Research on Algorithm Fusion for the Control of a Roots-Type Waste Heat Power Generation System

YANJUN XIAO, YAMENG ZHANG, WEI ZHOU, WEILING LIU, AND FENG WAN

School of Mechanical Engineering, Hebei University of Technology, Tianjin 300132, China

Corresponding authors: Yanjun Xiao (2504010909@qq.com) and Feng Wan (zymhebut@163.com)

ABSTRACT At present, the recovery of low-quality waste heat is a major problem in energy utilization. To solve this problem and improve energy efficiency, this research group designed a low-quality waste heat power generation device with a roots-type power machine as the core component. However, the power generation device produces a large hysteresis in power generation regulation. While the hardware can be improved, the design of the measurement and control system is also critical. In view of the problems existing in low-quality waste heat power generation devices, this research group introduced an internal model controller into the control system and designed an internal model controller and filter through the analysis of each module. In addition, to improve the performance of the controller, this research group applied the deep learning method to optimize the control system and used the prediction function of the deep learning method to further improve the stability of the device. The simulation and experimental results show that the control strategy can make this device for the recovery of low-quality waste heat respond quickly to fluctuations in the gas source and improve the hysteresis problem.

INDEX TERMS Deep learning, internal model control, low-quality waste heat, root-type power machine, waste heat power generation.

I. INTRODUCTION
A. RESEARCH BACKGROUND

With rapid economic and social development, energy consumption has increased rapidly, and method for its production and utilization have been continuously improved. The impact of energy production and consumption methods on the environment has become increasingly prominent. Energy and environmental issues have attracted increasing attention. In the current industrial production process, a large amount of industrial waste heat energy is dissipated into the environment in the form of gas, resulting in a huge waste of resources. If these thermal energy resources can be recycled, they can play a positive role in solving the current energy shortage problem.

At present, high-temperature flue gas and steam can be recovered by mature technology, but medium- and low-quality waste heat is directly discharged into the air due to immature technology for its recovery. However, low-quality waste heat resources are widely distributed, and if they can be effectively recycled and utilized, energy savings and emission reduction can be effectively achieved. Statistics show that the energy utilization rate in the industrial production process is not high, and nearly 50% of low-quality resources are eventually discharged directly with waste gas. From the perspective of environmental protection, this phenomenon has aggravated environmental pollution, and from the perspective of energy efficiency, it has wasted energy. Therefore, there is much opportunity for recycling and utilizing low-quality waste heat energy [1]. Research on low-quality waste heat recovery technology is conducive to comprehensive conservation and efficient use of resources, promotes the development of low-carbon cycles, advances the energy revolution, accelerates energy technology innovation, and builds a clean, low-carbon, safe and efficient modern energy system. In future developments, energy savings, emission reduction and environmental protection will be the top priorities of economic development.

B. LITERATURE REVIEW

Low-quality waste heat resources have huge utilization potential. To recover low-quality waste heat, a small waste
heat recovery device is needed. Therefore, small or ultra-small integrated low-quality waste heat recovery and power generation equipment will be a direction for new energy development [2]. In response to the problem of recovery of low-quality waste heat, this research group proposed the concept of a roots-type power machine based on a many previous studies. We designed a roots-type waste heat power generation device as the core to a new solution for recycling low-quality waste heat resources. The roots-type power machine is a positive displacement power machine. The displacement is proportional to the rotor speed. The three-lobe rotor has three suction and exhaust processes for each rotation [3], [4]. In the early test process, the control system response was slow, and the electric energy was unstable. By analyzing the system characteristics, we found that the main reason for this phenomenon is that fluctuations of the air source and external disturbances affect the speed of the generator. The fundamental cause of the problem is the slow response of the flow valve under the control of a traditional proportion integration differentiation (PID) controller, which is prone to oscillations and has difficulty coping with changes in flow. To improve the stability of the waste heat recovery system, it is necessary to optimize the control system and reduce its hysteresis and overshoot. Studying reasonable control algorithms to improve the response speed of the system and designing a stable and efficient control system will play a very important role in the stable operation of the waste heat recovery system. This will provide a new technological direction for energy conservation and emission reduction.

For control systems of low-quality waste heat recovery devices, PLC and single-chip controllers have many applications, and the control strategy often adopts a PID or a fuzzy PID control strategy. In power plant wastewater heat recovery, Luo Ye and others used Win CC configuration control software on the host computer and PLC as the controller and they used a PID control algorithm to maximize the recovery [5]. Some researchers also use fuzzy PID control strategies to control waste heat recovery systems. MATLAB simulations and experiments with air compressor waste heat recovery systems have shown that the control accuracy can be improved under the premise of meeting the basic requirements of the system. This kind of control method has a good effect under the conditions of low control requirements, but it cannot be applied to equipment that needs stable control, such as waste heat power generation equipment.

In the development of a diesel engine waste heat recovery system, researchers used the MotoTron rapid prototyping platform and optimized the strategy to control the exhaust gas and achieve fuel-saving effects [6]. Mingru proposed a set of map-based feedback closed-loop control algorithms in an internal combustion engine waste heat recovery system under driving conditions. First, the model reduction method was used to simplify the initial organic Rankine cycle model into a reduced-order model that could be used for control without losing an excessive amount of accuracy. Then, a rolling time domain optimization and a particle swarm optimization algorithm were combined to form a nonlinear model predictive controller. Finally, the nonlinear state estimator constituted the final feedback link, and the control effect was greatly improved [7]. Sylvain Quoilin et al. studied dynamic and static models of the organic Rankine cycle. In view of the time-varying nature of the heat exchanger, it was necessary to select different control strategies to obtain higher heat recovery efficiency [8]. This kind of optimized control algorithm effectively reduces the occurrence of oscillations and greatly improves the stability of the control system.

Pang Kuo Cheng et al. used a simulation platform to compare the VFD control strategy of the organic Rankine cycle and the pump curve control strategy. The results showed that under different heat conditions, the two control strategies have their own advantages and disadvantages [9]. To address the randomness and fuzziness of wind speed in wind power generating systems, an optimal power flow algorithm based on multiobjective random-fuzzy chance-constraint programming was proposed. The model integrated stochastic random-fuzzy simulations, a non-dominated sorting genetic algorithm (NSGA-II) and a fuzzy satisfaction maximization decision method, which is a secure and economical approach to solving voltage stability problems [10]. Wen Zhang et al. adopted a closed-loop PI control method in an internal combustion engine waste heat recovery system. The results of the world coordinated transition cycle (WHTC) showed that closed-loop PI control had a short response time and good tracking ability in the dynamic process [11]. Artificial neural networks and genetic algorithms also have shown outstanding performance in practice. Toffolo used a hybrid method that combined a genetic algorithm and sequential quadratic programming. Using his algorithm, he designed an organic Rankine cycle with no restrictions on its superstructure [12]. Combining the control methods of artificial intelligence and algorithm fusion, the control system for waste heat recovery can roughly predict the change in the data. According to the prediction, the recovery of low-quality waste heat can be controlled more effectively, avoiding situations where the system cannot recover heat energy in a stable manner due to air flow fluctuations.

In the field of machinery, Shengnan Tang et al. used a deep learning method to develop ideal automatic feature learning and fault classification, thus providing intelligent fault diagnosis based on deep learning [13]. In research on bearing fault diagnosis, Zhang et al. demonstrated the superiority of deep learning over traditional machine learning and other methods. The advantages of deep learning are mainly reflected in feature extraction and classification performance, while deep learning algorithms can also achieve many new functions [14]. In a motor control system, according to the nonlinear and coupling characteristics of the permanent magnet synchronous drive system, the loop terminal sliding mode controller is designed by using linear feedback optimization technology. In addition, the nonlinear disturbance observer is combined into the feed-forward compensation control of the system to address uncertainties in the system. The results
showed that the control system had good tracking performance and strong robustness [15]. Similarly, Toqeer et al. used static distribution compensators in a fractional-order sliding mode control to solve the power quality problem of grid voltage fluctuations and compensate the low-power distribution system with a certain amount of reactive power. The results of the new controller were compared with those of a fixed-frequency sliding mode control and a traditional proportional integral control, and the comparison showed that the new controller had the advantages of fast tracking speed and fast convergence speed [16]. In the process of researching a manipulator, Elsisi et al. used a modified neural network algorithm to optimize the controller gain, evaluated the algorithm by using a genetic algorithm and cuckoo search algorithm with a PID controller (CSA), and proved the superiority of the trajectory tracking performance of the new algorithm [17]. In terms of feature extraction, Amin Ullah et al. achieved great success in processing sequential multimedia data by using a recursive neural network and long- and short-term memory [18]. Some achievements in other fields have great reference value in solving the same types of problems. In the study of waste heat recovery systems, the characteristics of the device itself can be studied to solve problems, and problems can be solved by using the results of other fields.

C. RESEARCH GAPS AND MOTIVATIONS

In summary, there are two gaps in the field of low-quality waste heat recovery: one is the gap in the equipment, and the other is the gap in the control system. This research group designed a roots-type power machine for low-quality waste heat recovery, which solved the problem of waste heat recovery equipment to a certain extent. However, problems with the control system of this device have not been resolved. Therefore, this paper aims to study a control method that can control the stable operation of waste heat recovery equipment.

This research group summarized the characteristics of the control system through research and a literature review. Ordinary control methods cannot provide stable control of heat recovery. The optimized control method can achieve stable control to a certain extent, while the control strategy based on algorithm fusion can effectively improve the stability of waste heat recovery. For low-quality waste heat recovery power generation devices, stability is an important indicator, so its stability can be enhanced through algorithm fusion.

D. CONTRIBUTIONS AND PAPER ORGANIZATION

In this paper, the main purpose of the research on the control method of low-quality waste heat is to obtain stable electric energy. Through research, this paper proposes an internal model control strategy based on deep learning prediction, which greatly improves the tracking and anti-interference performance of the waste heat recovery system. This achievement is conducive to the development of a power supply for small equipment and provides the possibility of future grid connections. The first section of this paper describes the research background of the subject and the current problems and proposes the research content, purpose and significance of the subject. The second section analyzes the structure, working principle and process of a roots-type waste heat recovery system and shows the working characteristics of the system. In the third section, the internal model control theory based on deep learning is studied, and the control system is designed accordingly. The fourth section discussed the simulation and experimental research. Through the simulation and experimental verification, the advantages and disadvantages of the control method combining deep learning and internal model control in the control performance are obtained. The last part is the summary of this topic.

II. MODEL ANALYSIS OF WASTE HEAT RECOVERY DEVICES

A. WASTE HEAT RECOVERY PROCESS

The roots-type waste heat power generation device uses the roots-type power machine as the prime mover. It is a power device that uses a gas source containing waste heat as a working medium and the expansion effect of low-quality industrial waste heat to convert the pressure energy, flow rate, and internal energy of the gas into mechanical energy. The power generation device with a roots-type power machine as the core equipment is shown in Figure 1:

![Waste heat power generation device.](image)

The roots-type waste heat power generation device is mainly composed of the following parts: 1. Power output control cabinet; 2. Generator; 3. Roots-type power machine; 4. Pipeline for waste heat circulation; 5. Pipeline for cooling circulation; 6. Cooling fan; and 7. Base. The device is suitable for generators with rated power below 100 kW. The specific power needs to be determined according to the gas flow rate per unit time. The rated power of the generator selected in this paper is 10 kW, and the speed is 500 r/min.

Figure 2 shows the operation of the device: low-quality waste heat enters the roots-type power machine from the circulating pipeline, and the low-quality waste heat performs work in the power machine cavity to drive the rotation of the rotor. The output shaft of the roots-type power machine drives the synchronous generator to rotate through the coupling and reducer to generate electrical energy. The power output control cabinet controls the electric actuator to adjust the...
intake air volume to achieve a stable voltage value. It can also integrate the electrical energy generated by the system into the grid or withdraw electrical energy from the grid. The oil in the oil tank of the power engine enters the cooling circulation pipeline to cool the equipment. For cooling and lubrication, the oil accelerates heat dissipation, and finally, cooled oil returns to the oil tank. While dissipating heat, the transmission parts in the gearbox are also fully lubricated.

**B. CHARACTERISTICS OF WASTE HEAT RESOURCES**

1) **THE HEAT ENERGY CONTAINED IN WASTE HEAT RESOURCES**

The heat energy contained in waste heat refers to the heat energy released when a heated object is cooled to ambient temperature.

The recoverable heat energy value can be expressed as:

\[ Q = mC_p(T - T_{solid}) + mr + mC_p(T_{solid} - T_0) \]  

(2.1)

In formula 2.1, \( m \) is the mass flow rate of the sensible heat object, in t/h; \( C_p \) is the constant pressure specific heat of the sensible heat object, in J/(kg \cdot °C); and \( r \) is the latent heat of phase change of the sensible heat object, in kJ/kg. \( T \) is the discharge temperature of the sensible heat object, \( T_{solid} \) is the phase transition temperature of the sensible heat object, and \( T_0 \) is the ambient temperature, all in °C.

2) **THE EXERGY OF WASTE HEAT RESOURCES**

Calculating the exergy value of the sensible heat object can analyze the ability of the waste heat resource to do the maximum amount of work.

According to the principle of exergy analysis, if the sensible heat object changes from the steady flow opening system to the environmental state, then the energy value of the sensible heat object in the environmental state is calculated as:

\[ e_x = (h - h_0) - T_0(s - s_0) \]  

(2.2)

Since the pressure change of the sensible heat object can be ignored during the cooling process, the integral on both sides of equation 2.2 can be obtained:

\[ de_x = dh - T_0 ds \]  

(2.3)

In addition:

\[ dh = Tds + vdp \]  

(2.4)

\[ ds = \left( \frac{\partial s}{\partial T} \right)_p dT + \left( \frac{\partial s}{\partial p} \right)_T dp = \left( \frac{C_p}{T} \right) dT \]  

(2.5)

Then,

\[ dh = C_p dT \]  

(2.6)

Therefore,

\[ de_x = C_p dT - \frac{T_0}{T} dT = C_p \left( 1 - \frac{T_0}{T} \right) dT \]  

(2.7)

Therefore, the energy value of a sensible heat object per unit mass is:

\[ e_x = \int_{T_0}^{T_{solid}} C_p \left( 1 - \frac{T_0}{T} \right) dT + \left( 1 - \frac{T_0}{T_{solid}} \right) r \]  

(2.8)

In formula 2.8, \( T \) is the discharge temperature of the sensible heat object, in °C; \( C_p \) is the constant pressure specific heat of the sensible heat object, in kJ/(kg \cdot K); \( T_0 \) is the ambient temperature, in °C; and \( T_{solid} \) is the phase transition temperature of the sensible heat object, in °C.

From the above analysis, we concluded that waste heat resources have the characteristics of many research variables, mutual correlation, and strong coupling.

**C. CHARACTERISTICS OF THE POWER GENERATION DEVICE**

The roots-type waste heat power generation device uses the roots-type power machine as the prime mover and low-quality waste heat resources as the energy source. Through a series of complex physical changes, internal energy is converted into mechanical energy. During the whole process, the rotation speed of the roots-type power machine is mainly determined by the air volume in the air inlet per unit time, and the air volume per unit time is determined by the opening of the air inlet. The opening of the air inlet of the roots-type waste heat power generation device is controlled by an electric actuator.

The mathematical model of the electric actuator is:

\[ y = \alpha x + \beta \]  

(2.9)

In formula 2.9, \( x \) is the input current of the actuator, that is, the command; \( y \) is the feedback current of the actuator; \( \alpha \) is
the gain coefficient of the electric actuator; and $\beta$ is the zero error. The error of the electric actuator is mainly composed of the gain coefficient and zero error [19].

The electric actuator adopts a voltage signal with a control signal in the range of 1-5 V, and the output is the linear displacement of the electric actuator. The electric actuator is connected to the spool, and its transfer function is:

$$\frac{\bar{S}(S)}{\bar{I}(S)} = \frac{K_d}{T_D S + 1} \quad (2.10)$$

In formula 2.10, $I$ is the control signal of the electric actuator; $K_d$ is the gain of the electric actuator; and $T_D$ is the time constant of the electric actuator.

After the preliminary test, we found that under the condition of traditional PID control, the response time of the electric actuator was longer, and the time lag was more obvious. There are many system variables in the roots-type waste heat power generation device, there are more complex coupling relationships between these variables, and the system also has strong hysteresis. Therefore, the conventional control method has poor control quality and slow response, which makes the control of the roots-type waste heat power generation device inadequate and ineffective. Long- short-term memory (LSTM) has high accuracy and sensitivity in the aspects of preprocessing, feature selection and data analysis and a good ability to deal with strongly coupled data. The LSTM model can effectively deal with a large amount of data and improve the response speed of the control system while predicting the data. Internal model control (IMC) is obviously better than other control methods when it is applied to systems with large time delays. Due to its excellent tracking characteristics and anti-interference ability and a certain robustness for model mismatch, IMC can be used to solve the problems of slow response speed and poor stability under traditional PID control. Therefore, the research group proposed a control strategy based on algorithm fusion, that is, an internal model control strategy based on deep learning prediction.

III. DESIGN OF THE CONTROL STRATEGY

A. LONG- AND SHORT-TERM MEMORY DEEP LEARNING PREDICTION MODEL

Faced with a complex control object such as a low-quality waste heat power generation device, it is necessary to select the control theory and design the PID controller in a targeted manner. The roots-type power machine speed control needs to be adjusted according to the signal of the sensor, so the control system needs to process a large amount of data in a short time to predict the speed. The LSTM model is one of the typical representative methods of data prediction. Weibao-Qiao et al. established an SAE-LSTM model using LSTM, which improved the accuracy of PM2.5 prediction [20]. LSTM predicts future changes in data by extracting historical features from time series data. It is suitable for time series data processing and prediction applications in many fields [21]. Deep learning-based algorithms often have high accuracy and sensitivity in preprocessing, feature selection and data analysis [22]. Based on deep learning methods, combined with many time series historical data monitored by sensors and comprehensively considering the influence of various factors on the change of the roots-type power engine speed, the research group established an LSTM prediction model to predict the roots-type power machine speed.

The speed prediction model consists of an input layer, a hidden layer and an output layer. The model structure is shown in Figure 3.

The input layer is used to collect the pressure, temperature and flow data of the gas in the circulating pipeline. After processing by the acquisition system, these parameters enter the hidden layer in accordance with the timing sequence. The number of nodes in the input layer is $2^n$, and $n$ is the length of the historical time series.

The hidden layer mainly includes the LSTM sublayer. The LSTM sublayer is responsible for learning the long-term dependencies between each step of the time series data to perform interactions that help improve the long sequence gradient flow. Its structure is shown in Figure 4.

In Figure 4, the LSTM sublayer is composed of memory cells C, hidden state H, input gate I, forget gate F, candidate gate G, and output gate O. Among them, memory cells are a special hidden state of information flow. The forget gate is the memory cell that controls the previous time step. The function of the input gate is to control the input of the current time step. The function of the output gate is to control from the memory cell to the hidden state.
The calculation formulas of the memory cell state and hidden state at each step are:

\[
C_m = F_m \odot C_{m-1} + I_m \odot G_m \tag{3.1}
\]

\[
H_m = O_m \odot \sigma(C_m) \tag{3.2}
\]

In the formula: \(\sigma\) is the symbol for multiplying vector elements; and \(\sigma\) is the state activation function.

In each time step \(m\), the input gate \(I_m\), forget gate \(F_m\), output gate \(O_m\) and candidate gate \(G_m\) can be described as:

\[
I_m = \sigma_g(w_I x_m + R_I h_{m-1} + b_I) \tag{3.3}
\]

\[
F_m = \sigma_g(w_F x_m + R_F h_{m-1} + b_F) \tag{3.4}
\]

\[
G_m = \sigma_l(w_G x_m + R_G h_{m-1} + b_G) \tag{3.5}
\]

\[
O_m = \sigma_g(w_O x_m + R_O h_{m-1} + b_O) \tag{3.6}
\]

In the formula: \(\sigma_g\) is the state activation function, using the hyperbolic tangent function \(\tanh\) to calculate the state activation function; and \(\sigma_l\) is the gate state function.

The activation function is calculated by the formula \(\sigma(x) = (1 + e^{-x})^{-1}\). The weight in the LSTM layer is composed of a learnable input matrix \(W\), a regression weight matrix \(R\), and each component deviation matrix \(b\). These matrices are expressed as:

\[
W = \begin{bmatrix} W_I \\ W_F \\ W_G \\ W_O \end{bmatrix}, \quad R = \begin{bmatrix} R_I \\ R_F \\ R_G \\ R_O \end{bmatrix}, \quad b = \begin{bmatrix} b_I \\ b_F \\ b_G \\ b_O \end{bmatrix}
\]

All nodes in the fully connected layer are connected with the nodes in the LSTM sublayer and the external influence data to obtain all the characteristics of the input variables learned by the upper layer and external influence factors. Each step of the fully connected layer is executed independently. After the input variable is multiplied by the weight matrix \(W\), the bias matrix vector \(b\) is added. The number of output variables in this layer is equal to the number of input variables. The output is inverse normalized by the output layer \(O\) to the predicted value of the output speed of the roots-type power machine.

**B. INTERNAL MODEL CONTROL THEORY (IMC)**

The output speed of the roots-type power machine can be predicted by LSTM, and the control of the speed needs to control the valve through internal model control theory. IMC is a control method that implements controller design through process mathematical models. IMC has the characteristics of strong practicability, simple structure, easy design, few online control parameters, and easy adjustment. It can improve the robustness and anti-interference of a system. It is obviously better than other control methods when it is suitable for large time lag systems [23]. Because IMC has excellent tracking characteristics and anti-interference ability and it has a certain degree of robustness to model mismatch, the application of IMC in industrial automation is becoming increasingly widespread [24].

![Image](image-url)

**FIGURE 5. IMC structure diagram.**

The internal model controller includes a controller and a filter, and they have different roles in the control system. The controller exerts an influence on the response performance of the system, and the filter influences the robustness of the system [25], [26].

The IMC structure diagram based on the waste heat recovery system is shown in Figure 5:

Among the components, \(G_m(s)\) is the transfer function of the controlled process, \(G_m(s)\) is the internal process model function, its essence is the mathematical transfer function model of the controlled process, and \(G_{IMC}(s)\) is the internal model controller. \(r, u, y, y_m\) are the input signal (the set value), actual control value, output signal and model output of the system, respectively, and \(d\) is the external disturbance. The control objective is to keep the output signal \(y\) close to the reference value \(r\). \(y(s)\) is the output of the system, and \(y_m(s)\) is the output of the internal model \(G_m(s)\) of the controlled object. \(d(s)\) represents the influence of disturbance on output.

The waste heat power generation system contains two closed-loop systems, and the system equations are:

\[
y(s) = G_p(s)u(s) + d(s) \tag{3.7}
\]

\[
y_m(s) = G_m(s)u(s) \tag{3.8}
\]

After sorting, the following can be obtained:

\[
u(s) = G_{IMC}(s)[R(s) - (G_p(s) - G_m(s))u(s) - d(s)] \tag{3.9}
\]

To find the transfer function between the input signal \(r\) and process output signal \(y\) set in Figure 5, \(G_{IMC}(s)\) is equivalently decomposed into the area enclosed by the dotted line shown in Figure 6. Then, the internal model control in Figure 5 is transformed into the equivalent internal model control shown in Figure 6.

The internal model controller derived from Figure 6 is \(G_{IMC}(s)\):

\[
G_{IMC}(s) = \frac{G_C(s)}{1 + G_S(s)G_m(s)} \tag{3.10}
\]

According to the relationship between input and output shown in Figure 6, it can be inferred that the two model \(G_m(s)\) modules can be offset, so the equivalent internal model control structure shown in Figure 6 becomes a classic feedback control structure.
The feedback signal directly comes from the output of the system, which can be obtained from Figure 6:

\[ G_C(s) = \frac{G_{IMC}(s)}{1 - G_{IMC}(s)G_m(s)} \]  

(3.11)

The input and output relationships in Figure 6 can be expressed as:

\[ \frac{y(s)}{r(s)} = \frac{G_C(s)G_P(s)}{1 + G_C(s)G_P(s)} \]  

(3.12)

\[ \frac{y(s)}{d(s)} = \frac{G_C(s)G_P(s)}{1 + G_C(s)G_P(s)} \]  

(3.13)

Substituting formula 3.7 into formula 3.8 and formula 3.9, after sorting, the following can be obtained:

\[ \frac{y(s)}{r(s)} = \frac{G_{IMC}(s)G_P(s)}{1 + G_{IMC}(s)[G_P(s) - G_m(s)]} \]  

(3.14)

\[ \frac{y(s)}{d(s)} = \frac{G_{IMC}(s)G_P(s)}{1 + G_{IMC}(s)[G_P(s) - G_m(s)]} \]  

(3.15)

From this, it can be deduced that the closed-loop response of the system shown in Figure 6 is:

\[ y(s) = \frac{G_{IMC}(s)G_P(s)r(s)}{1 + G_{IMC}(s)[G_P(s) - G_m(s)]} + \frac{G_{IMC}(s)G_P(s)}{1 + G_{IMC}(s)[G_P(s) - G_m(s)]}d(s) \]  

(3.16)

Figure 6 shows that the feedback signal is:

\[ z(s) = [G_P(s) - G_m(s)]u(s) + D(s)d(s) \]  

(3.17)

If the system transfer function is accurate, that is, \( G_P(s) = G_m(s) \), and there is no interference signal, that is, \( d = 0 \), then the model output \( y_m \) is equal to the process output \( y \), and the feedback signal is zero. At the same time, when the system model is accurate and there is no unknown disturbance input, the internal model control system has an open-loop structure. This shows that for an open-loop and stable control process, feedback overcomes the uncertainty in the control process. That is, when the control process and process input are both clear, only feedforward (open loop) control is required, but feedback (closed loop) control is not required. However, in actual industrial control, overcoming external interference is the main task of the control system, and uncertainty of the system model is inevitable. Therefore, in the internal model control structure shown in Figure 6, the feedback signal \( z \) represents the uncertainty of the system model and the influence of external interference signals, thus forming a closed-loop control structure.

The closed-loop characteristic equation is:

\[ \frac{1}{G_{IMC}(s)} + [G_P(s) - G_m(s)] = 0 \]  

(3.18)

The necessary and sufficient condition for the stability of the internal model control closed-loop system is that all the characteristic roots of the characteristic equation are in the left half of the complex plane.

C. DESIGN OF THE INTERNAL MODEL CONTROLLER FOR THE ROOTS-TYPE WASTE HEAT POWER GENERATION DEVICE

Use the two-step design method to design the internal model controller of the roots-type waste heat power generation device and decompose the internal process model \( G_m(s) \) into two parts \( G_m(s) = G_{m+}(s) \cdot G_{m-}(s) \), where:

\[ G_{m+}(s) = e^{-T_2s} \]  

(3.19)

\[ G_{m-}(s) = \frac{K}{(T_1s + 1)(T_2s + 1)} \]  

(3.20)

The above formula \( G_{m-}(s) \) was substituted into the internal model controller filter. Since the system is a second-order system, the order of the filter \( f(s) \) is taken as \( \gamma = 2 \). After sorting, the internal model controller of the roots-type waste heat power generation device is obtained:

\[ G_{IMC}(s) = \frac{(T_1s + 1)(T_2s + 1)}{K \cdot (\lambda + 1)^2} \]  

(3.21)

For a second-order plus pure lag process, if the low-pass filter \( f(s) \) uses the second-order inertia link, then the feedback controller \( GC(s) \) can be implemented by a PID controller with a filter. In actual engineering design, the controller generally has an inertia link, so it is easier to implement.

IV. SIMULATION AND EXPERIMENT

The simplified system model obtained by modeling and calculating the system mechanism of the roots-type waste heat power generation device is a second-order pure lag system model. This part determines the parameters of the model based on the characteristics of the hardware system transfer function of the roots-type waste heat power generation device and then determines the system transfer function and the transfer function of the internal model controller. On this basis, an IMC controller based on deep learning prediction is simulated, and a roots-type waste heat power generation device system is tested.

A. SIMULATION

According to many previous experiments, the classical PID parameters based on the roots-type waste heat power generation device model are as follows: proportional gain \( K_p = 0.9775 \), integral time constant \( T_2 = 150 \), derivative time constant \( T_{d2} = 39 \), and filter coefficient \( T_{2} = 0.250 \). The above-mentioned classic PID and IMC parameters based on
deep learning predictions are integrated into the simulation function module. To test the step response control effect of the two controllers, a step signal is integrated in the functional module. The comparison simulation results of classic PID and IMC controls based on deep learning prediction are shown in Figure 6:

The dotted line in the figure is the simulation result of a classical PID, and the solid line is the simulation result of an IMC based on deep learning prediction.

In the simulation process, the transition process of the classic PID is very sensitive to parameter selection, the adjustment time and overshoot are relatively large, and the IMC controller based on deep learning prediction can converge to the optimal solution at the initial value. In contrast, the performance of IMC control based on the prediction of deep learning is significantly better than that of the classical PID control.

The actual working conditions are often not consistent with the simulation results, and there is often uncertainty. The uncertainty in this system is mainly divided into two kinds: model mismatch and small fluctuation disturbance of the air source. Model mismatch refers to the fact that the process model of the controlled object often does not match the nominal model obtained by the designer in the actual engineering control problem. Small fluctuations refer to the fluctuations in a range much smaller than the current flow value, which usually has little influence on the control results.

Keeping the control parameters of the two controllers unchanged, the input signal of the system is the same as the input of the set value tracking test of the nominal model. A certain proportion of the uncertain model is added to the process model of the controlled object, and two small amplitude fluctuations are added as small fluctuation disturbances. A simulation test is carried out on the system performance when the model is mismatched.

As seen from the curve in Figure 8, in the case of model mismatch, the system cannot return to stable output under the action of the classical PID controller. In contrast, the IMC control based on deep learning prediction can be adjusted to return to the set value after the step signal disturbance and can also be quickly recovered after the slope signal disturbance. Therefore, the IMC control based on deep learning prediction is far more robust than the classical PID controller and has a strong anti-interference performance.

The simulation results show that IMC control based on the prediction of deep learning can play a good regulatory control role for second-order pure lag links, such as roots-type waste heat power generation devices. It has better tracking and disturbance suppression capabilities for set values and disturbance signals.

**B. EXPERIMENTAL VERIFICATION AND ANALYSIS**

1) THE EXPERIMENT PLATFORM

In this paper, a roots-type waste heat power generation device is used as an experimental platform to verify the control effect of the control system for a fluctuating gas source. In this experiment, a gas storage tank with low-quality waste heat steam was used as the gas source, and the no-load experiment method was adopted to detect the output speed. The experimental platform of the roots-type waste heat power generation device is shown in Figure 9:

The specific test steps of the test with the fluctuating gas source are as follows:

A. Proofread the circuit schematic diagram and wiring diagram of the control system, and check the circuit wiring comprehensively in accordance with the relevant drawings to ensure the reliability of the control system hardware;

B. Power on to test whether the PLC, each sensor and the actuator are in normal working condition;

C. Write the test program into the controller;

D. Close the main valve, open the air compressor, and set the output gas pressure of the air storage tank to 0.6 MPa;

E. Slowly open the main valve and adjust the intake valve to the preset position to make the roots-type machine run;

F. After the synchronous generator speed stabilizes, adjust the output pressure of the gas storage tank to 0.6 MPa;

G. After stable operation of the equipment, continuously fine-tune the main valve by hand to simulate the state of interference and record data at the same time.

2) THE RESULTS OF THE EXPERIMENT

Apply the control strategy to the roots-type waste heat power generation device, set the test speed to 500 r/min, and collect the speed response curve as shown in Figure 10. During the experiment, the data on the screen were magnified by an order of magnitude to make changes in speed more apparent, with a rating of 5,000.
FIGURE 9. Experimental platform of the roots-type waste heat power generation device.

FIGURE 10. Speed curve of an air source fluctuation experiment.

Figure 10 shows a test with stable fluctuations. The simulation shown is a process in which the gas source suddenly increases in a relatively stable state, generates a fluctuation that is maintained for a period of time, and then suddenly decreases.

By analyzing the speed response curve, we concluded that the roots-type waste heat power generation device could quickly start and operate in a stable manner, accurately track the given speed, and meet the speed regulation requirements of the roots-type waste heat power generation device. When the intake pressure changes, the controller can respond quickly, adjust the intake air volume to make the roots-type power machine speed change accordingly, and achieve effective tracking of the set speed with small errors. The speed feedback value fluctuates within a small range above and below the set value, which also meets the speed regulation requirements of the output speed of the roots-type waste heat power generation device.

The test results show that under the action of the IMC controller based on deep learning prediction, the roots-type waste heat power generation device can overcome the influence of a certain range of flow changes on the speed. The static error of the control system is small, the control performance is good, and the dynamic performance is stable.

V. CONCLUSION

With the rapid development of today’s society and excessive energy consumption, waste heat recovery is an important way to conserve energy and reduce emissions. This research group has successfully developed roots-type waste heat power generation equipment and further studied its control system. The specific research content includes the following aspects:

1. By analyzing the model of a low-quality waste heat recovery system, we found that there are many variables in the system, and the coupling is strong. Traditional PID control has the characteristics of lag, slow response speed and poor stability.

2. LSTM models usually have high accuracy and sensitivity in preprocessing, feature selection and data analysis and a good ability to handle strongly coupled data. IMC has excellent tracking characteristics and anti-jamming capability and has a certain robustness to model mismatch. Therefore, the research group proposed an IMC control strategy based on deep learning prediction.

3. A deep learning prediction model was established based on the LSTM model, and the rapid prediction of the roots-type power machine was realized by combining a large amount of data recorded by sensors.

4. Combined with the parameters of the waste heat recovery system, an internal model controller is designed, and an IMC control strategy based on deep learning prediction is developed.

5. Simulation software is used to compare the previous PID control system with the current algorithm fusion control system, and the results show that the latter control performance is better. On this basis, the experimental verification of the algorithm fusion control system shows that the experimental results can meet the requirements of the indicators.

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YANJUN XIAO received the bachelor’s degree in industrial and the master’s degree in mechanical design and manufacturing and automation from Hebei University of Technology, in 2000 and 2009, respectively.

From 2001 to 2007, he worked with the Central Laboratory, School of Mechanical Engineering, Hebei University of Technology. Since 2017, he has been a Professor with the School of Mechanical Engineering, Hebei University of Technology. He is also a Professional with Jiangsu Career Leader Company Ltd. He is currently teaching at the School of Mechanical Engineering, Hebei University of Technology. His research interests include waste heat recovery and industrial control.

Prof. Xiao has won awards and honors include the title of “Three Three Three” three-level talent, Jiangsu, in 2018, the 2017 Hebei Science and Technology Innovation Award, the honorary title of “Hebei Science and Technology Talent” in 2017, and Hebei Science and Technology Innovation Award in 2019.

YAMENG ZHANG received the bachelor’s degree in measurement and control technology and electronics from Hebei University of Technology, in 2019, where he is currently pursuing the master’s degree in instrument science and technology.

His current research interests include low-quality waste heat recovery and root waste heat power generation devices.

Mr. Zhang won the Hebei Science and Technology Innovation Award in 2019.

WEI ZHOU received the bachelor’s, master’s, and Ph.D. degrees in mechanical engineering from Hebei University of Technology, in 2004, 2007, and 2010, respectively.

Since 2010, he has been working as an Associate Professor with the School of Mechanical Engineering, Hebei University of Technology. His research interests include detection technology and microfluidic technology.

WEILING LIU received the bachelor’s and master’s degrees in mechanical engineering from Hebei University of Technology, in 1995 and 1998, respectively, and the Ph.D. degree from Tianjin University, in 2006.

From 2009 to 2011, she conducted a postdoctoral research with Bao Jingling, Tianjin Academy of Environmental Protection Sciences. She is currently an Associate Professor at Hebei University of Technology. Her research interests include artificial intelligence and automation control.

FENG WANG received the bachelor’s degree in analytical instrumentation and the master’s and Ph.D. degrees in measurement and control technology and instrumentation from Tianjin University, in 1994, 2001, and 2006, respectively.

He currently teaches at the School of Mechanical Engineering, Hebei University of Technology. His research interests include thermodynamics and measurement and control technology. He has won Hebei Science and Technology Award.