algorithm uses the independent pruning strategy to mine the fuzzy sequential patterns, which could enhance the efficiency of the algorithm. Then, the optimal values of the process variables are determined by a searching method with the mined sequential patterns. The improved fuzzy sequential pattern support and the fuzzy sequential pattern confidence are adopted to ensure the accuracy of the mined sequential patterns. Moreover, the sliding time window technique is used to ensure the completeness of mining results. The experimental results for parameters optimization of ball mill pulverizing system also verify that the proposed algorithm could determine the optimal values correctly and the running time is not long. In addition, the proposed algorithm has been put into practice successfully and the statistic data show that the pulverizing capability of ball mill pulverizing system is increased and the energy consumption would be reduced.

Keywords: ball mill pulverizing system; parameters optimization; data mining; fuzzy sequential pattern mining; independent pruning strategy.

1. Introduction

Energy saving is very necessary with the increase of the development demand and the energy crisis [1]. Ball mill pulverizing system of the thermal power plant is a typical high energy consumption equipment. It provides the pulverized coal powder for the boiler and uses 15-25% of the whole energy consumption of the thermal power plant [2]. Moreover, ball mill pulverizing system has been used in more than sixty percent thermal power plants in China for its adaptability to various kinds of coal [3]. Therefore, optimizing the ball mill pulverizing system is of important theoretical significance and practical motivation for the serious situation of coal and power shortages [4].

To optimize the ball mill pulverizing system is to let it work on the optimal state, namely, the process variables of ball mill pulverizing system are set as their optimal values respectively. Some fuzzy technique based algorithm have been applied for ball mill pulverizing system. A new self-tuning fuzzy controller is proposed and the coefficients of the deviation and its differential can be adjusted automatically [5]. A Takagi-Sugeno fuzzy modeling based on subtraetive clustering is presented for ball mill pulverizing system and may be beneficial for the design of the advanced model-based controller [6]. An interpolation-based fuzzy controller is proposed and it uses the Newton interpolation algorithm to improve the control precision [7]. Although these methods are applied in field sucessfully, they control the plant based on the fixed setpoints. If the setpoints are set unsuitably, namely, they are far away from the optimal values of process variables, the controller would result in high energy costs of ball mill pulverizing system [8]. In general, the optimal values of process variables are the design values supplied by the manufacturer. Nevertheless, the ball mill pulverizing system is a multi-variable complex system [9], and the optimal values would shift with the change of coal hardness, the shatter of the steel ball, the abrasion of the mill wall, and so on. Although the optimal values of process variables could be calibrated by the periodical field experiments, the working strength of operators would be increased and the boiler may be disturbed by the field experiments. To deal with the disadvantages of the field experiment, a steady state optimization strategy [10] and a grid search method [11] are presented. These methods could be used effectively when there is sufficient knowledge of the mathematics model of the ball mill pulverizing system. Hill-climbing method could be implemented for ball mill pulverizing system conveniently [12,13], but the initial points and the searching direction always affect the optimization results. Particle swarm optimization (PSO) [14] and genetic algorithm (GA) [15] are the heuristics algorithms. However, PSO and GA may be trapped in the premature convergence. Hill-climbing method, PSO and GA perform based on a fitness function, and a precision optimization function for a complex industrial process may not be built easily. Because the industrial process always has large inertia, large delay and time-variance, the optimization function modeled by the history field data would become unsuitable with the working condition changing. Since these approaches would cost long time, the optimal values of process variables determined according to the fitness function only may represent the history working condition and may not be used for the current working condition. Furthermore, Hill-climbing method, PSO and GA usually try the different values of process variables and the efficiency of the industrial process would be affected. Especially, for PSO and GA, the initial values are selected randomly, and some initial values of process variables at the same time for representing the system states may not be exist in reality. Hence, the realization of these optimization algorithms would be limited in field. In addition, optimizing the industrial process is generally a multi-variables optimization task, and the coupling between the process variables would limit the application of these methods. If the system state of industry process could be represented by some form of knowledge, for example, linguistic rules, the feasibility of industry process optimization in field would be improved in a certain extent.

Sequential pattern mining is an important activity in data mining. It finds frequently occurring ordered events or subsequences as patterns [16] and has found a variety of applications, such as touring guiding service [17], web page access analysis [18], customer relationship management [19], etc. For an industrial process, such as the ball mill pulverizing system, the values of the process variables are typically measured at equal time intervals and recorded in the field database, and the database could be seemed as a sequence database. We perform the sequential pattern mining on the field data to obtain the sequential patterns and let them be represented in the form of the association rules, that the process values of variables are expressed by linguistic terms in the antecedent, and the steady-state values of variables and the optimization goal are expressed by linguistic terms in the consequence. Then, according to the mined sequential patterns and the measurement values, the optimal values of the process variables on the current working condition would be determined without tedious searching process. The sequential pattern mining algorithm is first introduced in [20] and some improved algorithms are presented recently [21-23].

However, they could not be adopted for the industrial process optimization directly. The current algorithms mainly focus on detecting all frequent sequential patterns rather than estimation of the association rules for optimization. Not all of mined sequential patterns are suitable for optimization, for example, the frequent sequential patterns denoting the relationship of a variable at different time would be useless. Although we could remove the unnecessary frequent sequential patterns in the postprocessing, some necessary frequent sequential patterns may not be found in mining process with the unsuitable threshold of the minimum support. Moreover, the field database of industrial process includes the measured values of the variables on the different working conditions. If the number of records in the database on any working condition is less, the sequential patterns of the working condition would be ignored because the supports of them are smaller.

In the paper, we propose a fuzzy sequential pattern mining algorithm based on independent pruning strategy for parameters optimization of ball mill pulverizing system. The algorithm partitions the quantitative attributes by the membership functions and uses an Apriori-alike process to mine the fuzzy sequential patterns based on the independent pruning strategy, which could enhance the efficiency of the algorithm. Then, the algorithm determines the optimal values of the process variables by a searching method with the mined sequential patterns. Furthermore, the sliding time window technique is adopted to ensure the completeness of mined results, and the improved fuzzy sequential pattern support and the fuzzy sequential pattern confidence are proposed to ensure the accuracy of the mined sequential patterns. The organization of this paper is as follows: In Section 2, the characteristics of ball mill pulverizing system are introduced. The proposed algorithm is explained in detail in Section 3. In Section 4, the experiments are presented to verify the effectiveness and the practicability of the proposed algorithm. Finally, Section 5 concludes the paper.

2. Ball Mill Pulverizing System

The schematic representation of a ball mill pulverizing system is shown in Fig. 1. The ball mill is fed with raw coal, and at the same time, the hot air and the recycle air are blown into the ball mill to dry and deliver the coal powder. After pulverizing, the coal powder is transferred into the coarse classifier and the fine classifier. The unqualified powder is fed back for further pulverizing while the accepted powder is stored in the pulverized coal bunker finally.

Pulverizing capability is the most important measurement for the efficiency of ball mill pulverizing system and is related to ball mill load [24]. The ball mill load is the ratio between the volume of coal powder in the mill and the interstitial volume of the static ball charge. The characteristics of ball mill pulverizing system are shown in Fig. 2. l is ball mill load, functions $p(l)$ and

$pc(l)$ versus l represent the power of ball mill motor and the pulverizing capability, respectively. p_m and pc_m are the maximum values of $p(l)$ and $pc(l)$, respectively. For $l < l_1$, the pulverizing capability is so small that the ball mill works inefficiently and the lower level of the ball mill load leads to the mill wall worn faster. For $l > l_2$, the ball mill works in the unstable region and the higher level of the ball mill load may lead the ball mill to be clogged. For l is in the interval (l_1, l_2), the pulverizing capability is larger and the change of the power of ball mill motor becomes less, so the ball mill works efficiently. However, for enhancing the pulverizing capability, it is no use merely increasing the coal feed based on the ball mill load, and the outlet temperature and the inlet negative pressure should be controlled in the suitable value respectively. For example, if the outlet temperature is too low, the drying will not be sufficient with the coal feed increasing and the pulverizing capability would be decreased. Furthermore, letting the outlet temperature be higher would be a risk that the coal powder in the mill might be ignited [25]. The inlet negative pressure affects the delivery of coal powder. If the value of the inlet negative pressure is not enough high with the coal feed increasing, the pulverized coal powder would not be transferred efficiently and the pulverizing capability could not be increased. Moreover, increasing the inlet negative pressure blindly would make some coal powder be released outside the ball mill causing environmental pollution and bodily injury. Therefore, to optimize the ball mill pulverizing system is to determine the optimal values of the ball mill load, the outlet temperature and the inlet negative pressure respectively with the pulverizing capability being maximal.

3. The Algorithm

In this section, the proposed algorithm will be discussed in detail. The proposed algorithm includes two procedures. One is the fuzzy sequential patterns mining algorithm based on independent pruning strategy, the other is the optimal values searching method based on the mined fuzzy sequential patterns. Some notations would be explained beforehand. For an industrial process, $x_1, x_2, \dots, x_p$ are the process variables and p is the number of process variables. $y_1, y_2, \dots, y_q$ are the regulation variables, which are used for adjusting the actuators, and q is the number of regulation variables. z is the optimization goal variable. We assume that $sx_1, sx_2, \dots, sx_p$ are the steady-state values of $x_1, x_2, \dots, x_p$, respectively. Since the mined sequential pattern should be represented in the form of the rules, $AS = \{x_1, x_2, \dots, x_p, y_1, y_2, \dots, y_q\}$ and $CS = \{z, sx_1, sx_2, \dots, sx_p\}$ could be regarded as the antecedent set and the consequent set, respectively. If these variables are deemed as the dimensions of the sequence database, the database used for sequential pattern mining is $D = \{x_1, x_2, \dots, x_p, y_1, y_2, \dots, y_q, z, sx_1, sx_2, \dots, sx_p\}$.

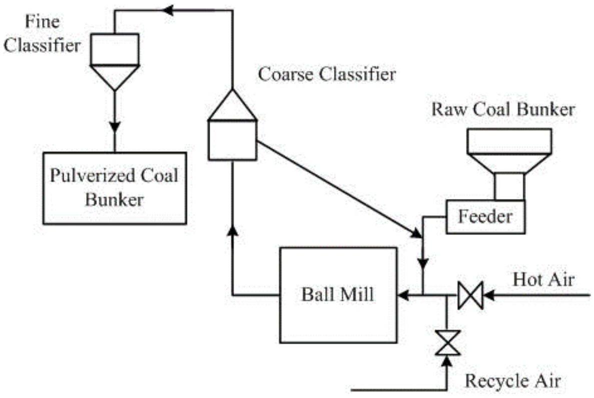

Figure 1. Ball mill pulverizing system

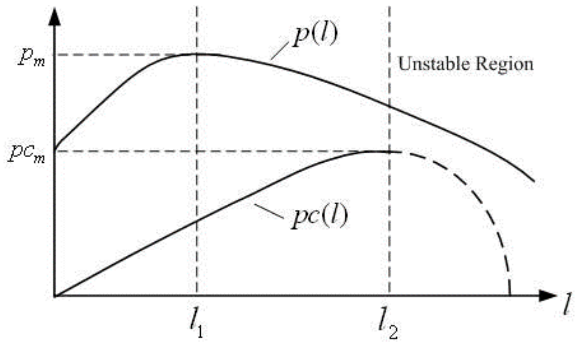

Figure 2. Characteristics of ball mill pulverizing system

Procedure 1. Fuzzy Sequential Patterns Mining Algorithm Based on Independent Pruning Strategy.

Input: D, the minimum support $\sigma(sup)$, the minimum confidence $\sigma(conf)$, the size of sliding time window w_s, the gap of sliding time window w_g.

Output: fuzzy sequential patterns.

Step 1. Transforming the AS to AS^* by considering the changes of the variables.

In the actual working, the operators always adjust the regulation variables according to the working condition and the industrial process would be from one steady state to the other steady state. Consequently, the changes of the process variables and the regulation variables should be considered for fuzzy sequential pattern mining. The antecedent set AS is trans formed to AS^*, which is

$$AS^* = \{x_1, x_2, \dots, x_p, y_1, y_2, \dots, y_q, \Delta x_1, \Delta x_2, \dots, \Delta x_p, \Delta y_1, \Delta y_2, \dots, \Delta y_q\}$$

where $\Delta x_1, \Delta x_2, \dots, \Delta x_p$, represent the changes of $x_1, x_2, \dots, x_p$ and $\Delta y_1, \Delta y_2, \dots, \Delta y_q$, represent the changes of $y_1, y_2, \dots, y_q$.

Because the variables are recorded in the database at equal time intervals, the changes could be calculated based on a record with its next neighbor record. For example, $x_1(t)$ and $x_1(t+1)$ are the measured values of x_1 at time t and $t+1$, respectively, and $\Delta x_1 = x_1(t+1) - x_1(t)$.

Then the sequence database D becomes D^*, which is

$D^* = \{x_1, x_2, \dots, x_p, y_1, y_2, \dots, y_q, \ \Delta x_1, \ \Delta x_2, \dots, \Delta x_p, \ \Delta y_1, \ \Delta y_2, \dots, \ \Delta y_q, z, sx_1, sx_2, \dots, sx_p\}$.

The number of dimensions of D^* is $(3p + 2q + 1)$.

Step 2. Partitioning the quantitative dimensions of D^*.

For fuzzy sequential patterns mining, we use an Apriori-alike process which could be implemented in field easily. Since every dimensions of D^* are quantitative, they should be partitioned firstly. Nevertheless, the sharp boundary may under-emphasize or over-emphasize the objects near the boundaries of intervals in the mining process. To deal with the problem, fuzzy sets are used in partitioning [26].

We assume that the linguistic variables of $x_1, x_2, \dots, x_p, y_1, y_2, \dots, y_q, z, sx_1, sx_2, \dots, sx_p$ are $X_1, X_2, \dots, X_p, Y_1, Y_2, \dots, Y_q, Z, SX_1, SX_2, \dots, SX_p$, respectively. To facilitate the quantitative dimension partition, they use the same fuzzy universe and the linguistic terms. The unified fuzzy universe is [0, 1], and the set of fuzzy linguistic terms are {S, RS, M, RB, B}, where S, RS, M, RB and B represent smallest, relatively smaller, middle, relatively bigger, biggest, respectively. Moreover, the triangular function is adopted as membership function and the variables use the same membership function shown in Fig. 3.

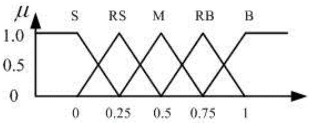

Figure 3. Membership function of the variables

It is assumed that the linguistic variables of $\Delta x_1, \Delta x_2, \dots, \Delta x_p, \Delta y_1, \Delta y_2, \dots, \Delta y_q$ are $\Delta X_1, \Delta X_2, \dots, \Delta X_p, \Delta Y_1, \Delta Y_2, \dots, \Delta Y_q$, respectively, and the unified fuzzy universe of them are all [-1, 1]. The set of fuzzy linguistic terms is {NB, NS, ZO, PS, PB}, where NB, NS, ZO, PS and PB represent negative big, negative small, zero, positive small and positive big, respectively, and they use the same membership function shown in Fig. 4.

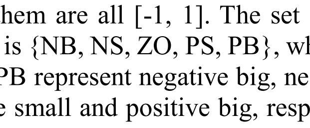

Figure 4. Membership function of the change-variables

After the quantitative dimensions are partitioned, each dimension of D^* is extended to a set of sub-dimensions. For example, the sub-dimensions of x_1 are $x_1^S, x_1^{RS}, x_1^M, x_1^{RB}$ and x_1^B, respectively, and the sub-dimensions of Δy_2 are $\Delta y_2^{NB}, \Delta y_2^{NS}, \Delta y_2^{ZO}, \Delta y_2^{PS}$ and Δy_2^{PB}, respectively.

The partitioned sequence database is named $\widetilde{D}$. $\widetilde{D} = \{x_1^S, x_1^{RS}, x_1^M, x_1^{RB}, x_1^B, \dots, x_p^S, \dots, x_p^B, y_1^S, \dots, y_1^B, \dots, y_q^S, \dots, y_q^B, \Delta x_1^{NB}, \Delta x_1^{NS}, \Delta x_1^{ZO}, \Delta x_1^{PS}, \Delta x_1^{PB}, \dots, \Delta x_p^{NB}, \dots, \Delta x_p^{PB}, \Delta y_1^{NB}, \dots, \Delta y_1^{PB}, \dots, \Delta y_q^{NB}, \dots, \Delta y_q^{PB}, z^S, \dots, z^B, sx_1^S, \dots, sx_1^B, \dots, sx_p^S, \dots, sx_p^B\}$. Since the number of dimensions of D^* is $(3p + 2q + 1)$, the number of dimensions of $\widetilde{D}$ is $5 \cdot (3p + 2q + 1)$.

Moreover, each object in D^* is transformed into the fuzzy membership value. d_1^* is an object in D^*, and $d_1^* = \{v(x_1), \dots, v(x_p), v(y_1), \dots, v(y_q), v(\Delta x_1), \dots, v(\Delta x_p), v(\Delta y_1), \dots, v(\Delta y_q), v(z), v(sx_1), \dots, v(sx_p)\}$, where $v(\cdot)$ represents the measured value of the corresponding variable. d_1^* is transformed into the fuzzy membership values and becomes d_1. $d_1 = \{\mu^S(v(x_1)), \mu^{RS}(v(x_1)), \mu^M(v(x_1)), \mu^{RB}(v(x_1)), \mu^B(v(x_1)), \dots, \mu^S(v(x_p)), \dots, \mu^B(v(x_p)), \mu^S(v(y_1)), \dots, \mu^B(v(y_1)), \dots, \mu^S(v(y_q)), \dots, \mu^B(v(y_q)), \mu^{NB}(v(\Delta x_1)), \mu^{NS}(v(\Delta x_1)), \mu^{ZO}(v(\Delta x_1)), \mu^{PS}(v(\Delta x_1)), \mu^{PB}(v(\Delta x_1)), \dots, \mu^{NB}(v(\Delta x_p)), \dots, \mu^{PB}(v(\Delta x_p)), \mu^{NB}(v(\Delta y1)), \dots, \mu^{PB}(v(\Delta y_1)), \dots, \mu^{NB}\left(v(\Delta y_q)\right), \dots, \mu^{PB}\left(v(\Delta y_q)\right), \mu^S(v(z)), \dots, \mu^B(v(z)), \mu^S(v(sx_1)), \dots, \mu^B(v(sx_1)), \dots, \mu^S\left(v(sx_p)\right), \dots, \mu^B(v(sx_p))\}$, where, for example, μS(v(x1)) represents the membership value with respect to v(x1) for the fuzzy linguistic term S.

Step 3. $\widetilde{D}$ is divided into several sub-sequence datasets by the sliding time window.

Since $\widetilde{D}$ records the field data of different working conditions, the longer time span for sequence pattern mining may reduce the significance of the pattern and weaken the strength of the implication of the pattern [27]. Moreover, if the number of the records of any working condition is relatively small, namely, the support values is small, the sequence pattern for the working condition may not be detected. Therefore, the sliding time window is adopted to ensure the completeness of mining results, and $\widetilde{D}$ would be divided into several sub-sequence datasets. The mth sub-sequence dataset could be written as $DS_m = \{d_{(m-1)w_g+1}, d_{(m-1)w_g+2}, \dots, d_{(m-1)w_g+w_s}\}$, where $m \in \{1, 2, \dots, M\}$, M is the number of subsequence datasets, and d_c, $c \in \{(m-1)w_g + 1, (m-1)w_g + 2, \dots, (m-1)w_g + w_s\}$, is an object in DS_m.

Step 4. Load the first sub-sequence dataset DS_1 and perform the following steps on DS_1.

Step 5. Choose only one sub-dimension from the sub-dimensions set of x_i and Δx_i, respectively, where $i \in \{1, 2, \dots, p\}$, and join them to be a candidate sequence pattern antecedent (CSPA). For example, $\{x_1^S, \Delta x_1^{NB}\}$ and $\{x_1^{RS}, \Delta x_1^{ZO}\}$ are two different CSPAs. The fuzzy sequential pattern support (SSup) of the CSPA is calculated as given below:

$$\mathrm{SSup(CSPA)} = \sum_{k=1}^{w_s} [\prod_{o_k \in \mathrm{CSPA}} \mu(o_k)]$$

where o_k is an element of CSPA for the kth object in the sub-sequence dataset, $\prod_{o_k \in \mathrm{CSPA}} \mu(o_k)$ is the product of the membership value with respect to each element of the CSPA.

If $\mathrm{SSup(CSPA)} \geq \sigma(sup)$, the CSPA is the strong sequence pattern antecedent(SSPA). The strong sequence pattern antecedent set of x_i is $\mathrm{SSPAS}(x_i)$ and could be obtained by the ergodic process of all possible combinations of the sub-dimensions set of x_i and Δx_i, where $i \in \{1, 2, \ldots, p\}$. Because both x_i and Δx_i have five sub-dimensions, the number of all possible combinations of the sub-dimensions set of x_i and Δx_i is 25.

Step 6. By the same way as in Step 5, the strong sequence pattern antecedent sets of all process variables would be obtained and they are $\mathrm{SSPAS}(x_1)$, SSPAS (x_2) ,..., SSPAS (x_p). The strong sequence pattern antecedent sets of all regulation variables would be obtained also and they are $\mathrm{SSPAS}(y_1)$, $\mathrm{SSPAS}(y_2)$, , $\mathrm{SSPAS}(y_q)$.

Step 7. Choose one SSPA form SSPAS (x_1), $\mathrm{SSPAS}(x_2)$, ..., $\mathrm{SSPAS}(x_p)$, $\mathrm{SSPAS}(y_1)$, $\mathrm{SSPAS}(y_2)$, ..., SSPAS (y_q) respectively, and join them to be a candidate combination sequence pattern antecedent (CCSPA). If the SSup value of the CCSPA is larger than or equal to $\sigma(sup)$, the CCSPA is strong combination sequence pattern antecedent (SCSPA). After doing the ergodic process of all possible combination of SSPA of $\mathrm{SSPAS}(x_1)$, $\mathrm{SSPAS}(x_2)$, ..., $\mathrm{SSPAS}(x_p)$, $\mathrm{SSPAS}(y_1)$, $\mathrm{SSPAS}(y_2)$, ..., $\mathrm{SSPAS}(y_q)$, we could get the strong combination sequence pattern antecedent set (SCSPAS).

The Apriori Principle is an important theorem and it means that if an itemset is infrequent, then all of its supersets must be infrequent too [28]. Therefore, for Steps 5-7, we determine SSPA of every two antecedents firstly and then obtain SCSPAS based on the Apriori Principle, that would decrease the complexity of the proposed algorithm.

Step 8. Choose only one sub-dimension from the sub-dimensions set of $z, sx_1, sx_2, \ldots, sx_p$ respectively, and join them to be a candidate combination sequence pattern consequence (CCSPC). If the SSup value of the CCSPC is larger than or equal to $\sigma(sup)$, the CCSPC is the strong combination sequence pattern consequence (SCSPC). The strong sequence pattern consequence set (SCSPCS) could be obtained by the ergodic process of all possible combinations for the sub-dimensions set of $z, sx_1, sx_2, \ldots, sx_p$.

Step 9. Join one CCSPA of SCSPAS, which is represented by A, and one CCSPC of SCSPCS, which is represented by B, to be a candidate sub-sequence pattern (CSSP). The fuzzy sequential pattern confidence (SConf) of CSSP could be computed as given below:

$$\mathrm{SSup(CSPA)} = \frac{\sum_{k=1}^{w_s}\left[\prod_{a_k\in A}\mu(a_k) \times \prod_{b_k\in B}\mu(b_k)\right]}{\sum_{k=1}^{w_s}\left[\prod_{a_k\in A}\mu(a_k)\right]}$$

where a_k is an element of A for the kth object in the sub-sequence dataset, b_k is an element of B for the kth object in the sub-sequence dataset, $\prod_{a_k\in A}\mu(a_k)$ is the product of the membership value with respect to each element of A, $\prod_{b_k\in B}\mu(b_k)$ is the product of the membership value with respect to each element of B, and "×" is the product operation.

If the SConf value of the CSSP is larger than or equal to $\sigma(conf)$, the CSSP is the strong subsequence pattern(SSSP), and the strong sub-sequence pattern set(SSSPS) would be obtained by doing the ergodic process of all possible combinations of CCSPA of SCSPAS and CCSPC of SCSPCS.

For Steps 5-9, we present the independent pruning strategy on the antecedent set and the consequent set respectively, that not only ensures the standardization of mined sequence patterns but also enhances the efficiency of the algorithm.

Step 10. Slide the time window and load the next sub-sequence dataset. Repeating Steps 5-9, we can obtain other strong sub-sequence pattern sets.

Step 11. If all of sub-sequence datasets have been loaded, then do the next step, otherwise, go to Step 10.

Step 12. Merge all strong sub-sequence pattern sets of every sub-sequence dataset to get the fuzzy sequential patterns of D and output the results.

Let $mfsp_t$, $t \in \{1, 2, \ldots, N\}$ represent a mined fuzzy sequential pattern and N be the number of mined fuzzy sequential patterns. So, the set including all mined fuzzy sequential patterns is represented by MFSP. In the field, the following procedure could be implemented easily for determining the optimal values of $x_1, x_2, \ldots, x_p$.

Procedure 2. Optimal Values Searching method with Fuzzy Sequential Patterns

Input: MFSP.

Output: the optimal values of $x_1, x_2, \ldots, x_p$.

Step 1. We assume that $x_1', x_2', \ldots, x_p', y_1', y_2', \ldots, y_q'$ are the measurement values of $x_1, x_2, \ldots, x_p, y_1, y_2, \ldots,$ y_q respectively on the current working condition. Fuzzificate $x_1', x_2', \ldots, x_p', y_1', y_2', \ldots, y_q'$ based on the membership functions shown in Fig. 3 and Fig. 4, respectively. Then, combine the linguistic terms of them to obtain some initial antecedents. An initial antecedent is represented by $\{X_1', X_2', \ldots, X_p', Y_1', Y_2', \ldots,$ $Y_q'\}$, where $X_1', X_2', \ldots, X_p', Y_1', Y_2', \ldots, Y_q'$ are the corresponding linguistic terms of $x_1', x_2', \ldots, x_p', y_1', y_2', \ldots, y_q'$, respectively.

Step 2. Scan the MFSP, the sequential pattern including $\{X_1', X_2', \ldots, X_p', Y_1', Y_2', \ldots, Y_q'\}$ is named as the initial sequential pattern (ISP), namely, $\mathrm{ISP} \supset \{X_1', X_2', \ldots, X_p', Y_1', Y_2', \ldots, Y_q'\}$.

Step 3. The linguistic terms of $\Delta x_1, \Delta x_2, \dots, \Delta x_p$ in ISP are $\Delta X_1, \Delta X_2, \dots, \Delta X_p$, respectively. Defuzzificating $\Delta X_1', \Delta X_2', \dots, \Delta X_p'$ and transferring them to the corresponding real value ranges could obtain $\Delta x_1', \Delta x_2', \dots, \Delta x_p'$. It is assumed that the temporary optimal values of $x_1, x_2, \dots, x_p$ are $(x_1' + \Delta x_1'), (x_2' + \Delta x_2'), \dots, (x_p' + \Delta x_p')$ respectively.

Step 4. Operate the actuators according to these temporary optimal values. If there is a controller for the industrial process in the field, the set values of $x_1, x_2, \dots, x_p$ are adjusted to be $(x_1' + \Delta x_1'), (x_2' + \Delta x_2'), \dots, (x_p' + \Delta x_p')$ respectively.

Step 5. After the industrial process enters the other steady state again, the change of the optimization goal z is evaluated. For example, the optimization goal is pulverizing capability. The larger the value of pulverizing capability, the better the optimization goal. If z becomes better, then calculate the current values of $\Delta y_1, \Delta y_2, \dots, \Delta y_q$, which are named as $\Delta y_1', \Delta y_2', \dots, \Delta y_q'$, respectively. Fuzzificate $\Delta y_1', \Delta y_2', \dots, \Delta y_q'$ to obtain their linguistic terms $\Delta Y_1', \Delta Y_2', \dots, \Delta Y_q'$, respectively.

Step 6. Scan MFSP to find the sequential pattern including $\{X_1', X_2', \dots, X_p', Y_1', Y_2', \dots, Y_q', \Delta Y_1', \Delta Y_2', \dots, \Delta Y_q'\}$, which is named as the candidate sequential pattern (CSP), namely, CSP $\supset \{X_1', X_2', \dots, X_p', Y_1', Y_2', \dots, Y_q', \Delta Y_1', \Delta Y_2', \dots, \Delta Y_q'\}$, then the CSP is recorded in the target sequential pattern set (TSPS).

Step 7. Scan the MFSP based on $\{X_1', X_2', \dots, X_p', Y_1', Y_2', \dots, Y_q'\}$, and find other ISP. Repeating Steps 3-6, we would obtain other CSP.

Step 8. If no new ISP is found, then do the next step, otherwise, go to Step 7.

Step 9. If the ergodic process of all possible initial antecedents has been completed, then do the next step, otherwise, go to Step 2.

Step 10. If TSPS $= \phi$, it means that the industrial process has been in proximity to the optimal state for the current working condition. If TSPS $\neq \phi$, then defuzzificate the corresponding linguistic terms of $SX_1, SX_2, \dots, SX_p$ and transfer them to their real value range. So, the optimal values of $x_1, x_2, \dots, x_p$ for the current working condition would be obtained.

By the proposed algorithm, the optimal values of process variables are determined and the optimization for industrial process is realized. For the optimal values searching procedure of the proposed algorithm, the optimization goal must be evaluated after the industrial process enters the steady state. Because the number of ISP is small, the proposed algorithm would not spend much time. In Section 4, we will use the experiment results based on the real data and the field curves of ball mill pulverizing system to further verify the effectiveness of the proposed algorithm.

4. Experimental Results

In this section, we present some experiments to evaluate the effectiveness of our algorithm. We would compare our algorithm with the hill-climbing method, PSO and GA for the ball mill pulverizing system. The field database of QinLing Thermal Power Plant is used for the experiments. All algorithms are implemented in MATLAB 7.0.4 and the running environment is an Athlon64 X2 3600+ machine with 1 GB of RAM and running Windows XP Professional. In addition, our proposed algorithm has been put into practice in QinLing Thermal Power Plant and the results of field operation would be presented.

For the ball mill pulverizing system, the ball mill load, the outlet temperature and the inlet negative pressure are process variables and represented by l, ot and np, respectively. The opening degree of hot air damper and the opening degree of recycle air damper are regulation variables and represented by u_h and u_r, respectively. Because the objective of optimization is to maximize the efficiency of ball mill pulverizing system, pulverizing capability (pc) is the optimization goal variable. Hence, the sequence database used for sequential pattern mining is $\{l, ot, np, u_h, u_r, pc, l_s, ot_s, np_s\}$, where l_s, ot_s and np_s represent the steady state value of l, ot and np, respectively. $\{l, ot, np, u_h, u_r\}$ and $\{pc, l_s, ot_s, np_s\}$ are the antecedent set and the consequent set, respectively.

Although our algorithm does not need the fitness function, hill-climbing method, PSO and GA need a fitness function. Therefore, for analyzing and comparing our algorithm with hill-climbing method, PSO and GA expediently, the model of pc on l, ot and np, which is named as $pc(l, ot, np)$, would be built and used as the fitness function for the hill-climbing method, PSO and GA. The data used for modeling are chosen from the field database of QinLing Thermal Power Plant and shown in Table 1. The data are the average value of the variables for different steady states and the ranges of $pc(l, ot, np)$ are[0, 100]%, [0, 300]°C and [-1000, 0]Pa, respectively. When ball mill pulverizing system works stably, it accords with the rule of indestructibility of matter, namely, the coal feed per unit of time equals the quantity of pulverized coal powder per unit of time. Although pc could not be measured directly, it equals the coal feed per unit of time in the steady state. Therefore, we adopt the coal feed per unit of time to represent the pulverizing capability and the range is [0, 100]ton/h. In Table 1, the pulverizing capability of ID.6, 49.3ton/h, is largest among the data, namely, 79.5%, 95.1°C and -657.4Pa are the optimal values of l, ot and np, respectively. Moreover, the least square support vector machine [29] is adopted for modeling.

According to different initial values, we perform the hill-climbing method on $pc(l, ot, np)$ to search the optimal values. The experiment results are shown in Table 2. For the hill-climbing method, the step size is 0.1 and the initial values are the real data in Table 1

Table 1. Real data of ball mill pulverizing system for modeling

ID	l(%)	ot(°C)	np(Pa)	pc(ton/h)
1	76.1	109.5	-730.8	40.7
2	71.9	125.4	-807.9	38.7
3	78.2	102.7	-549.4	45.3
4	77.1	107.9	-907.4	44.7
5	82.0	111.6	-585.7	42.3
6	**79.5**	**95.1**	**-657.4**	**49.3**
7	81.2	101.6	-926.6	48.3
8	83.7	109.3	-887.1	42.0
9	86.3	108.8	-944.8	38.0
10	65.9	122.5	-928.3	38.0
11	75.1	95.6	-945.3	41.7
12	69.1	110.0	-894.1	43.0
13	67.9	113.5	-794.8	42.3
14	69.0	102.3	-742.8	44.3
15	68.7	101.2	-842.2	43.7

except the ID.6. In Table 2, for the initial value of l, ot and np being 78.2 %, 102.7°C and-549.4Pa, respectively, the optimal value of l, ot and np are 79.3%, 96.1°C and -654.3Pa, respectively, and the calculation value of pc is 49.13ton/h, which approximates the real maximum, 49.3ton/h, namely, the hillclimbing method succeeds in finding the approximate optimal values. However, for other initial values, the hill-climbing method could not find the optimal values for the calculation value of pc approximating the real maximum. Especially, for the initial values of l, ot and np being 71.9%, 125.4°C and -807.9Pa, the calculation value of pc is only 42.26ton/h and the corresponding values of l, ot and np, which are 90.1%, 130.1°C and -807.8Pa, respectively, would not be the real optimal values. Therefore, although the hill-climbing method could find the optimal values for a certain initial values, the local optimization problem would impact the optimization effectiveness of the ball mill pulverizing system. Furthermore, since the minimum value of running time is 0.085 second and the maximum value of running time is 5.044 second, the running time of the hill-climbing method would be affected by the initial values greatly.

Table 2. Optimization results of the hill-climbing method

ID	The initial values of (%), ot(°C), np(Pa)	The search results of l(%), ot(°C), np(Pa)	The calculation value of pc(ton/h)	Running time (s)
1	76.1, 109.5, -730.8	84.3, 96.4, -674.4	46.88	2.566
2	71.9, 125.4, -807.9	90.1, 130.1, -807.8	42.26	0.760
3	78.2, 102.7, -549.4	79.3, 96.1, -654.3	49.13	3.756
4	77.1, 107.9, -907.4	79.2, 101.4, -897.8	47.91	0.599
5	82.0, 111.6, -585.7	85.5, 95.7, -665.9	46.06	3.304
7	81.2,101.6, -926.6	80.8, 100.7, -894.5	48.48	1.143
8	83.7, 109.3, -887.1	79.1, 101.3, -892.4	47.85	0.596
9	86.3, 108.8, -944.8	78.3, 102.1, -900.3	47.29	1.953
10	65.9, 122.5, -928.3	64.9, 105.4, -794.6	44.02	5.044
11	75.1, 95.6, -945.3	82.3, 99.8, -889.9	48.28	2.200
12	69.1, 110.0, -894.1	67.7, 105.8, -803.3	44.12	3.198
13	67.9, 113.5, -794.8	64.9, 104.0, -788.9	44.06	0.619
14	69.0, 102.3, 742.8	68.0, 101.1, -742.9	44.33	0.085
15	68.7, 101.2, -842.2	66.9, 104.8, -792.9	44.23	1.812

Table 3. Optimization results of GA and PSO

Algorithm	The search results of (%), ot(°C), np(Pa)	The calculation value of pc(ton/h)	Running time (s)
GA	79.4, 98.3, -634.5	48.5	71.527
PSO	78.9, 98.6, -673.6	48.3	35.591

The operating parameters of PSO and GA are set according to the values used in [14] and [15], respectively. The maximum number of iterations is 200 and the size of the initial population is 100. For PSO, the acceleration coefficients, c_1 and c_2, are both 2, and the inertia weight, w, is calculated by $w = w_{max} - \frac{w_{max}-w_{min}}{n_{max}} \cdot n$, where w_{max} is the maximum value of w and equals 0.9, w_{min} is the minimum value of w and equals 0.4, n_{max} is the maximum number of iterations, and n is the nth iteration. For GA, the crossover and mutation factors are 0.6 and 0.1, respectively. We perform the PSO and GA based on $pc(l, ot, np)$, and the initial values of populations of PSO and GA are both random within the known range of l, ot and np. The optimization results of GA and PSO are presented in Table 3, and the optimization process of GA and PSO is shown in Fig. 5. The experimental results show that the effectiveness of GA is relatively better than that of PSO, and PSO has faster convergence speed. However, the unsuitable parameters, for example, the maximum number of iterations, would affect the optimization results of the GA and PSO. For instance, in Fig. 5, the fitness function values of PSO and GA are still relatively small until the 80th iterations and PSO and GA begin convergence after about the 100th iterations. Although the experimental results verify that both PSO and GA outperform the hill-climbing method, the running time of PSO and GA is much larger than that of hill-climbing method. Moreover, for PSO and GA, more than one initial point is selected randomly. Nevertheless, for a real industrial process, such as ball mill pulverizing system, searching from multi-initial points at the same time can not be operated. Moreover, random initialization would let some initial values represent the states which do not exist in reality. Hence, the actual situation of the field would limit the application of the kinds of optimization algorithms.

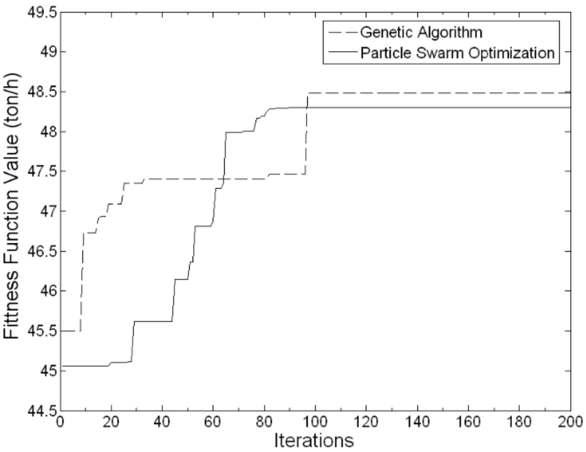

Figure 5. Optimization process of GA and PSO

For our algorithm, the time complexity of the proposed fuzzy sequential pattern mining algorithm is far less than that of current sequential pattern mining algorithm. Hence, we firstly evaluate the time performance and the scalability of the proposed fuzzy sequential pattern mining algorithm. The field data of the ball mill pulverizing system of QinLing Thermal Power Plant are adopted as the test dataset and it includes 10000 objects. Let $\sigma(sup) = 1$, $\sigma(conf) = 1$, $w_s = 1000$ and $w_g = 500$. Experimental results with the number of objects increasing are shown in Fig. 6. With the number of objects increasing from 500 to 10000, the running time increases about only 0.1 second. For the number of objects being 10000, the running time is only 0.223 second. Therefore, the proposed algorithm has better performance. To evaluate the scalability of the minimum support, the number of objects in the field dataset is fixed at 10000. Let $\sigma(conf) = 1$, $w_s = 1000$ and $w_g = 500$. Experimental results with $\sigma(sup)$ increasing from 0.01 to 1 are shown in Fig. 7. When $\sigma(sup)$ changes from 0.01 to 0.8, the size of SSPA, SCSPA and SCSPC becomes smaller gradually with $\sigma(sup)$ increasing, and the running time decreases greatly. When $\sigma(sup)$ changes from 0.8 to 1, the size of SSPA, SCSPA and SCSPC does not change significantly, and the running time barely changed at all. To evaluate the scalability of the minimum confidence, the number of objects in the field dataset is still fixed at 10000. Let $\sigma(sup) = 1$, $w_s = 1000$ and $w_g = 500$. Experimental results with $\sigma(conf)$ increasing from 0.01 to 1 are shown in Fig. 8. When $\sigma(conf)$ changes from 0.01 to 1, the running time decreases about only 0.04 second. Because the size of SCSPA and SCSPC would determine the size of CSSP, they affect the running time greatly. Since $\sigma(conf)$ is only used for obtaining SSSP from CSSP, $\sigma(conf)$ would not affect the running time. Hence, the proposed algorithm has better scalability for $\sigma(sup)$ and $\sigma(conf)$.

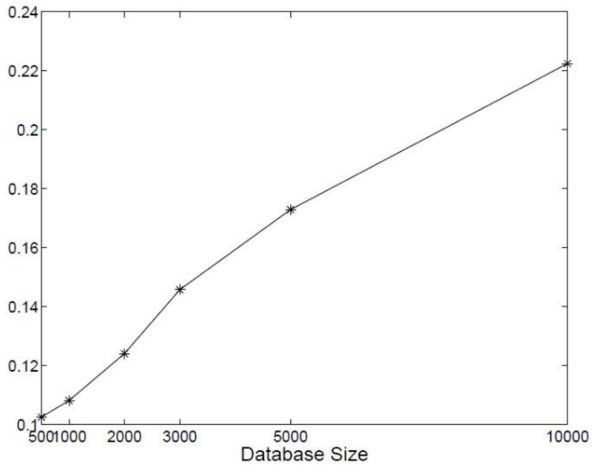

Figure 6. Running time with the number of objects increasing

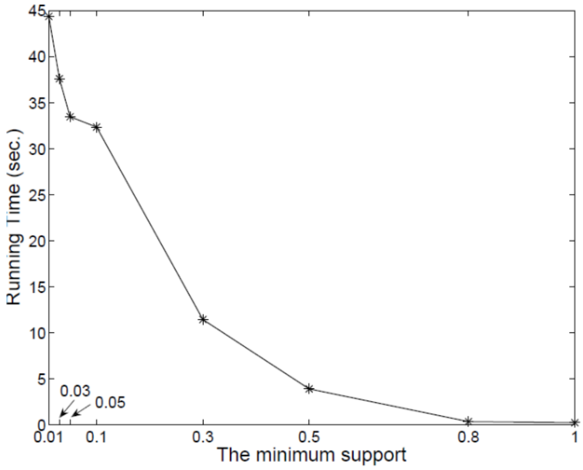

Figure 7. Scalability of the minimum support

Table 4. Mined fuzzy sequential patterns

IF										**THEN**			
L	OT	NP	U_h	U_r	ΔL	ΔOT	ΔNP	ΔU_h	ΔU_r	PC	L_{sv}	OT_{sv}	NP_{sv}
RB	RB	M	RB	M	PS	PS	NS	NS	PS	RS	M	M	M
RB	B	RB	M	PS	PS	PS	NS	NS	PS	RS	RB	RB	M
RB	RS	M	B	RB	PS	PS	NB	PS	NB	RB	RB	RB	RB
RB	RS	M	M	RS	PS	NS	ZO	NS	PS	RB	B	RS	RB
RB	RS	B	RS	RS	PS	ZO	PB	ZO	PB	RB	B	RS	RB
B	M	RB	RS	M	ZO	ZO	NS	ZO	NS	M	RB	M	M
B	RB	M	RB	B	PS	NB	NB	PS	PS	RB	RS	M	RB
B	S	M	RB	RB	PS	NS	NS	PS	PB	B	RS	RB	M
B	B	M	RS	M	NB	PS	NB	NS	NS	B	RB	RB	RS
B	M	M	M	M	NB	NS	NS	PS	PS	RB	B	M	RS
M	M	RS	M	RB	NS	PS	NS	PS	NS	B	B	RB	RB
M	M	RB	S	S	PB	NS	PS	NS	PB	M	RB	M	M
M	B	M	M	M	NS	NB	NB	NS	NS	M	M	M	B
M	S	B	M	RB	PS	NS	NS	NB	NS	S	M	RS	M
M	RS	B	RB	RB	PS	PS	PS	NS	PS	S	M	RB	RB
M	M	S	M	RS	PS	NS	PS	NS	NS	B	RB	M	M
RS	M	S	M	B	PS	PS	NS	PS	NB	B	RB	M	RS
RS	S	M	RB	B	PS	PB	NS	PB	NS	B	M	M	RB
RS	M	M	M	M	PS	PS	NS	ZO	NS	M	M	RS	RS
RS	RS	M	RB	RS	PS	RS	PB	NS	PS	RS	M	S	M
S	S	M	RB	S	PB	PS	NS	NB	PB	RS	RB	M	RB
S	S	B	M	S	PB	PS	NS	PS	PS	S	B	RB	M
S	RB	M	RB	RB	PS	PS	PS	PB	NS	RS	M	RB	RS
S	B	M	RB	B	PS	PS	NS	NS	NS	RS	RS	M	M

Table 5. Optimization results of our algorithm

ID	The initial values of (%), ot(°C), np(Pa)	The search results of l(%), ot(°C), np(Pa)	The calculation value of pc(ton/h)	Running time (s)
1	76.1, 109.5, -730.8	79.7, 97.0, -657.0	48.98	0.966
2	71.9, 125.4, -807.9	81.2, 97.0, -657.3	48.70	0.881
3	78.2, 102.7, -549.4	79.8, 95.4, -656.0	49.17	0.821
4	77.1, 107.9, -907.4	79.5, 96.9, -657.0	49.01	0.930
5	82.0, 111.6, -585.7	80.4, 96.7, -655.7	48.97	0.883
7	81.2, 101.6, -926.6	80.4, 95.5, -656.1	49.09	0.858
8	83.7, 109.3, -887.1	81.4, 96.2, -655.6	48.75	0.956
9	86.3, 108.8, -944.8	81.0, 95.6, -656.6	48.93	0.907
10	65.9, 122.5, -928.3	79.6, 97.0, -656.2	48.98	0.949
11	75.1, 95.6, -945.3	80.2, 96.3, -655.7	49.07	0.960
12	69.1, 110.0, -894.1	81.3, 95.6, -656.1	48.83	0.891
13	67.9, 113.5, -794.8	80.0, 96.6, -656.5	49.05	0.902
14	69.0, 102.3, 742.8	79.6, 96.2, -656.7	49.13	0.888
15	68.7, 101.2, -842.2	79.7, 96.8, -655.7	49.03	0.851

For evaluating the effectiveness of our algorithm, we firstly perform our fuzzy sequential pattern mining algorithm on the field database of ball mill pulverizing system of QinLing Thermal Power Plant, which includes 10000 objects, and let $\sigma(sup) = 1$, $\sigma(conf) = 1$, $w_s = 1000$ and $w_g = 500$. Then, we could obtain the fuzzy sequence patterns for the optimization of ball mill pulverizing system. Some fuzzy sequence patterns, which are represented by the sequential association rules, are shown in Table 4. In addition, the running time of mining fuzzy sequential patterns is about 0.223 second.

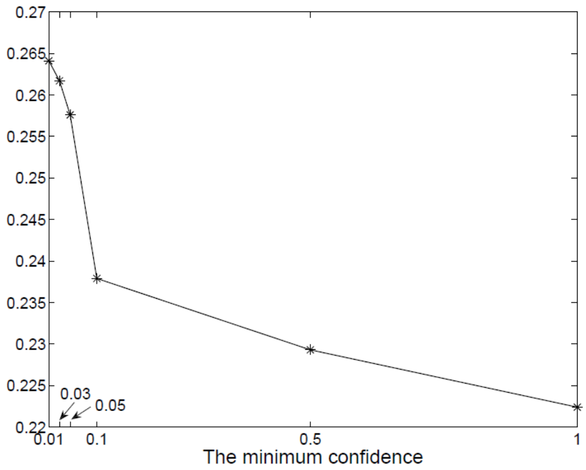

Figure 8. Scalability of the minimum confidence

Based on the mined fuzzy sequential patterns, we perform our searching method with the same initial values as shown in Table 2. Our searching method dose not need the fitness function and is used directly on the field database of ball mill pulverizing system of QinLing Thermal Power Plant. For example, our algorithm could directly obtain the change of pc, and the current values of Δu_h and Δu_r by scanning the field database. The optimization results of our algorithm are shown in Table 5. For evaluating the effectiveness of our algorithm, we use the model $pc(l, ot, np)$ to calculate the value of pc. Moreover, the defuzzification is accomplished by the centroid of area method. For Table 5, the search results show that our algorithm could determine the approximate optimal values with different initial values. For the initial value of l, ot and np being 78.2%, 102.7°C and-549.4Pa, respectively, our algorithm could find two target sequential patterns, which are {RB, RS, M, M, RS, PS, NS, ZO, NS, PS, RB, B, RS, RB} and {B, M, RB, RS, M, ZO, ZO, NS, ZO, NS, M, RB, M, M}. Defuzzificating the two target sequential patterns can obtain the values of l, ot and np, which are 79.8%, 95.4°C and -656.0Pa, respectively, and the calculation value of pc is 49.17ton/h. For the initial value of l, ot and np being 71.9%, 125.4°C and -807.9Pa, respectively, we could obtain the target sequential patterns, which are {RB, RS, B, RS, RS, PS, ZO, PB, ZO, PB, RB, B, RS, RB} and {M, M, RB, S, S, PB, NS, PS, NS, PB, M, RB, M, M}. The optimal values of l, ot and np are 81.2%, 97.0°C and -657.3Pa, respectively, and the calculation value of pc is 48.70ton/h. Since our algorithm includes fuzzificating process and defuzzificating process, the search result does not absolutely equal the real maximum, that barely affect the real effectiveness of the ball mill pulverizing system. In addition, the running time of our algorithm is not larger than that of the hill-climbing method and much smaller than that of PSO and GA.

Numerical results verify that our algorithm could determine the approximate optimal values correctly and is not affected by the initial values of process variables. Moreover, our algorithm has been put into practice in QinLing Thermal Power Plant successfully. Before finding the optimal values, the ball mill load, the outlet temperature, and the inlet negative pressure are set according to the values supplied by the operating rules. The running curves of thirty minutes are shown in Fig. 9. To facilitate analysis, the measured values of all variables are normalized to [0, 1]. In Fig. 9, although the ball mill load, the outlet temperature and the inlet negative pressure are relatively stable, the coal feed per unit of time is not large, namely, the pulverizing capability is not high. After our algorithm was performed in the field, the ball mill load, the outlet temperature, and the inlet negative pressure are set according to the results of our algorithm. The running curves of thirty minutes are shown in Fig. 10. Similarly, the measured values of all variables are normalized to [0, 1]. In Fig. 10, the ball mill load, the outlet temperature and the inlet negative pressure are almost stable, and the coal feed per unit of time becomes larger. The statistic data show that the coal feed per unit of time is increased about 20%, namely, the pulverizing capability is increased about 20%, and the energy consumption would be reduced.

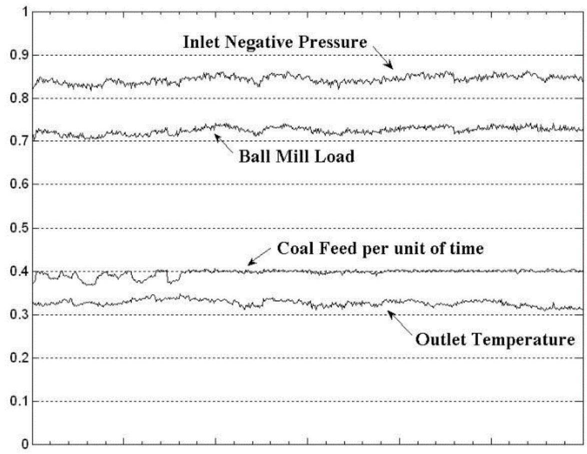

Figure 9. Running curves of real thermal power plant before optimization

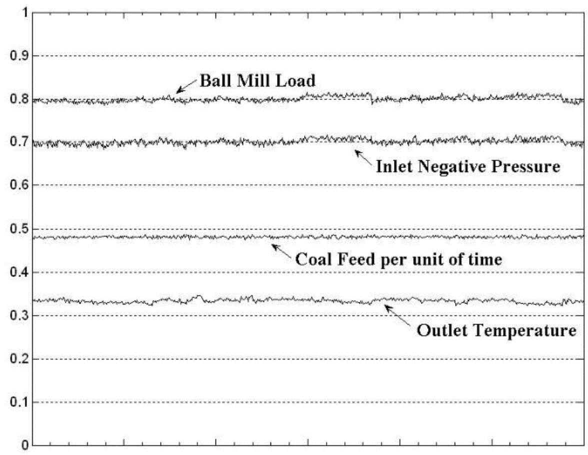

Figure 10. Running curves of real thermal power plant after optimization

5. Conclusions

In the paper, we propose a fuzzy sequential pattern mining algorithm based on independent pruning strategy for parameters optimization of ball mill pulverizing system. The algorithm uses the independent pruning strategy to mine the fuzzy sequential patterns and then determines the optimal values of the process variables by the searching method with the mined sequential patterns. The proposed algorithm has some advantages as follows. First, the proposed algorithm could determine the close enough approximate value of the real optimal value of process variables effectively. Second, the optimization results of our algorithm are almost not affected by the initial values of process variables and the running time of our algorithm is smaller than that of the other tested algorithms. Third, the proposed algorithm presents the independent pruning strategy to enhance the efficiency of the algorithm. Fourth, the proposed algorithm adopts the improved fuzzy sequential pattern support and the fuzzy sequential pattern confidence to ensure the accuracy of the mined sequential patterns. Fifth, the proposed algorithm uses the sliding time window technique to ensure the completeness of mining results. The experimental results for parameters optimization of ball mill pulverizing system also verify the effectiveness of the proposed algorithm. Our algorithm has been put into practice successfully and the statistic data show that the pulverizing capability is increased and the energy consumption is reduced. Moreover, the algorithm could be applied in other complex industry systems, for example, the mineral processing. In the future research work, we will use some advance methods to further decrease the running time of our algorithm.

Acknowledgements

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