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Case-based Reasoning for Energy Consumption Analysis in Steel Process

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Abstract: Energy conservation is more and more important in the iron and steel industry. We propose a method on Case-based reasoning to analyze energy consumption during the steel processes. The innovation of the proposed method lies in the combination of CBR and equal-dimension new information. We select the highly interpretive, discriminative and predictive attributes among the different processes and assign the weights to those non-linear factors according to the importance from the investigation. The similarity is calculated on the basis of the knowledge-based repository. We use the equal-dimension new information to enhance the real-time and effectiveness of case library, so that, we can shorten the time of ergodic case library and improve the efficiency of retrieval. Given a similarity baseline, the production process and energy conservation proposal could be referred. A real-world example verifies the proposed method is effective for energy conservation in the iron and steel industry.

Key words: CBR, equal-dimension new information, iron and steel process similarity, energy consumption

INTRODUCTION

The steel industry is an Energy-intensive Industry while its energy consumption accounts for about 11-15% of the national total energy consumption and about 15-20% of industrial total energy consumption (Ma *et al.*, 2012). Energy consumption has become an important factor that restricts the sustainable development of Chinese iron and steel industry. Many scholars have done a lot of work in theoretical study and practical application in order to improve the energy efficiency in the iron and steel industry. Related researches are divided into two directions, one is to improve the Waste-Heat Recovery and Utilization (Azadeh *et al.*, 2010), the other is the Reasonable Forecast and Control of Energy Consumption (There are many methods of prediction and control of energy consumption at home and abroad that mainly divided into Analytical-Methods and Modeling-Methods including grey prediction method, subjective inference method, trend extrapolation, prediction method of GDP single energy consumption, elastic coefficient method, causal forecasting method, time regression analysis, exponential smoothing method and neural network method etc. (Zhou *et al.*, 2004; Zhang *et al.*, 2009). Gong *et al.* (2007) applied Case-based Reasoning (CBR) to energy calculations and predictions in discrete manufacturing industry.

In conclusion, the neural network method especially BP neural network method is widely used for energy consumption prediction for its good fault tolerance and associative memory function, robust adaptive capacity and self-learning ability. However, the neural network method also has many disadvantages such as many times of iteration, slow convergence speed, vibration in convergence process, the contradiction between learning efficiency and stability, weak global search capability which are due to its inherent faults (Khaddour and Hammami, 2008; Azadeh and Ghaderi, 2008). In order to make full use of data from the iron and steel process and avoid above shortcomings, this study adopts CBR technology to the energy consumption reference and control in the steel process. Gong and Ma (2011) presented a process model of energy consumption prediction based on case-based reasoning and take turbine rotor as example to verify the feasibility and validity of the approach. Xiong (2013) proposed fuzzy similarity rules to express the knowledge and criteria between cases and built a similarity model as knowledge container to guide the CBR process. These studies have shown the CBR's superiority in the following situation: solving complex environment, difficult knowledge acquisition and non-structural problems.

Based on the above studies, we propose the Case-based reasoning to analyze energy consumption during the steel processes. The innovation of the proposed method lies in the combination of CBR and equal-dimension new information. We address the improvement of traditional CBR retrieval strategies,

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introducing equal-dimension new information to update case library. A detailed description of the retrieval algorithm is presented after that. Finally, this study puts a steel factory's actual production data into the retrieval algorithm. The results show that this study provides the feasibility to get rid of excessive dependence on personnel experience prediction mode and to be useful to compile process considering energy consumption.

PROBLEM DESCRIOTION

We should rationally reduce energy waste and the prediction and control of energy consumption plays an important part in the steel production process. So far, most energy consumption predictions of domestic steel enterprises are based on artificial experience. Hence, it's urgent to put forward a relatively accurate method. It is meaningful to put forward a method to make full use of the experts' experience to predict and control the energy consumption. We address the improvement of traditional CBR retrieval strategies as follows.

CBR retrieval model of energy consumption: Because of the complex process and non-linear correlation factors, the calculation of energy consumption is difficult to be accurate. A competent model of energy consumption not only need consider the features that characteristics are various and relationships are complex in iron and steel process but also need to take simplicity and reliability into account. CBR presents an important cognitive methodology in Artificial Intelligence which advocates the use of previous experiences to solve new problems (Lopez De Mantaras *et al*., 2005). One of the most important applications of CBR is where it has a great deal of hidden knowledge and the relations among cases are not easy to collect. However, the historical case implies a lot of tacit knowledge that determines the expert judgment and decision-making. Energy forecasting in iron and steel industry is satisfied. Process of CBR system can be divided into 5R: Retrieve; Reuse; Revise; Review; Retain as shown in Fig. 1. The 5R link constructs the energy consumption analysis model together with case library, knowledge base and so on.

Detailed explanation: The detailed application of CBR in the process of solving energy consumption is as follows:

- **Representation:** Abstracting the objectives and specific information of historical data into cases to build the knowledge-based repository. ENRIC Plaza *et al*. (2005) indicated that suitable explanation can be derived from building symbolic descriptions of similar aspects among cases. Therefore, we need to select the appropriate attributes to effectively distinguish cases and improve the retrieval accuracy. Attribute values should be determined with the

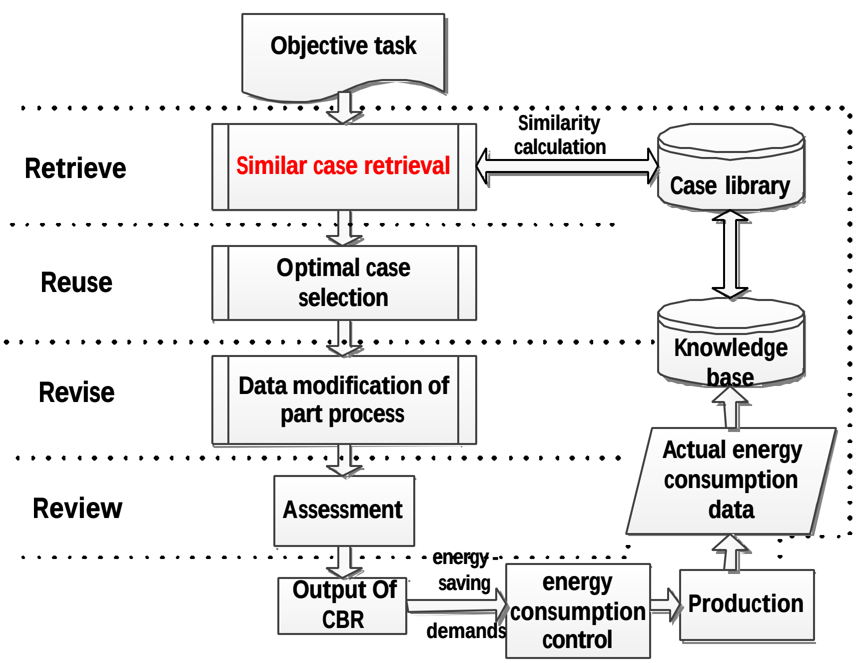

Fig. 1: Case-based reasoning for energy consumption analysis in steel process

Table 1: List of iron and steel process attributes

Iron and steel process	Sequence number	Sintering	Coking	Iron-making	Steel-making
	(1)	Sintering method	Quenching method	Pig iron type	Heat size
	(2)	Mixed method	Coke moisture	Utilization factor of effective volume	Furnace volume ratio
	(3)	Sintering raw material	Ash content	Ratio of putting coke into furnace	Hot metal composition
Attributes	(4)	Leakage rate of sintering machine	Volatiles	Rate of driving	Temperature of hot metal
	(5)	Sinter temperature after waste heat recovery	Coke size	Delay ratio	End-point carbon content
	(6)	Material thickness	Coke temperature after dry quenched coke process	Oxygen enrichment percentage	Oxidation method
	(7)		Air blast temperature	Direct reduction of iron	Tapping temperature
	(8)				Lance Position

following criteria: the retrieval attributes used should have the interpretability, introversion and predictability with high distinguished ability. Major production processes generally involve sintering, coking, iron-making, steel-making and rolling in the analysis of process energy consumption. The rolling process must be arranged in terms of the specific form of the product, so there is a big gap between different businesses. We won't take it into consideration in this study. In accordance with the above analysis and referring to other scholars' researches, we ultimately determine the properties of the steel process including 4 first-ranking attributes-process name and 28 second-ranking attributes-sub-attributes of each process. They are shown in the Table 1

- **Retrieve:** Retrieval plays a key role in CBR system which is directly related to the system's performance and results. Its core is to search the most similar case from the case library within a relatively short time. Now the common case retrieval methods are as follows: the Nearest-neighbor Strategy, the Inductive Strategy, the knowledge-based Indexing Strategy and the Template Retrieval Strategy

The energy consumption information is standardized, so it's easy to find a set of universal weights to reflect the importance of various attributes in the steel industry production processes. The Nearest-neighbor Strategy shows excellent performance under this situation. However, taking the complex process and mass design information into account, cases will continue to increase over time. The traditional CBR retrieval method needs to traverse the entire case library. It means that retrieval time will increase accordingly. In fact, the case and the data early in the history have little effect on current prediction and control. Namely, it has weak correlation between historical information and the latest prediction. Therefore, this study proposes a new retrieval strategy that use Nearest-neighbor Strategy combined with equal-dimension new information. The combination of two methods can not only make full use of the advantages of CBR incremental active learning to solve the problem but also fill the new data to the case library. This strategy is more in line with people's normal mode of thinking.

- **Reuse:** Reuse is to filter out the optimal case in accordance with the business conditions. We have calculated the similarity in retrieval process by traversing the case library, so this, link only needs to sort the similarity values
- **Revise:** The minimum link similarity should be modified by adjusting relevant parameters such as coke moisture, material thickness, blast temperature, etc. in this procedure. Finally, we can get a complete case that meet the energy-saving demands
- **Review:** Evaluating the complete case generated in forth link to ensure that the output results satisfy both energy-saving demands and requirements of energy supply

In the end, the output of CBR is the prediction of energy consumption that meets the objectives. Next we optimize the process that exceeds energy supply plan and control energy consumption strictly. We aim at adjusting the process data to achieve energy balance. Certainly, the actual production will be affected by multi-dimensional factors such as season, temperature, workers and so on. Hence, there must exist some certain differences between actual and predicted energy consumption. Afterwards, we can get the successful complete energy consumption through intelligent algorithms and data processing methods. When the cases are obtained, they are stored in the case library to replace the old case to realize case library updating in real-time.

CONSTRUCTION OF RETRIVAL MODEL

Retrieval is paramount to the success of CBR solution. This section combines CBR with equal-dimension new information effectively. We have proposed a new retrieval strategy on the basis of the traditional retrieval methods: Optimizing the attribute description and updating case library dynamically to avoid a lengthy search process. As a result, the retrieval accuracy and rapidity could be improved greatly.

Values of relevant attributes

Weights: Appropriate values of weights play a key role in some expert systems. In the Nearest-neighbor Strategy, the weights are used to measure the degree of importance in all participating attributes. Expert scoring is the easiest and most direct method for determining the weights by far (Liu and Ben, 2012). The other commonly used methods are Weight Factor Judgment Table Method, Probabilistic Analysis Method and Analytic Hierarchy Process (AHP). The distribution of weight must comply with the following principles:

$$0 \le W_i \le 1, \sum_{i=1}^{m} W_i = 1 \tag{1}$$

Statistical analysis method is adopted in this section. Through practical investigation, we get the key energy consumption of the main production processes from some steel enterprises (from 2005 to 2010). They are as follows: the average energy consumption in sintering, coking, iron-making, steel-making process were 56.41, 120.86, 427.14, 10.05 (kgce/t). After calculating the proportion of each process accounts for total energy consumption, we assign the weights approximately to (0.092, 0.197, 0.695, 0.016).

Similarity: The overall similarity evaluation of two cases is actually calculated by summing the similarity values for each attribute between the target case and known cases. Whether it's far or near between two objects is measured by the magnitude of distance. But it's difficult to demonstrate the distance between two cases with mathematical distance. Similarity can help to explain the distance between two cases exactly. The more minimum the distance is, the more similar the two cases are. Usually a threshold value will be set before calculating the similarity. The similarities that are less than the given threshold value are treated as the final suitable cases which could meet the requirements and consist of a result set. Specific implementation process of similarity algorithm is given in next part.

Algorithm implementation: Retrieval is the key of CBR, so this study will focus on it. The process of case retrieval is the process of similarity calculation. Similarity assessment plays a key part in CBR in that it decides the quality of retrieved cases. A competent similarity model has to reflect the real utility/relevance of cases for solving new problems (Ralph *et al*., 2001).

Calculation formulas of case similarity in iron and steel process are given below:

$$\mathrm{SIM}(A^x, A^y) = \sum_{i=1}^{m} W_i \bullet D_i \tag{2}$$

$$D_i = S_i(A^x, A^y) = \frac{\sum_j [w_{ij} \bullet \mathrm{sim}(d_{ij}^x, d_{ij}^y)]}{\sum_j w_{ij}} \tag{3}$$

SIM represents the total similarity between case A^x and A^y, W_i denotes the importance that ith attribute occupies among the whole case attributes and D_i means the similarity of ith attribute. It bears mentioning that w_{ij} represents the function it plays in the secondary attribute of d_{ij} and $\mathrm{sim}(d^x_{ij}, d^y_{ij})$ indicates the similarity of attribute d_{ij} between case A^x and A^y.

In the solution of steel process energy consumption based on CBR, the conventional energy consumption data is stored in the case library. We mark a set of complete production process which includes sintering, coking, iron-making, steel-making as a known case. Let set A as the case library, if A contains n cases, it can be expressed as:

$$A = \{A^1, A^2, A^3, \ldots, A^n\} \tag{4}$$

As mentioned above, to ensure the case library doesn't growth linearly over time leading to retrieval time increased seriously, the equal-dimension new information is adopted to replace the old information with new information. It is clear that the case library that at this moment to the previous one is represented as:

$$A = \{A^2, A^3, \ldots A^n, A^{n+1}\} \tag{5}$$

Let $D_i (i = 1, 2, 3, 4)$ represents the first-ranking attributes of a case. Each process contains many parameters, that is, each first-ranking attribute is divided with a plurality of second-ranking attributes (d_{ij}). So, each first-ranking attribute is precisely indicated as follows according to Table 1:

$$\begin{aligned} D_1 &= \{d_{21}, d_{22}, \ldots, d_{27}\} \\ D_2 &= \{d_{21}, d_{22}, \ldots, d_{27}\} \\ &\vdots \\ D_4 &= \{d_{41}, d_{42}, \ldots, d_{48}\} \end{aligned} \tag{6}$$

The values of the parameters are affected by the production conditions and other factors, so, each second-ranking attribute is limited in a certain range described as Con.$d_{ij} \in [\alpha_{ij}, \beta_{ij}]$, such as Volatiles is usually about 0.9~1.6%, Hot metal composition is generally about 70-85%. In this constraint conditions combined with the actual data, we can easily obtain the values of all attributes.

Then assign weights to each first-ranking attribute D_i, we get 4 weights corresponding to 4 attributes. They have been calculated in the part of "Weights".The set of all attribute weights are denoted as:

$$W = \{W_1, W_2, W_3, W_4\} = \{0.092, 0.197, 0.695, 0.016\} \quad (7)$$

The weight of second-ranking attribute W_{ij} can be obtained by calculating the average of W_i. For example, there are 6 sec-ranking attributes under W_1, so $W_{1j} = 1/6\ W_1 = 0.0153$ (j =1, 2, ..., 6).

Now suppose that d_{ij} can be determined in terms of the specific targets, the overall similarity between the target case C^0 and any cases in the case library is represented as:

$$\mathrm{SIM}(C^0, A^p) = \sum_{i=1}^{4} (W_i \times S_i(C^0, A^p)) \quad (8)$$

where, S_i (C^0, A^p) indicates the similarity of first-ranking attribute D_1 (i)$\in$(1~4) between C^0 and A^p. It can be obtained by accumulating the values of all the similarities of second-ranking attributes (sim (d^0_{ij}, d^p_{ij}). For linear continuous variables, such as Leakage rate of sintering machine, Sintering temperature after the heat recovery, calculate them by Eq. 9 as follows:

$$\mathrm{SIM}(d^o_{ij}, d^p_{ij}) = 1 - \frac{\left|d^o_{ij} - d^p_{ij}\right|}{k_{ij}} \quad (9)$$

(k_{ij} denotes the range of attribute d_{ij})

For the nonlinear logical variables, including Sintering method, Mixed method, Sintering raw material, Coke size, Pig iron type and Heat size, calculate them by Eq. 10:

$$\mathrm{Sim}(d^o_{ij}, d^o_{ij}) = \begin{cases} 0, & d^o_{ij} \neq d^p_{ij} \\ 1, & d^o_{ij} = d^p_{ij} \end{cases} \quad (10)$$

Next we calculate the overall second-ranking similarities for every candidate according to Eq. 9 and 10. As a result, we get the similarity matrix D of 4 first-ranking attributes of n candidates as follows:

$$D = \begin{bmatrix} D_1^1 & D_1^2 & \cdots & D_1^n \\ D_2^1 & D_2^2 & \cdots & D_2^n \\ \vdots & \vdots & \ddots & \vdots \\ D_4^1 & D_4^2 & \cdots & D_4^n \end{bmatrix} \quad (11)$$

Each column of matrix D of $\{D_{1p}, D_2^p, \ldots, \}^T$ addresses the similarity of each first-ranking attribute in A^p.

By analyzing the values in Eq. 11, it's easy to find higher similarity between C^0 and A^p and obtain a few cases of the most similar:

$$\mathrm{Min}\,(\mathrm{SIM}\,(C^0, A^p)) = \{C_{k0}, C_{k1}, C_{k2}, \ldots, C_{kv}\} \quad (12)$$

C_{k0} is the most similar one.

APPLICATION

This section demonstrates CBR for energy consumption analysis in steel process. We put a steel factory's actual production data into the retrieval algorithm above-mentioned. Randomly extracting several known cases from historical repository are showed in the Table 2.

First, determine the attributes value of C_0. We randomly selected four cases from the historical case library due to the limited space. The similarity of 28 sec-ranking attributes of the four candidates are calculated according to Eq. 9 and 10. It follows that the total similarity of each case by Eq. 8 is calculated. The similarity results are as follows:

$$\mathrm{SIM} = [0.092\ \ 0.197\ \ 0.695\ \ 0.016] \times \begin{bmatrix} 0.917 & 0.570 & 0.470 & 0.616 \\ 0.930 & 0.710 & 0.930 & 0.925 \\ 0.866 & 0.606 & 0.633 & 0.715 \\ 0.795 & 0.930 & 0.808 & 0.690 \end{bmatrix} \quad (13)$$

$$\begin{bmatrix} & A^1 & 0.084 & 0.052 & 0.043 & 0.057 \\ & A^2 & 0.183 & 0.140 & 0.183 & 0.182 \\ & A^3 & 0.602 & 0.421 & 0.440 & 0.500 \\ & A^4 & 0.013 & 0.015 & 0.013 & 0.011 \\ \mathrm{SIM} & (C^0, A^p) & = 0.882 & = 0.628 & = 0.679 & = 0.750 \end{bmatrix} \quad (14)$$

Figure 2 draws a similarity comparison chart based on the results above. It indicates the total similarity of different cases clearly. We can find that A^1 is the optimal similar candidate which similarity is up to 0.882 higher than the other 3 samples.

Some special process will be particularly concerned in actual prediction and control of energy consumption.

Table 2: Case list of energy consumption

Process of iron and steel industry	Attribute list	Target case C^0	Case A^1	Case A^2	Case A^3	Case A^4
Sintering process	(1) Sintering method	Sintering	Sintering	Pelletization	Pelletization	Sintering
	(2) Mixed method	Primary mixing	Primary mixing	Primary mixing	Secondary mixing	Secondary mixing
	(3) Sintering raw material	Magnetite	Magnetite	Limonite	Siderite	Hematite
	(4) Leakage rate of sintering machine	21%	20%	18%	25%	22%
	(5) Sinter temperature after waste heat recovery	150°C	180°C	160°C	150°C	130°C
	(6) Material thickness (mm)	400	300	250	400	450
Coking Process	(1) Quenching method	Dry quenching	Wet quenching	Wet quenching	Dry quenching	Dry quenching
	(2) Coke moisture (Mad)	4.50%	5%	4.50%	3.50%	4%
	(3) Ash content (Ad)	13%	12%	13%	12.50%	14.50%
	(4) Volatiles (Vdaf)	1.10%	1.10%	1.50%	1.20%	1.30%
	(5) Coke size (mm)	Breeze	Breeze (<25)	Large coke (>40)	Block coke (25~40)	Large coke (>25)
	(6) Coke temperature after dry quenched coke process (°C)	200	210	250	190	200
	(7) Air blast temperature (°C)	1250	1050	1100	1250	1200
Iron-making process	(1) Pig iron type	Conversion pig	Conversion pig	Foundry pig	Foundry pig	conversion pig
	(2) Utilization factor of effective volume (t/m^3.d)	2.6	2.3	2.5	3.7333	2
	(3) Ratio of putting coke into furnace (kg/t)	297.15	380	400	410	420
	(4) Rate of driving (t/m^3.d)	1.25	1.2	1.2	1.3	1.3
	(5) Delay ratio	1.20%	1.50%	1.60%	1.30%	1.50%
	(6) Oxygen enrichment percentage	0.44%	0.45%	0.50%	0.45%	0.55%
	(7) Direct reduction of iron	50%	48.50%	47.50%	50%	45%
Steel-making process	(1) Heat size (m^3)	Large-sized furnace	Large-sized furnace (>620)	Large-sized furnace (>620)	Medium-sized furnace (255~620)	Small-sized furnace (<100)
	(2) Furnace volume ratio (m^3/t)	1.0	0.95	0.95	1.0	1.05
	(3) Hot metal composition	78%	75%	76%	72%	80%
	(4) Temperature of hot meta (°C)	1500~1550	1400~1450	1500~1550	1300~1350	1500~1550
	(5) End-point carbon content	0.25%	0.35%	0.16%	0.18%	0.3%
	(6) Oxidation method	Indirect oxidation	Direct oxidation	Indirect oxidation	Indirect oxidation	Direct oxidation
	(7) Tapping temperature (°C)	1640	1689	1630	1580	1602
	(8) Lance Position (mm)	900	1000	1000	890	1060
SIM (C^0, A^P)			0.882	0.628	0.679	0.75

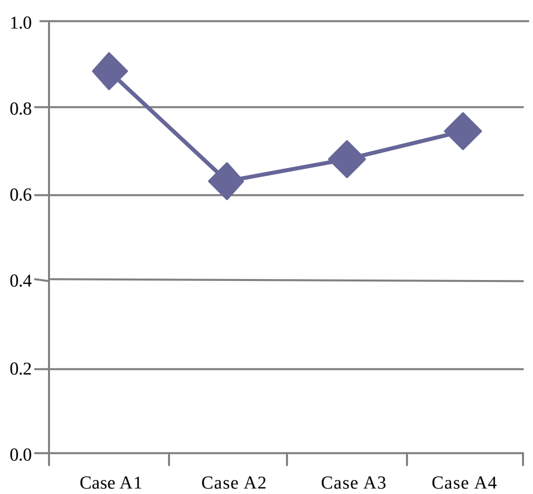

Fig. 2: Similarity comparison chart

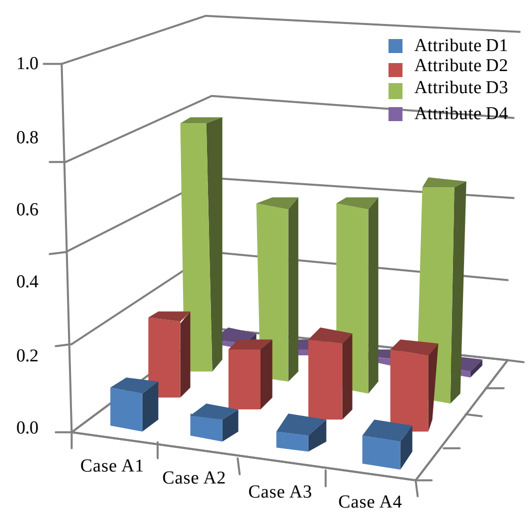

Fig. 3: Similarity of preferable-attribute

For example, iron-making process and hot rolling process cost a large amount of energy, accounting for 60 and 10% in the long process energy consumption. So, more attention should be given to them. To evaluate the data clearly when analyzing the results, we build Similarity of preferable-attribute as shown in Fig. 3. It illustrates the preferable-attribute similarity that puts case A^p as X abscissa, attribute D_i as ordinate with the similarity of S_i

(C^0, A^p) as the vertical coordinate. Since the particular purpose is to compare the special similarity of some procedure within a short time, model user's preference can quickly achieved through Fig. 3.

Now it's time to revise and reuse the case. The result shows there is a big difference between the target case and similar known case in the sintering and iron-making process. After a serious comparison on these two processes, we find the conspicuous different parameters are "Sinter temperature after waste heat recovery", "Material thickness", "Utilization factor of effective volume" and "Ratio of putting coke into furnace". By compensating energy consumption caused by these different parameters, the prediction of the energy consumption is returned as the result of CBR. Subsequently, we can optimize the energy consumption in the production.

CONCLUSION

This study proposes the solution to analyze the energy consumption based on CBR in the steel process. The results show that this strategy is effective in decision-making under complex conditions that are unstructured and hard to acquire related knowledge. In the further research, the CBR technology will be integrated with other technologies, such as agent technology convergence, neural networks, genetic algorithms and combining soft computing methods.

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