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Smart Process Manufacturing toward Carbon Neutrality—Article

An Intelligent Control Method for the Low-Carbon Operation of Energy-Intensive Equipment

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ABSTRACT

Based on an analysis of the operational control behavior of operation experts on energy-intensive equipment, this paper proposes an intelligent control method for low-carbon operation by combining mechanism analysis with deep learning, linking control and optimization with prediction, and integrating decision-making with control. This method, which consists of setpoint control, self-optimized tuning, and tracking control, ensures that the energy consumption per tonne is as low as possible, while remaining within the target range. An intelligent control system for low-carbon operation is developed by adopting the end–edge–cloud collaboration technology of the Industrial Internet. The system is successfully applied to a fused magnesium furnace and achieves remarkable results in reducing carbon emissions.

1. Introduction

In April 2016, after the Paris Agreement on global climate change came into effect, China committed to reducing its carbon dioxide (CO_2) emissions intensity per unit of gross domestic product (GDP) by 60%–65% in 2030, compared with 2005. In 2021, the United Nations Economic Commission for Europe (UNECE) pointed out that the carbon emissions per kilowatt-hour of coal-fired power generation are as high as 751–1095 g [1]. The 13th Five-Year Development Plan for Energy Conservation and the Environmental Protection Industry reported that improving energy efficiency will contribute about 82% to China's 2030 target for reducing the intensity of carbon dioxide emissions. Thus, conserving industrial electricity has become an important means of realizing the low-carbon industry.

Process industries mainly include raw material industries (e.g., petrochemicals, steel, nonferrous metals, building materials, and mining) and the energy industries (e.g., electric power). The scale of China's process industries is the largest in the world, and they serve as important basic support for China. However, their energy consumption accounts for more than half of China's total energy consumption. In the process industry, the energy consumption is concentrated in energy-intensive equipment. Examples include the submerged arc furnaces widely used in the metallurgical industry, the fused magnesium furnaces used for the production of fused magnesia, the crystalline silicon furnaces used for the production of metallic silicon, and the yellow phosphorus furnaces used for the production of phosphorus. Other examples include the grinding equipment in the beneficiation industry, electrolytic aluminum equipment for producing metal aluminum, electric arc furnaces for producing alloy steel in the iron and steel industry, and the large-scale cracking furnaces that are widely used in the petrochemical industry. The total number of industrial furnaces is about 120 000, and their annual energy consumption is as high as 260 million tonnes of standard coal, accounting for 25% of China's total energy consumption and 60% of industrial total energy consumption [2]. Energy-intensive equipment is the key equipment in China's manufacturing industries. The five major industries of China—namely, the iron and steel, non-ferrous metallurgy, petrochemical, power, and machinery industries—greatly rely on energy-intensive equipment. The energy consumption of these industrial enterprises accounts for about 70% of China's total energy consumption [3].

Carbon emission refers to the emissions of greenhouse gases generated during the production, transportation, use, and recycling of products. The main sources of carbon emissions from

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energy-intensive equipment are the electric energy consumed by the production of products and the waste discharged. Therefore, energy conservation and emissions reduction are the key to achieving low-carbon operational control. Since the raw ore or raw materials loaded by such equipment are fixed, the key to the low-carbon operational control of energy-intensive equipment is to convert as much of the loaded raw ore or raw materials into qualified products as possible while ensuring that the energy consumption is as low as possible—that is, to minimize the energy consumption per tonne of qualified products. Therefore, the energy consumption per tonne is a comprehensive production index used to measure the operation status of energy-intensive equipment, known as the operation index. Achieving the energy conservation of energy-intensive equipment is the key to realizing low-carbon operational control.

The electric arc furnace is a type of energy-intensive equipment that is widely used in industry, and its modeling and control are therefore of wide concern [4,5]. Predictive control for the arc current has been proposed in order to reduce the flicker caused by electrode short-circuits [4]. A control strategy for the arc furnace has also been proposed, to obtain the maximum active power of the electric arc by modifying the speed and the direction of electrodes; the effectiveness of this strategy has been verified by simulation [5]. Such control methods focus on arc furnaces with an open arc and are difficult to apply to submerged arc furnaces, with their frequent changes in dynamic characteristics. When the melting temperature of mineral resources is high, the submerged arc method is adopted. The three-phase electrodes of a submerged arc furnace are buried in the raw ore, and the raw ore is melted by controlling the electrode to form an arc. The material is fed while being melted, which consumes a great deal of energy. Submerged arc furnaces are widely used in the production of national strategic minerals and include the fused magnesium furnace, crystalline silicon furnace, yellow phosphorus furnace, ferrochrome furnace, and matte furnace. The fused magnesia, silicon metal, and phosphorus produced by these energy-intensive pieces of equipment play an important role in China's industrial production and national defense security. For example, fused magnesia has the characteristics of high purity, a high melting point, anti-oxidation, a complete structure, and strong insulation. It is mainly used to produce various magnesium refractories with excellent properties. Magnesium and magnesium alloys are important materials for the production of key products in China's strategic emerging industries and are widely used in aerospace, aviation, national defense, metallurgy, and other industries.

There are challenges and difficulties in realizing the low-carbon operational control of the energy-intensive equipment described above. First of all, modeling is difficult. The process of converting raw ore and raw materials into qualified products by means of energy-intensive equipment is an interactive process involving material flow, information flow, and energy flow (i.e., three flows). These are often accompanied by physical and chemical reaction processes whose reaction mechanisms are unclear. The dynamic characteristics change in interactive processes. A process model is composed of an operation layer and a control layer with different time scales. The dynamic model changes with the batch production, and the operation index of the energy consumption per tonne is difficult to measure online. Second, operational control is difficult. The process under control has comprehensive complexities such as strong nonlinearity, strong coupling, strong interference, and frequent changes in dynamic characteristics, and the optimal decision-making and operational control of the energy consumption per tonne involve the scientific problems of global non-convex non-stationary optimization and optimization of the whole production process [6,7]. Therefore, the low-carbon operational control of energy-intensive equipment presents challenges to the theory and technology of modeling, control, and optimization.

Although some achievements have been obtained in the modeling, control, and optimization of industrial processes [8–15], due to the comprehensive complexity of energy-intensive equipment, it is difficult to use existing methods to realize the operational optimized control of energy-intensive equipment [16]. Therefore, manual operational control methods are adopted in energy-intensive equipment. Many human activities are a bottleneck in progress [17]. For example, it is difficult for people to perceive dynamic changes in operating conditions and process heterogeneous information in a timely manner. Human decision-making and operations are subjective and inconsistent. Thus, manual operational control methods are a key reason for the high energy consumption of energy-intensive equipment.

Smart manufacturing has become a well-recognized core high-level technology to enhance the overall competitiveness of the manufacturing industry. The technical foundation of smart manufacturing, as represented by Germany's Industry 4.0, is the cyber–physical systems (CPSs). The term CPS refers to the tight conjoining of and coordination between computational and physical resources. We envision that the CPS of tomorrow will far exceed those of today in terms of adaptability, autonomy, efficiency, functionality, reliability, safety, and usability [18]. CPS provides new research ideas for realizing the low-carbon operational control of energy-intensive equipment.

The development of artificial intelligence (AI) technology provides a new technical foundation for realizing the low-carbon operational control of energy-intensive equipment. AI is not a single technology, but rather a collection of technologies that are applied to specific tasks [19]. Although the boundaries of AI can be uncertain and have tended to shift over time, what is important is that a core objective of AI research and applications over the years has been to automate or replicate intelligent behavior [20]. Machine intelligent systems have already begun to quietly pervade a growing share of businesses, governments, and individual lives around the world [21]. AI system developers commonly recognize that machine learning will have a broad impact on industry [22]. AI can accelerate production capabilities through more reliable demand forecasting, increased flexibility in operations and the supply chain, and better prediction of the impacts of change to manufacturing operations [23]. On 10 May 2018, the US White House hosted the Summit on Artificial Intelligence for American Industry and issued a statement focusing on the development of high-impact, domain-specific AI. According to the Summit, AI holds tremendous potential as to empower the American worker, drive growth in American industry, and improve the lives of the American people [24]. The US National Science Foundation also stated that AI is transforming every segment of American industry. It is making agriculture more precise and efficient, providing new medical diagnostics that save lives, and creating the promise of autonomous transportation and advanced manufacturing [25]. The Development Plan for the New Generation of Artificial Intelligence released by the State Council of the People's Republic of China has emphasized the development directions of the deep integration of AI technology and manufacturing [26]. However, the evolution of AI to deep learning does not consider how it can be applied to the manufacturing process, and smart manufacturing presents the challenges of multi-scale and multi-source information acquisition, predictive models, and the integration of resource planning decisions and control processes [27]. Thus, the development of operational control intelligent systems through the tight conjoining of and coordination between AI, industrial automation and information technology, and energy-intensive equipment opens up a new way to achieve the low-carbon operational control of energy-intensive equipment.

With the development of the mobile internet represented by the fifth generation of wireless technology (5G), edge computing, cloud computing, and cloud platform software, the Industrial Internet has been born. The Industrial Internet creates conditions for obtaining industrial big data. The end–edge–cloud collaboration technology of the Industrial Internet creates conditions for the realization of big-data-driven industrial AI algorithms and the low-carbon intelligent operation of energy-intensive equipment [28]. This paper proposes an intelligent control method for the low-carbon operation of energy-intensive equipment by combining control and optimization with prediction, linking system identification with deep learning, and integrating decision-making with control. The proposed method consists of setpoint control, self-optimized tuning, and setpoint tracking control. An intelligent control system for low-carbon operation was developed by adopting Industrial Internet end–edge–cloud collaboration technology. The system has been successfully applied to a fused magnesium furnace and achieved remarkable results in reducing carbon emissions.

2. Description of the low-carbon operational control of energy-intensive equipment

2.1. Status of the operational control of energy-intensive equipment

In energy-intensive equipment, such as a typical submerged arc furnace, with raw ore as the raw material, the submerged arc method is adopted. The current control system controls the three-phase electrodes, forming an arc and generating a melting current. This melts the raw ore, forming a molten pool. The raw ore is fed while being melted. When the liquid level rises to the top of the furnace, the processing ends. It is difficult to observe the operating conditions in the furnace and difficult to establish a dynamic model of the three-flow (i.e., material, information, and energy) interaction process. The submerged arc furnace adopts the batch production method. It takes several hours to complete the production of one batch, and the production conditions—such as the raw ore composition, the operation (feeding, melting, exhausting), and the equipment conditions—of the next batch will change randomly. Therefore, it is difficult to establish a dynamic model of the energy consumption per tonne for different batches, and the operation index of energy consumption per tonne cannot be measured online, but can only be obtained by means of laboratory calculation after processing. Thus, a manual operational control mode is used for the operation of a submerged arc furnace, as shown in Fig. 1. The "knowledge workers" referred to in Fig. 1 include enterprise managers and process engineers. Enterprise managers obtain production data through the information system and decide the target value range of energy consumption per tonne, based on their experience and knowledge. Process engineers obtain the operating condition data through the monitoring system and process control system, and decide on the range of the melting current according to the target value range of the energy consumption per tonne, based on their experience and knowledge. Operators obtain the operating condition data through the control system, they judge the operating condition in combination with the onsite perception of the operating condition information, and then decide the setpoint of the melting current, which is sent to the current-control system through the monitoring system. The current-control system controls the three-phase electrode current to track the setpoint of the melting current. Due to the comprehensive complexity of the process under control, including its strong nonlinearity, strong coupling, strong disturbance, and dynamic characteristics that change with the melting process, it is difficult for a proportional–integral–derivative (PID) control system to track the setpoint well, and the tracking error is large and fluctuating. Thus, it is difficult to achieve the low-carbon operation of energy-intensive equipment, which results in a high energy consumption per tonne or even abnormal and faulty conditions.

2.2. Description of the low-carbon operational control of energy-intensive equipment

The operational control target is given by the following:

$$\min(r(T)), \quad r_{\min} < r(T) < r_{\max} \tag{1}$$

where $r(T)$ represents the energy consumption per tonne, T represents the end time of the production, and $r_{\max}$ and $r_{\min}$ are the upper and lower bounds, respectively, of the target range of the energy consumption per tonne.

The dynamic model under operational control consists of a dynamic model for operation and a dynamic model under control. The dynamic model for operation is described by

$$\dot{r}(T) = g(r(T), y(t), d_r(t)) \tag{2}$$

The dynamic model under control is described by

$$\dot{y}(t) = f\left(y(t), u(t), d_y(t)\right) \tag{3}$$

where $g(\cdot)$ and $f(\cdot)$ are unknown nonlinear functions, and the disturbances d_r and d_y mainly involve environment and material variation, wear and tear, and so forth. $y(t)$ and $u(t)$ are the output and input of the dynamic model under control.

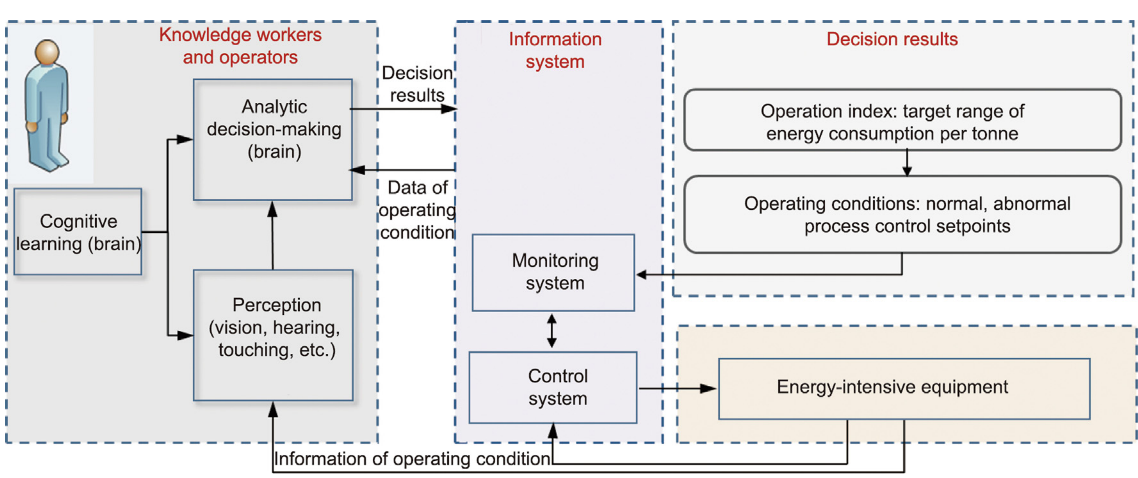

Fig. 1. Structure of the operational control of energy-intensive equipment.

The operational optimized control law includes the optimal setpoint of the controller $\bar{y}(t)$ and the control law $u(t) = p\left(\bar{y}(t) - y(t)\right) = pe(t)$, where p and $e(t)$ respectively represent the control law and the tracking error. It is necessary for the control law to have a good dynamic performance—that is, to ensure that the tracking error and the fluctuation of the control input are within their target range for the entire operational time. This requirement is described as follows:

$$|e(t)| < \delta_1, \ \ |u(t)| \le \delta_2, \ \ 0 < t \le T \tag{4}$$

where δ_1 and δ_2 are the upper bounds of the tracking error and the control input fluctuation, respectively.

Based on the problem description, some challenging problems can be identified. The process under operational control has a hybrid complexity. First, the dynamic model has a different time scale. Second, the operational processes are strongly nonlinear; thus, it is difficult to establish a mathematical model due to the unclear mechanisms. The energy consumption per tonne cannot be measured online. Third, the process under control also has a hybrid complexity; for example, it has unknown variation of model dynamics, frequent unmeasurable disturbances, and continuous dynamical variation in status. Thus, when there are frequent changes of the setpoint according to the optimal operation of the energy-intensive equipment, the integral action of the controller loses its effect. In such a case, a PID controller cannot deliver a good performance.

The operational optimized control law also has hybrid complexity. One type of complexity involves the optimal setpoints of the controller, which change along with the dynamical variation of the operational process under control. The other is the controller with good dynamic performance—that is, the tracking error is controlled within the target range throughout the operation time. This operational optimized control problem is dynamic optimization with multiple conflicting objectives. Therefore, solving this problem falls beyond the suitable range of the control and optimization method [10,15]. Thus far, no unified method has been developed for the operational optimized control of complex energy-intensive equipment.

2.3. Intelligent control method for low-carbon operation

To address the difficulties in decision-making regarding the optimal setpoint for tracking control $\bar{y}(t)$, with the aim of achieving low-carbon operational control, as shown in Eq. (1), setpoint control is proposed, based on an analysis of the operational control behavior of operation experts working with energy-intensive equipment (Fig. 1), by combining control and optimization with prediction. The setpoint control consists of a tracking control presetting model, a prediction model of the energy consumption per tonne, a feedforward compensator, and a feedback compensator. To address the difficulties of the online measurement of the energy consumption per tonne, a prediction model of energy consumption per tonne driven by industrial big data is proposed, which combines mechanism analysis with deep learning. Since the dynamic characteristics of energy-intensive equipment based on the submerged arc mode change with the charging and melting process, the setpoint for tracking control is not suitable. To deal with this problem, self-optimized tuning is proposed, which consists of operating condition recognition and a self-tuning compensator. The frequent changes in the dynamic characteristics of the process under control lead to the failure of the integral action of the feedback control. Therefore, it is difficult to control the tracking error within the target range throughout the entire operation time. To ensure that the tracking control has good control performance—that is, to meet the constraint shown in Eq. (4)—setpoint tracking control driven by a signal compensation method is proposed, which combines PID with data-driven signal compensation. In order to realize the low-carbon operational control of energy-intensive equipment, it is necessary to integrate the decision-making of the optimal setpoint for tracking control with the control of the optimal tracking setpoint. Thus, by integrating decision-making and control, an intelligent control method for the low-carbon operation of energy-intensive equipment is proposed, as shown in Fig. 2. This method consists of setpoint control, self-optimized tuning, and setpoint tracking control. The setpoint control, which is intended to control the energy consumption per tonne $r(k)$ within the target range—that is, $[r_{\max}, r_{\min}]$—and to keep it as low as possible, generates the setpoint $\tilde{y}(k)$ for the setpoint tracking control. Self-optimized tuning identifies the operating conditions in real time. When non-optimal operating conditions are found, the tuned value $\Delta\tilde{y}(k)$ of the setpoint value is generated, and the setpoint of the tracking control is adaptively tuned; that is, $\bar{y}(k) = \tilde{y}(k) + \Delta\tilde{y}(k)$. In this way, abnormal operating conditions can be avoided, and the energy-intensive equipment can run under optimal operating conditions. The setpoint tracking control causes the output $y(k)$ of the process under control to track the setpoint and controls the tracking error $e(k)$—that is, $e(k) = y(k) - \bar{y}(k)$—to fluctuate within the target range.

The structure of the setpoint control is shown in Fig. 3. It consists of a tracking control presetting model, a prediction model of the energy consumption per tonne, a feedforward compensator, and a feedback compensator. The tracking control presetting model generates the pre-setpoint $y_{\rm P}(k)$ of the tracking control based on the target range $[r_{\max}, r_{\min}]$ and the target value r^* of the energy consumption per tonne. The prediction model of the energy consumption per tonne takes $y_{\rm P}(k)$ as input and generates the predicted value $\bar{r}(T)$ of the energy consumption per tonne. Based on the error $\Delta\bar{r}(T)$ between the predicted value and the target value

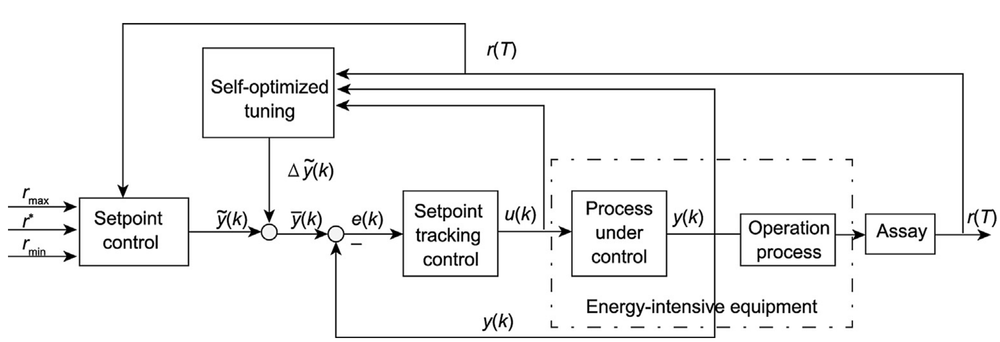

Fig. 2. Structure of the intelligent control method for low-carbon operation.

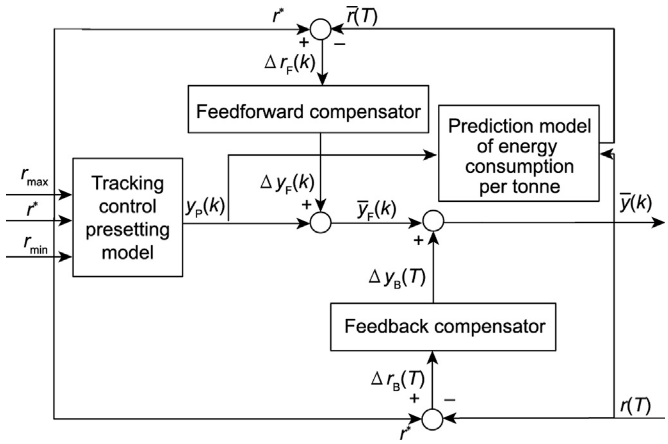

Fig. 3. Structure of the setpoint control.

of the energy consumption per tonne, the feedforward compensator generates the feedforward compensating value $\Delta y_F(k)$. The tuned tracking control setpoint can be obtained by $\bar{y}_F(k) = y_P(k) + \Delta y_F(k)$. Based on the error $\Delta r_B(T)$ between the actual value $r(T)$ and the target value r^* of the energy consumption per tonne, the feedback compensator generates the feedback compensating value Δy_B. The tracking control setpoint can be obtained by $\bar{y}(k) = \bar{y}_F(k) + \Delta y_B(k)$. The tracking control causes the output $y(k)$ of the process under control to track the setpoint $\bar{y}(k)$. The tracking control presetting model, the feedforward compensator, and the feedback compensator can be designed through case reasoning or rule reasoning [10].

The structure of the prediction model of the energy consumption per tonne is shown in Fig. 4. It consists of a main model based on the mechanism and an adaptive deep learning compensation model [29]. The latter consists of an online deep learning compensation model, a self-tuning deep learning compensation model, and a self-tuning mechanism. The main model that is based on the mechanism takes the tracking control pre-setpoint $y_P(k)$ as input and generates a prediction $\hat{r}(T)$ of the energy consumption per tonne. The adaptive deep learning compensation model adopts the big data of all the factors affecting energy consumption per tonne and takes the prediction error $\Delta r(T)$ of the main model—that is, $\Delta r(T) = r(T) - \hat{r}(T)$—as the label. The estimated value $\Delta\hat{r}(T)$ of the main model prediction error $\Delta r(T)$ can be obtained through the adaptive deep learning method. The predicted value of the energy consumption per tonne can be obtained by $\bar{r}(T) = \hat{r}(T) + \Delta\hat{r}(T)$.

The structure of the setpoint tracking control is shown in Fig. 5. To realize optimal operation of energy-intensive equipment, the tracking error between the setpoint and the output must be controlled within its target range throughout the operation time. Therefore, the tracking controller must have a good dynamic performance. The process under control has hybrid complexity. For example, the parameters of the model are unknown nonlinear functions. Unknown frequent and random disturbances cause the controlled process to continually be in a state of dynamic variation. The setpoint control causes the setpoint to change frequently, according to the optimal operation of the energy-intensive equipment. The integral action of the PID controller loses its effect, making it difficult to use PID. In such a case, we use the physical resources of the process. Since the energy-intensive equipment operates near the working points, we can use a combination of a lower-order linear model and an unknown high-order nonlinear term obtained via virtual unmodeled dynamics to describe a dynamic model of the complex energy-intensive equipment. The unmodeled dynamics contain unknown variations of the dynamics of the process under control and can be represented by a combination of the known unmodeled dynamics of a previous time and its change rate. We design the controller based on a low-order linear model, such as PID. Using this controller, we can obtain $u(k)$. We put $u(k)$ into controller-driven model to obtain the output, $y^*(k)$. Then, we can obtain $y(k)$ through the process under control. Using $y(k)$ and $y^*(k)$, we can obtain the unmodeled dynamic from a previous time, $v(k-1)$. We can use the new data for $v(k-1)$ to design the compensator, $u_2(k)$. Although $\Delta v(k)$ is unknown, the tracking error $e(k)$ produced by $\Delta v(k)$ can be obtained. We can design a compensator to eliminate $e(k)$—that is, to eliminate $\Delta v(k)$. The objectives of the design for the compensator, u_2 and u_3, are to eliminate the effect of $v(k-1)$ and $\Delta v(k)$ as much as possible. The compensation signals, u_2 and u_3, are added to the feedback controller based on a low-order linear model. For a controlled process with unknown varying parameters or one that is always in a state of dynamic variation, existing forms of control via PID, for example, cannot be adopted. For this complex process, compensation signal-driven tracking control has robust adaptive control functions and good dynamic performance. The compensated observations of the disturbance and adaptive control have estimation errors, which cause a tracking error outside of the target range.

The structure of the self-optimized tuning is shown in Fig. 6. It consists of operating condition recognition, a prediction model of the energy consumption per tonne, and a self-tuning compensator. In complex energy-intensive equipment, the unknown random changes of the production condition result in an unsuitable setpoint of the tracking controller, which will lead to abnormal or non-optimal operation conditions. In the case, the operating condi-

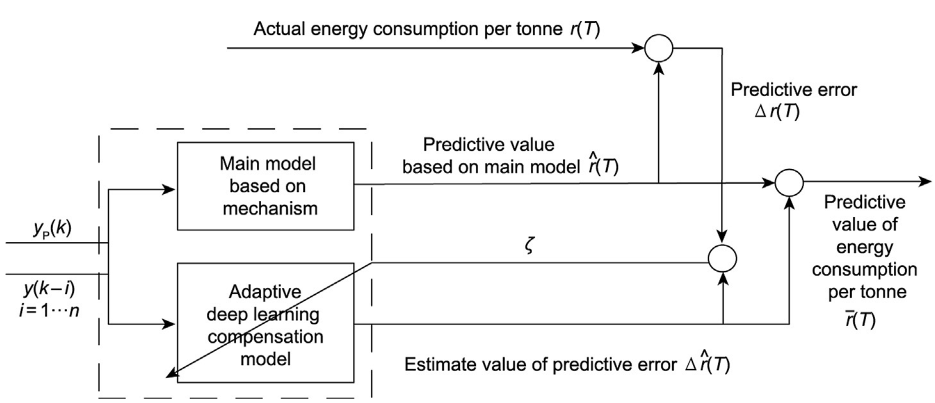

Fig. 4. Structure of the prediction model of the energy consumption per tonne.

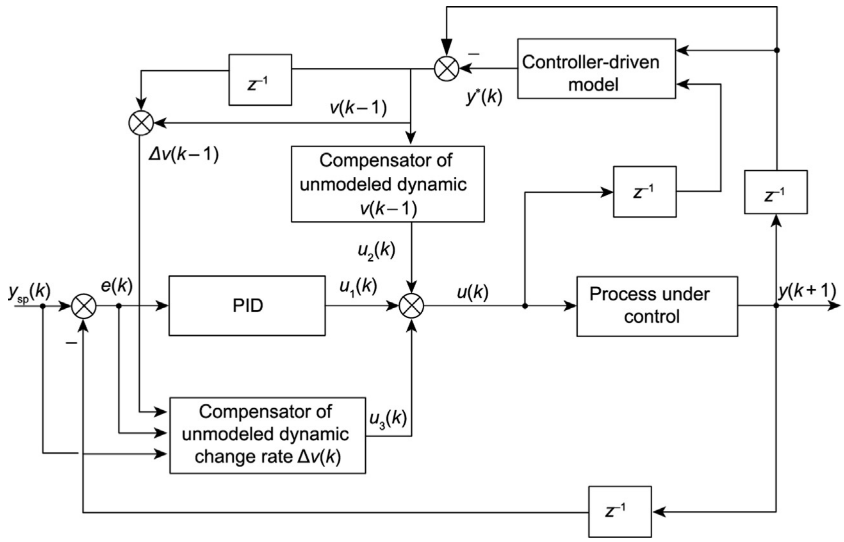

Fig. 5. Structure of the setpoint tracking control.

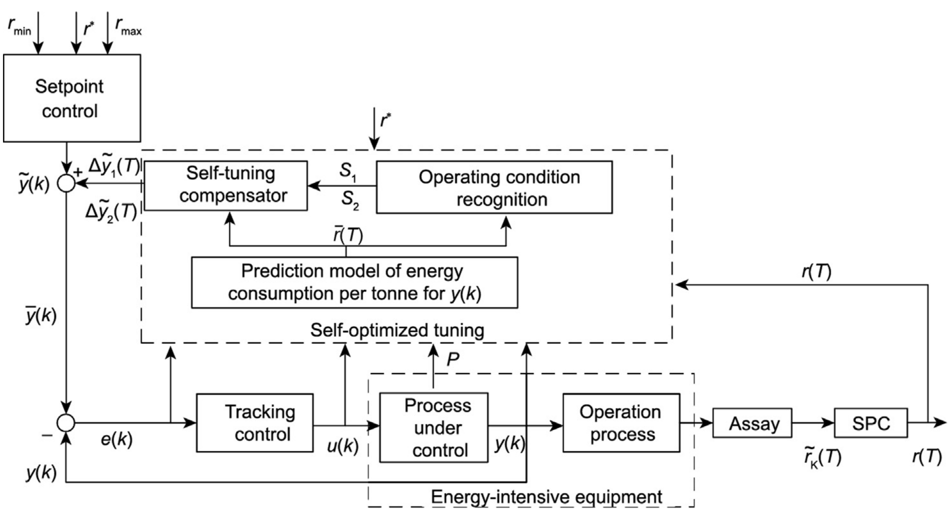

Fig. 6. Structure of the self-optimized tuning. SPC: statistical process control.

tion recognition, which consists of abnormal condition diagnosis and non-optimal condition diagnosis, produces diagnosis results for the operating condition S (i.e., abnormal, non-optimal, or optimal) using the target value of the energy consumption per tonne, the predicted value, the input, the output, and the tracking error of the tracking control system. The self-tuning compensator consists of a self-healing compensator and a self-optimized compensator. The self-healing compensator generates the compensated value $\Delta\tilde{y}_1(T)$ of the setpoints for an abnormal operating condition. The self-optimized compensator generates the compensated value $\Delta\tilde{y}_2(T)$ for the non-optimal condition, so as to realize optimal operation of the energy-intensive equipment. In the case, the prediction model of the energy consumption per tonne predicts the energy consumption per tonne $\bar{r}(T)$ at time T using the process output $y(t)$ at time t.

The self-optimized tuning adopts data-driven modeling and control methods, including case-based reasoning, fuzzy-logic-based reasoning, and rule reasoning. The prediction model of the energy consumption per tonne in the self-optimized control adopts system identification and adaptive deep learning.

The end–edge–cloud collaboration technology of the Industrial Internet is used to realize the above intelligent control algorithm for low-carbon operation. The end programmable logic controller (end-PLC) control system executes setpoint tracking control and data collection. The edge–edge control system executes the tracking control presetting model, the feedforward compensator, and the feedback compensator in the setpoint control, as well as the main model and the online deep learning compensation model in the prediction model of the energy consumption per tonne. The edge control system also performs the recognition of the operating conditions, the self-tuning compensator in the self-optimized tuning, and the main model and online deep learning compensation model of the prediction of the energy consumption per tonne for the setpoint tracking control output. The generated setpoint of the tracking control is taken as the setpoint of the end-PLC tracking control system. The cloud-data server and AI computing platform, which use the industrial big data of the current moment and the previous moment, adopting a self-tuning deep learning model and self-tuning mechanism of setpoint control and self-optimized tuning, adaptively tune the weight parameters and bias parameters of the online deep learning compensation model of the energy consumption per tonne, so as to ensure the accuracy of the prediction of the energy consumption per tonne.

3. Industrial application

The proposed intelligent control method for low-carbon operation has been successfully applied to a fused magnesium furnace, an energy-intensive piece of equipment in a fused magnesia production enterprise, as shown in Fig. 7. The parameters of the fused magnesium furnace are provided in Table 1. The fused magnesium furnace is the key equipment for the production of fused magnesia, which is an important raw material in the production of refractory materials for aerospace and industrial production. Since the melting temperature of fused magnesium is as high as 3000 °C, the fused magnesium furnace adopts the submerged arc method. The three-phase electrode is buried in the magnesite. By controlling the electrode, an arc is generated to melt the magnesite, forming a molten pool. The material is fed while being melted. Production is completed when the liquid level of the molten pool reaches the top of the furnace. This process generally takes 10 h, and the average power consumption of each furnace is 4000 kW·h. The process of melting the magnesite into fused magnesium involves physical and chemical changes. The raw materials and other production conditions differ among different batches, and the energy consumption per tonne cannot be measured online. Thus, it is difficult to establish a dynamic model between the energy consumption per tonne and the melting current. The parameters of the dynamic model of the melting current are nonlinear functions that vary with the impedance, the height of the molten pool, and so forth. The three-phase electrode currents affect each other, and their dynamic characteristics change frequently. Therefore, it is difficult to use existing operational optimization and control methods for a fused magnesium furnace, and manual operation control is still adopted, as shown in Fig. 8. When the feeding and composition of the raw ore change, it is difficult for engineers and operators to make timely and accurate decisions regarding the setpoint of the melting current and the control input, resulting in high energy consumption or even abnormal operating conditions.

Fig. 7. Energy-intensive equipment: the fused magnesium furnace.

Table 1
Parameters of the fused magnesium furnace

Item	Parameter
Electrode diameter	350 mm
Electrode length	1500 mm
Furnace body diameter	2.5 m
Drive motor rated power	7.5 kW
Drive motor rated voltage	380 V
Drive motor rated speed	960 $\text{r}\cdot\text{min}^{-1}$
Melting voltage	100–200 V
Melting time	10 h
Design production capacity	18 t
Minimum yield	15 t
Maximum energy consumption per tonne	2650 kW·h

The key to realizing the low-carbon operation of a fused magnesium furnace is to control the energy consumption per tonne of each furnace within the target range $[r_{\max}, r_{\min}]$ while reducing it as much as possible. This can be written as follows:

$$\min(r(s)),\quad r_{\min} < r(s) < r_{\max} \tag{5}$$

where $r(s)$ represents the energy consumption per tonne; s represents the batch, where $s = 1, \ldots, n$; and $s = 1$ represents one batch and its production time is T.

The magnesite loaded into the fused magnesium furnace are fixed. The magnesite can be converted into fused magnesia as long as the melting current and power are controlled within the target range. Therefore, the operational control objective, Eq. (5), can be expressed as follows:

$$\begin{aligned} &\min(p(k)) \\ &p_{\min} < p(k) < p_{\max} \\ &y_{\min} < y_i(k) < y_{\max} \\ &u_{\min} < u_i(k) < u_{\max} \\ &0 < k \le T,\quad i = 1, 2, 3 \end{aligned} \tag{6}$$

where $p(k)$ represents the power; $p_{\max}$ and $p_{\min}$ are the upper and lower bounds of the target range of the power; y_i and u_i represent the ith phase electrode current and control input; $y_{\max}$ and $y_{\min}$ are the upper and lower bounds of the target range of the melting current; and $u_{\max}$ and $u_{\min}$ are the upper and lower volatility bounds of the control inputs.

An intelligent control method for the low-carbon operation of the fused magnesium furnace, as shown in Fig. 9, is designed by adopting the proposed method, which consists of setpoint control for the melting current, tracking control, and self-optimized tuning.

Setpoint control for the melting current, as shown in Fig. 10, consists of a presetting model that relies on case-based reasoning, a prediction model of the power based on system identification and adaptive deep learning, and feedforward compensation based on rule-based reasoning.

The tracking control for the melting current, as shown in Fig. 11, adopts PID control based on signal compensation. The method reported in Ref. [30] is used to design adaptive PID tracking control for the melting current, based on signal compensation.

Self-optimized tuning, as shown in Fig. 12, consists of a prediction model of the power based on the three-phase electrode current $y_i(k)$, operating condition recognition driven by data, and a self-tuning compensator driven by rule-based reasoning. The method reported in Ref. [31] is used to design the operating condition recognition and self-tuning compensator.

The prediction model of the power, shown in Fig. 13, consists of a linear model and an adaptive deep learning model for unknown nonlinear dynamic systems.

The prediction model of the power is designed by adopting the method reported in Ref. [29]. A prediction model of the power can be established by using a melting current-tracking control closed-loop system, described by

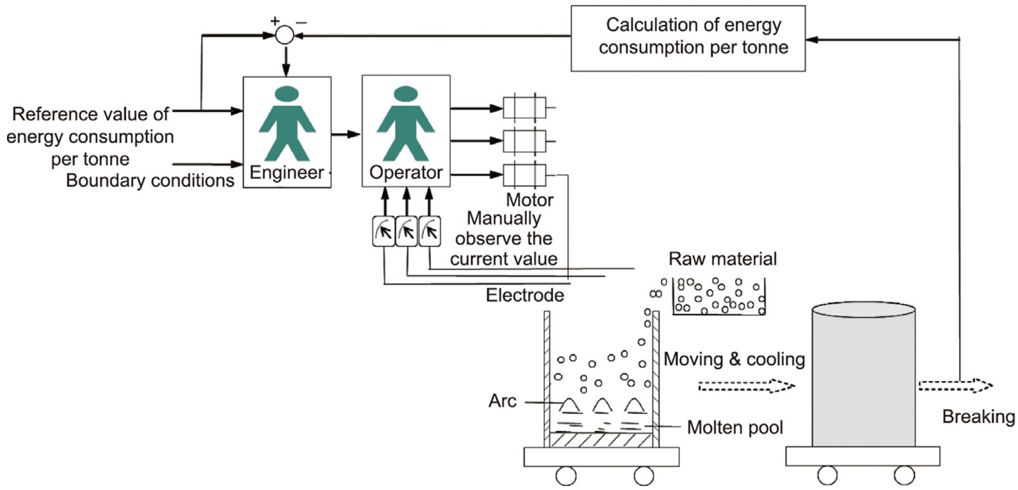

Fig. 8. Manual operation control of energy-intensive equipment.

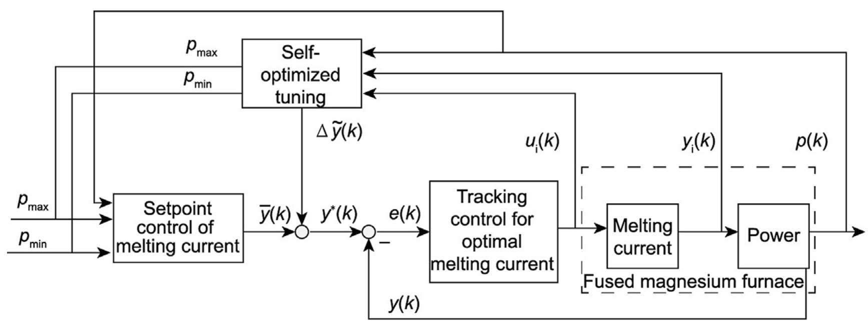

Fig. 9. Intelligent control method for the low-carbon operation of a fused magnesium furnace.

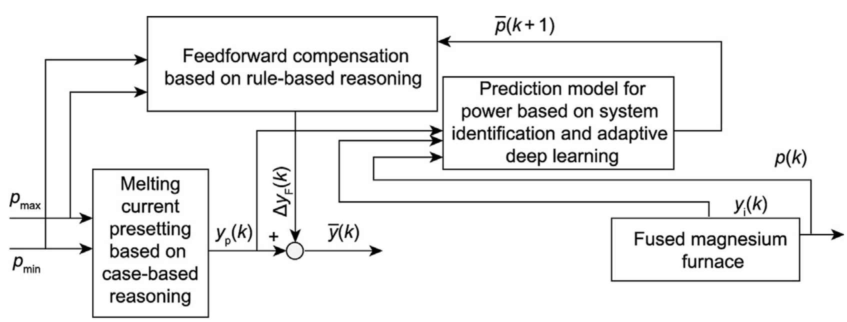

Fig. 10. Structure of setpoint control for the melting current.

$$p(k+1) = \boldsymbol{\theta}\boldsymbol{\phi}(k) + \bar{v}(k+1) \tag{7}$$

where $\boldsymbol{\theta} = [a_1, a_2, a_3, b_1, b_2, b_3]$ and $\boldsymbol{\phi}(k) = [y(k), y(k-1),\ y(k-2), y^*(k), y^*(k-1), y^*(k-2)]^{\mathrm{T}}$, in which $y(k)$ is the sum of the three-phase electrode currents $y_i(k)$—that is, $y(k) = \sum_{i=1}^{3} y_i(k)$, $y^*(k)$ is the setpoint of the melting current; and $\bar{v}(k+1)$ is an unknown nonlinear function.

The least-squares algorithm is used to identify the model parameter vector $\boldsymbol{\theta}$ offline, and its estimated value $\widehat{\theta}$ is obtained. Thus, Eq. (7) can be expressed as follows:

$$p(k+1) = \hat{\theta}\boldsymbol{\phi}(k) + v(k+1) \tag{8}$$

where $v(k+1) = \left(\boldsymbol{\theta} - \widehat{\theta}\right)\boldsymbol{\phi}(k) + \bar{v}(k+1)$, $v(k+1) = f(y(k), y(k-1), \ldots, y^*(k), y^*(k-1), \ldots)$. $v(k+1)$ is a nonlinear dynamic system with an unknown model structure and system order. Using the method

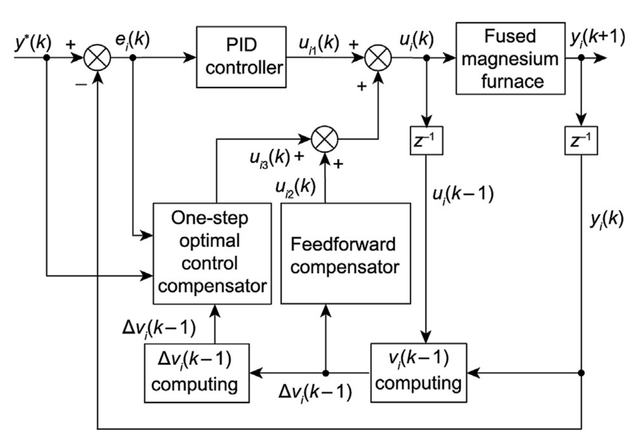

Fig. 11. Structure of signal compensation-based tracking control for the melting current.

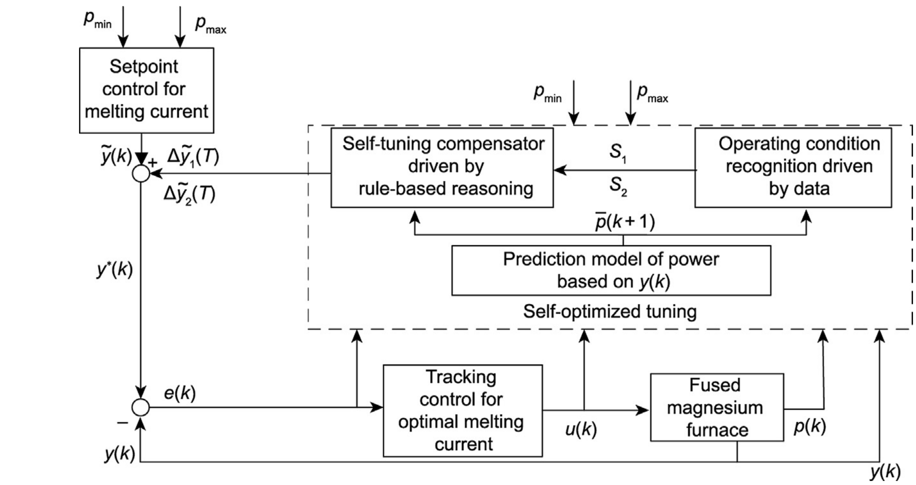

Fig. 12. Structure of the self-optimized tuning.

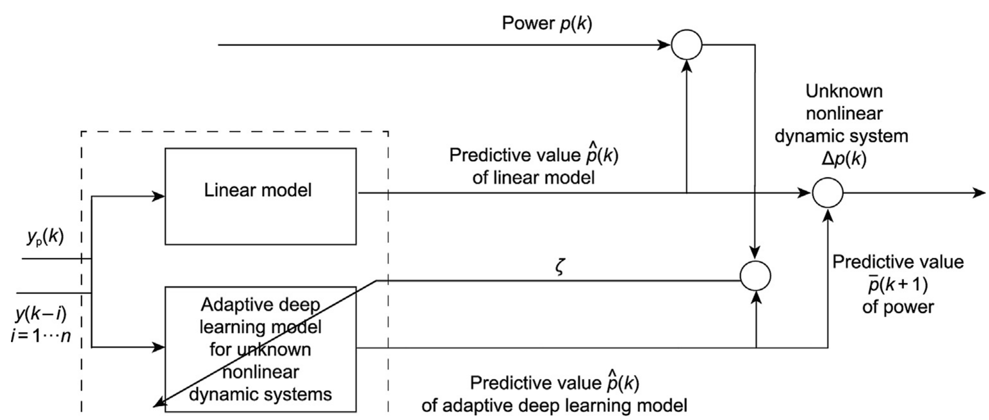

Fig. 13. Structure of the prediction model for the power.

reported in Ref. [29], the prediction model of $v(k+1)$ can be established. The prediction model consists of an online deep learning prediction model, a self-tuning deep learning model, and a self-tuning mechanism. The online deep learning prediction model and the self-tuning deep learning model adopt the same network architecture of long short-term memory (LSTM) [32]. Since $v(k+1)$ is a nonlinear system with an unknown model structure and unknown system order, its input variable is the sum of the three-phase electrode current $y(k)$ and the melting current set value $y^*(k)$, according to Eq. (8). Therefore, it is regarded as the input of a single neuron. The number of neurons n is expressed as the order of the system, and the number of nodes h and the number of network layers L of a single neuron represent the structure of the system. Although the system structure and the order of $v(k+1)$ are unknown, they can be estimated by means of the adaptive deep learning training method and big data reported in Ref. [29]. When the selected data is large enough, the estimated results remain unchanged. The deep learning model structure of $v(k+1)$ is trained offline with 30 000 sets of power and melting current data, determining that the number of neurons $n = 10$, the number of neuron nodes $h = 160$, the number of network layers $L = 3$, and the online training data window length $N = 1550$. An intelligent power-prediction algorithm is implemented using the end–edge–cloud collaboration structure shown in Fig. 14.

The prediction model of the power of the melting current setpoint control replaces $y^*(k)$ in Eq. (8) with the pre-setpoint $y_P(k)$ generated by the presetting model. The generated power-prediction value is used for the feedforward compensator, which brings $\bar{p}(k+1)$ within the target range $[p_{max}, p_{min}]$ and generates a setpoint $y^*(k)$ of the melting current that is as low as possible. The prediction model of the power of the self-optimized tuning replaces $y(k)$ in Eq. (8) by the sum of three-phase electrode currents $y_i(t)$ at the instant k, which is written as $\sum_{i=1}^{3} y_i(k)$. The generated power-prediction value $\bar{p}(k+1)$ is used for operating condition recognition and for the self-tuning compensator driven by rule-based reasoning. Self-optimized tuning eliminates abnormal operating conditions and controls $\bar{p}(k+1)$ to be as low as possible within the target range, in order to tune the setpoint of the melting current.

An intelligent control algorithm for the low-carbon operation of the fused magnesium furnace is realized by adopting an operational control system based on end–edge–cloud collaboration, as shown in Fig. 15. Fig. 16 and Table 2 show a comparison of the effects of the melting current setting and the control under manual operation control with the setpoint control for the melting current and the current-tracking control using the proposed method. The setpoint of the melting current under manual operation control

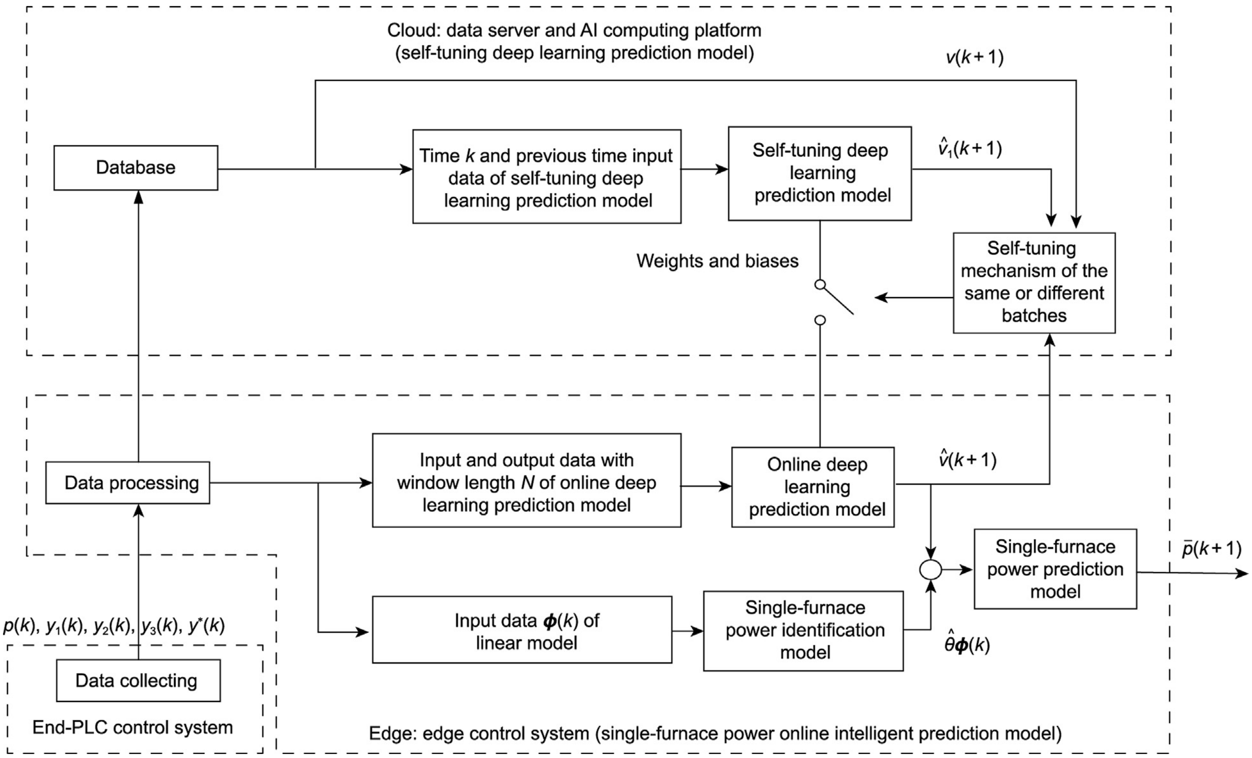

Fig. 14. Structure of single-furnace intelligent power prediction based on end–edge–cloud collaboration.

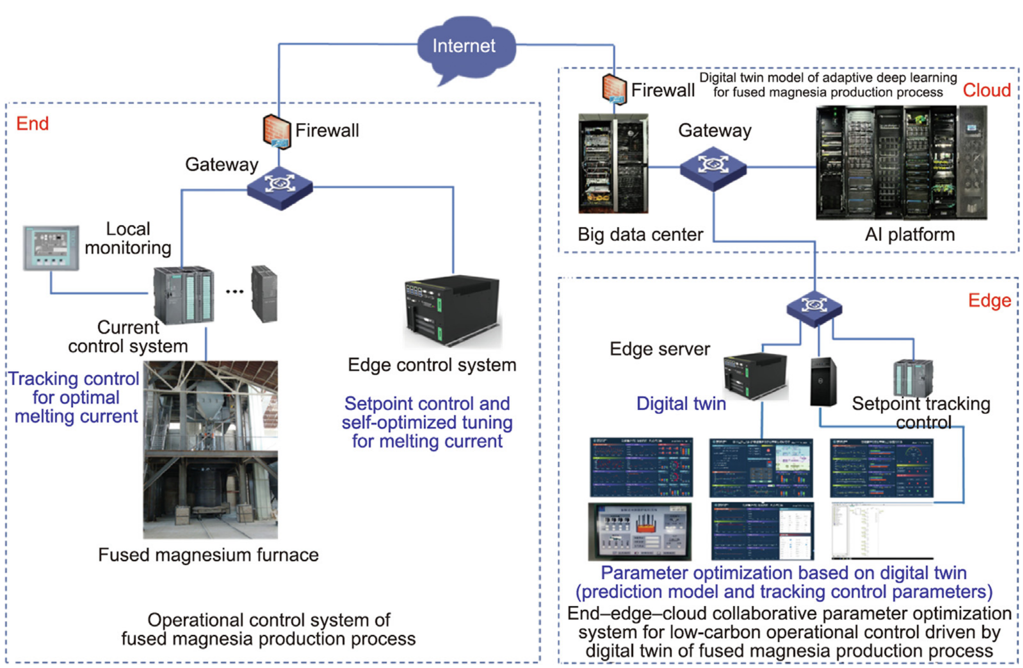

Fig. 15. Architecture of the operational control system based on end–edge–cloud collaboration.

remains unchanged. The proposed method changes the setpoint of the melting current in order to control the energy consumption per tonne to be as low as possible within the target range. Compared with manual operation control, the proposed method clearly reduces the tracking error between the three-phase electrode current and the setpoint of the melting current. The integral absolute

Table 2
A comparison of the effects of the current-tracking control.

Item	IAE			MSE		
	A-phase	B-phase	C-phase	A-phase	B-phase	C-phase
Manual control	2.12×10^6	2.08×10^6	2.19×10^6	2.28×10^6	2.31×10^6	2.01×10^6
Compensation signal drive PID control	1.35×10^6	1.61×10^6	1.32×10^6	1.37×10^6	1.74×10^6	1.26×10^6
Decrease	36.3%	22.6%	39.7%	39.9%	24.7%	37.3%

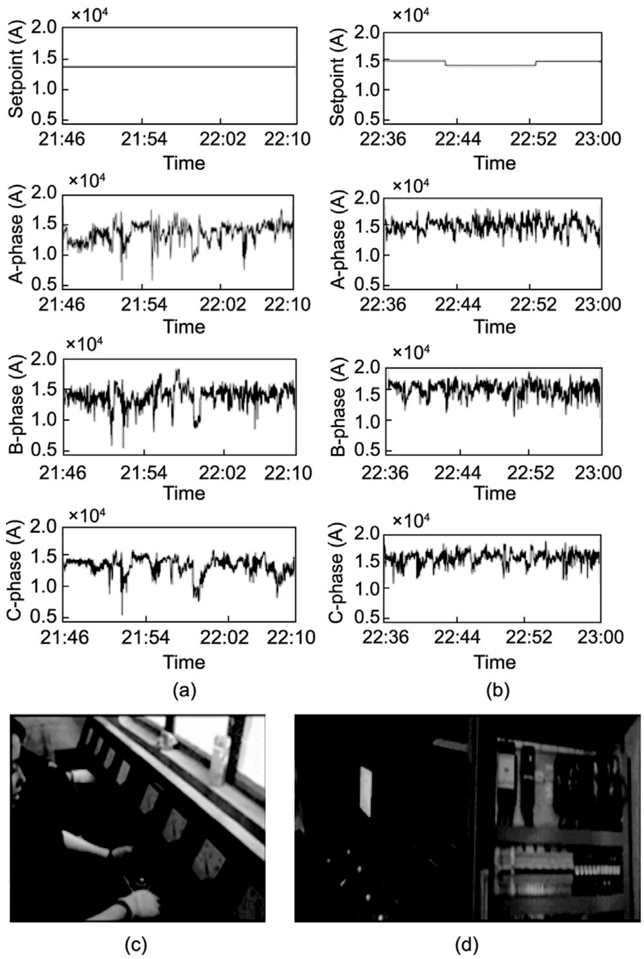

Fig. 16. (a) Manual operational control and (b) intelligent operational control curves; (c, d) images of (c) manual operational control and (d) intelligent operational control.

error (IAE) and mean square error (MSE) of the tracking error are reduced by 36.3%, 22.5%, and 39.7% and by 39.9%, 24.7%, and 37.3%, respectively. The energy consumption per tonne is reduced by 8.82%, the output rate of high-quality products is increased by 3.65%, the electrode consumption is reduced by 3.73%, and the CO_2 emissions are reduced by 8.82%.

4. Conclusions

In this paper, an intelligent control method for the low-carbon operation of energy-intensive equipment based on end–edge–cloud collaboration was proposed. The proposed method includes setpoint control, self-optimized tuning, and tracking control. The setpoint control consists of a tracking control presetting model, a prediction model of energy consumption per tonne, a feedforward compensator, and a feedback compensator. The self-optimized tuning consists of operating condition recognition, an intelligent prediction model of the energy consumption per tonne, and a self-tuning compensator. The tracking control adopts an adaptive PID controller based on signal compensation.

The proposed method was successfully applied to a fused magnesium furnace, reducing the CO_2 emissions by 8.82%, increasing the yield of high-quality products by 3.65%, and reducing the electrode consumption by 3.73%. The intelligent operational control method proposed in this paper opens up a new way to realize low-carbon operational control in the process industry. However, the following challenges will be encountered: the development of a modeling method based on digital twin technology, optimal decision-making of the setpoint for process control with conflicting objectives, the controller parameter optimization of a high-performance control system, integration of the optimal decision-making of the setpoint, and tracking control for process control. In order to realize the low-carbon operational control of complex industrial systems, the following issues require further study: developing a modeling method based on digital twins for complex production processes by combining mechanism analysis with deep learning; developing a method for high-performance control systems by combining digital twins with machine learning; developing a low-carbon operational control method for complex industrial systems based on the industrial metaverse; and establishing end–edge–cloud collaborative implementation technology for realizing the low-carbon operational control of complex industrial systems.

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Compliance with ethics guidelines

Tianyou Chai, Mingyu Li, Zheng Zhou, Siyu Cheng, Yao Jia, and Zhiwei Wu declare that they have no conflict of interest or financial conflicts to disclose.

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