

Article

Outlet Temperature Prediction and Hierarchical Energy-Saving Regulation for Air-Cooling Systems of Underground Gas Storage Injection Compressors

Jiayi Liu ¹, Tingting Jiang ¹, Hongbo Zeng ¹, De Tang ¹, Jianguo Miao ^{2,*} , Qiang Wu ³, Minyang Wang ³ and Congying Deng ³ 

¹ Chongqing Xiangguosi Underground Gas Storage Co., Ltd., Chongqing 401121, China; liujiayi2013@petrochina.com.cn (J.L.); jiangtingting@petrochina.com.cn (T.J.); jzzzenghongbo@petrochina.com.cn (H.Z.); tang_de@petrochina.com.cn (D.T.)

² School of Automation, Chongqing University of Posts and Telecommunications, Chongqing 400065, China

³ College of Integrated Circuits, Chongqing University of Posts and Telecommunications, Chongqing 400065, China; s242132022@stu.cqupt.edu.cn (Q.W.); s250601013@stu.cqupt.edu.cn (M.W.); dengcy@cqupt.edu.cn (C.D.)

* Correspondence: miaojg@cqupt.edu.cn

Abstract

The air-cooling system for injection compressors in underground gas storage (UGS) facilities is critical to operational safety. Its control must balance outlet temperature safety with fan energy savings. However, traditional empirical methods struggle to balance these dual objectives, especially for parallel multi-unit operations where quantitative scheduling guidelines are lacking. To address this, we take the eight parallel air-cooling units at the Chongqing Xiangguosi UGS facility as the research object. We propose an integrated framework that covers multi-condition outlet temperature prediction, heat transfer performance evaluation under a unified baseline, and hierarchical fan speed control. First, an adaptive sample selection mechanism is established using joint evaluation criteria that include gradient uncertainty and diversity metrics. By selecting samples with high information density, a deep neural network (DNN) model is trained to predict the outlet temperature of the air-cooling system. Second, a two-dimensional operating-condition zoning system is constructed based on ambient temperature and natural gas volumetric flow rate. This prediction model is used to fill data gaps under various conditions, enabling a performance ranking of all units under the same baseline. This ranking provides a quantitative basis for optimal unit selection at the system level. Furthermore, for individual units, multi-condition fan speed sweep simulations are conducted using HTRI Xchanger Suite. These simulations establish the mapping between thermal margin and fan speed. Consequently, a hierarchical control strategy is developed that coordinates system-level scheduling with equipment-level speed regulation. This strategy covers both normal energy-saving scenarios and over-temperature emergency scenarios, while clearly defining engineering safety constraints for low-speed operation. The application results show that the proposed method significantly reduces fan energy consumption while ensuring process safety. It offers a valuable technical reference for intelligent and energy-efficient operation of similar multi-unit heat exchange systems.



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Keywords: air-cooling system; outlet temperature prediction; thermal margin; energy-saving operation

1. Introduction

Underground gas storage (UGS) is a critical infrastructure for alleviating the spatiotemporal imbalance between natural gas supply and demand, enhancing pipeline network peak-shaving capacity, and ensuring energy security. It plays an irreplaceable role in seasonal peak shaving, emergency supply, and strategic reserve scenarios [1,2]. During the injection process, the compressor air-cooling system is responsible for cooling the high-temperature natural gas after compression, and serves as a key component in ensuring the safety of the injection operation. As the role of UGS facilities expands from single-peak-shaving to integrated peak-shaving, reserve, and security assurance [3], the operational intensity and flexibility requirements of the injection system have continued to rise. Consequently, the safe and efficient operation of the air-cooling system has become a core concern in surface facility engineering management.

In practice, however, the operating conditions of the air-cooling system exhibit pronounced time-varying behavior due to multiple factors, including injection load fluctuations, ambient temperature variations, and equipment performance degradation. For example, seasonal ambient temperature fluctuations during the gas injection period directly affect the air-cooling system and further influence the peak-shaving capacity of the gas storage facility. During the gas injection period (usually from April to October), ambient temperature varies considerably with the seasons. This fluctuation primarily affects the air-cooling system of the injection compressor. During hot summer periods, the inlet air temperature of the air cooler increases, reducing the heat transfer temperature difference. Under the same cooling load, the outlet gas temperature of the air-cooling system (i.e., the injection temperature) increases accordingly. In cold winter periods, the heat transfer capacity of the air cooler increases, and the injection temperature decreases accordingly. Changes in injection temperature subsequently affect the working gas volume of the gas storage facility through thermodynamic mechanisms. This volume represents the effective gas that can be withdrawn during peak-shaving periods. Previous studies have shown that an increase in injected gas temperature reduces the available peak-shaving gas volume of the gas storage facility under operating pressure constraints [4]. In addition, the reduced heat transfer capacity of the air cooler at high temperatures can limit the available load of the compressor during the gas injection period. This further limits the reserved peak-shaving capacity. Therefore, seasonal ambient temperature fluctuations during the gas injection period not only affect the operation of the air-cooling system but also influence the peak-shaving load of the gas storage facility through changes in working gas volume. These effects impose higher requirements on precise temperature control and coordinated energy optimization.

The compressor air-cooling system of UGS faces the dual control objectives of temperature safety and energy saving. On the one hand, if the outlet temperature is too high, the high-pressure natural gas carries a large amount of heat into the underground, which may cause thermal damage to wellhead facilities, downhole strings, and reservoir properties, threatening long-term injection-production safety. Therefore, the outlet temperature must be strictly controlled within the permissible process range. On the other hand, when sufficient cooling margin exists, the fan speed and air flow should be reduced in time to cut unnecessary energy consumption, thus achieving economical system operation. These two objectives are mutually constrained in practice. Specifically, when cooling margin is insufficient, the temperature tends to approach or exceed the limit; when margin is excessive, the fans continue running at high load, resulting in energy waste. As a typical heat exchange equipment, the air-cooling system exhibits nonlinearity, strong disturbances, and time-delay characteristics. It is difficult for traditional control methods based on operator experience to establish accurate mechanistic models, and their control strategies are often

inadequate under varying operating conditions, leading to unsatisfactory performance [5]. For direct air-cooling systems specifically, operators rely on experience to adjust back pressure, which easily deviates from the optimal operating point, adversely affecting both economic efficiency and safety [6]. Moreover, such systems are nonlinear, time-varying, multi-variable, and have large time delays, making it extremely difficult to build precise mathematical models, and conventional control schemes are often ineffective [7]. The above studies indicate that neither sole reliance on empirical experience nor purely mechanistic models can effectively address the time-varying characteristics and control demands of the air-cooling system.

To coordinate the above dual control objectives, it is first necessary to accurately obtain the dynamic evolution trend of the air-cooling system outlet temperature, so as to provide a decision basis for safety warning and energy-saving regulation. Given the inherent limitations of empirical experience and mechanistic modeling in dealing with complex operating conditions, data-driven methods have been adopted to build outlet temperature prediction models directly from historical operating data. Industrial distributed control systems (DCS) and supervisory control and data acquisition (SCADA) systems have accumulated abundant field operation data. Although these data contain noise and missing values, the dynamic information embedded within them can still support data-driven soft sensing techniques to extract key features and identify evolution patterns, thereby providing a model foundation for deploying advanced control strategies [8]. Unlike white-box mechanistic models that rely on complete physical parameters and complex mathematical equations, black-box data-driven models do not require in-depth analysis of the internal heat transfer mechanisms. They are therefore more suitable for engineering scenarios where physical parameters are incomplete and rapid modeling and simulation are needed [9,10]. In recent years, recurrent neural networks (RNNs), represented by long short-term memory (LSTM) and gated recurrent unit (GRU), have proven effective in capturing long-term dependencies in time-series data. They have been widely applied to state prediction, fault diagnosis, and health assessment of equipment such as compressors and refrigeration units [11]. For example, Ding et al. [12] successfully predicted developed a compressor performance prediction model using a genetic algorithm-back propagation (GA-BP) model. Sapmaz et al. [13] utilized a temporal neural network model to capture typical compressor operating behaviors, enabling performance prediction and anomaly detection. Ferreira et al. [14] used artificial neural networks to learn the complex nonlinear relationship between operating parameters and discharge temperature in a transcritical CO₂ refrigeration system, significantly reducing the prediction error compared with the conventional isentropic model. These studies confirm the applicability of data-driven methods for temperature prediction modeling in complex thermal equipment. The UGS injection compressor air-cooling system has accumulated a large volume of operating data, and data-driven methods can similarly circumvent the difficulty of accurately modeling complex heat transfer mechanisms, directly extracting temperature evolution patterns from data to support temperature prediction and operational regulation of the air-cooling system.

For air-cooling system outlet temperature prediction, data-driven methods have also achieved positive progress. Liu et al. [15] constructed a BP neural network optimized by the quantum genetic algorithm, achieving accurate prediction of the cooling system outlet temperature based on the intelligent control system (ICS) platform. Duan et al. [16] proposed a novel deep learning method integrating deep cross network (DCN), LSTM, and attention mechanism, achieving accurate prediction and evaluation of the equivalent heat transfer performance of two-phase heat exchangers. The above studies provide methodological references for our outlet temperature prediction model. However, most existing studies adopt random sampling to split training and test sets when building

prediction models, which cannot guarantee that the training samples effectively cover the multi-condition feature space. This limits prediction accuracy and generalization ability. Therefore, it is necessary to introduce an adaptive sample selection mechanism to accommodate the complex operating conditions of the air-cooling system.

Accurate outlet temperature prediction only solves the information acquisition problem in the safety-energy co-optimization, but is not sufficient to generate actionable energy regulation strategies directly. Therefore, to improve energy efficiency under safety constraints, the fan energy regulation problem must be further addressed, which first requires a quantitative evaluation of the current heat transfer performance of the air-cooling system. Existing evaluation methods are based on mechanistic analysis, mainly including the log mean temperature difference (LMTD) method [17], the effectiveness–number of transfer units (ϵ -NTU) method [18], and the finned tube bundle heat transfer factor correlation model [19]. However, these methods share common limitations. On the one hand, their calculation requires numerous prior parameters, such as tube bundle geometric parameters, fluid properties, and fouling resistance, making the procedure complicated and costly. In particular, for time-varying parameters such as fouling degree and fan performance degradation, obtaining them accurately is extremely difficult. On the other hand, these methods fail to incorporate the long-term operating data accumulated in the field into the evaluation framework, leaving the data value untapped and making it difficult to support large-scale performance evaluation across multiple air-cooling units.

On the basis of heat transfer performance evaluation methods, how to effectively translate the results into energy regulation strategies is a key step in the operational optimization of air-cooling systems. Existing studies have explored this direction. For example, Lyu [20] studied the air-cooling system along the western section of the Second West-East Gas Pipeline. He fitted temperature drop formulas using numerical simulation, built an optimization model aiming to minimize the total energy consumption of air coolers and compressors, and solved it using genetic algorithm, particle swarm optimization (PSO), and simulated annealing (SA) algorithms. The proposed summer-winter optimized startup schemes effectively reduced the overall energy consumption of the entire pipeline. Catrini et al. [21] addressed the high fan energy proportion in air-cooled chillers. They systematically investigated the performance characteristics of variable-frequency fans under different operating conditions and load levels, constructed performance maps between fan speed and chiller energy efficiency ratio (EER), and proposed an optimal energy-saving control strategy for variable-frequency fans, achieving significant energy reduction. Xiao et al. [22] addressed the problems of rising back pressure and increasing energy consumption in air-cooled units under high-temperature conditions. They proposed a retrofit scheme using water spray cooling, which reduces the inlet air temperature of the air cooler and enhances heat transfer through liquid film evaporation on the tube bundle surface. This approach effectively reduces back pressure and improves operational economy. The above studies explored energy optimization paths for air-cooling systems from perspectives such as system-level scheduling, control strategy optimization, and hardware retrofitting, providing methodological references for cooling system operational optimization. However, most existing methods rely on complex mechanistic models or fixed rules tailored to specific conditions, making it difficult to provide precise quantitative guidance for fan speed regulation under varying conditions. Meanwhile, insufficient attention has been paid to performance differences among multiple parallel units, and performance evaluation has not been effectively linked to unit start-stop and load allocation decisions. Moreover, the above studies are mostly oriented toward relatively steady industrial processes such as power generation and refrigeration, whose condition classification and control targets differ significantly from those of UGS injection air-cooling systems. The latter features

seasonal injection-production cycles, large load fluctuations, and parallel operation of multiple air-cooling units, imposing higher demands on adaptability and flexibility of energy regulation methods. Therefore, further research is needed on energy regulation methods that combine operational data with numerical simulation, by mining historical data to establish a quantitative relationship between cooling capacity and regulation demand, so as to achieve refined energy management in multi-unit parallel scenarios.

To address the deficiencies of existing air-cooling system regulation methods in the above three aspects—temperature prediction, performance evaluation, and energy regulation—this paper focuses on the eight parallel injection compressor air-cooling units at the Chongqing Xiangguosi UGS facility, and proposes an integrated refined regulation method that combines multi-condition temperature prediction, performance ranking under a unified baseline, and hierarchical speed regulation. First, targeting the air-cooling system outlet temperature, we construct a deep neural network (DNN) model embedded with an adaptive sample selection mechanism. This mechanism dynamically screens training samples with high information density using joint evaluation criteria, so as to enhance prediction robustness under complex multi-condition scenarios. Second, targeting the heat transfer performance of each unit, we define a thermal margin index and establish an operating-condition zoning system. The prediction model is used to fill missing data under various conditions, enabling performance ranking under a unified baseline. This provides a quantitative basis for system-level prioritized unit selection. Finally, targeting fan speed as the regulation variable, we establish the mapping relationship between thermal margin and fan speed based on simulations using HTRI Xchanger Suite. This leads to a hierarchical control strategy that coordinates system-level scheduling with equipment-level speed regulation. The outlet temperature prediction provides full-condition data support for heat transfer performance evaluation, and the performance ranking results provide the basis for prioritized unit selection in energy regulation. Thus, a closed-loop method is formed, covering state perception, performance diagnosis, and control execution, offering methodological support for the safe and energy-efficient operation of UGS injection compressor air-cooling systems.

The rest of this paper is organized as follows. Section 2 introduces the working principle and energy regulation mechanism of the injection compressor air-cooling system. Section 3 establishes the outlet temperature prediction model that integrates the adaptive sample selection mechanism with the deep neural network (DNN), validates its prediction accuracy, and compares it with other typical models. Section 4 proposes the performance evaluation and energy regulation strategy for the air-cooling system based on thermal margin. This includes the definition of the thermal margin index, the operating-condition zoning method, multi-unit performance ranking, and the construction of the mapping relationship between thermal margin and fan speed based on HTRI simulations, as well as the hierarchical regulation method. Section 5 summarizes the conclusions of this study.

2. Working Principle and Energy Consumption Control Mechanism of the Gas Injection Compressor Air-Cooling System

2.1. Operating Principle of the Cooling System

The Chongqing Xiangguosi Underground Gas Storage Gathering Station is equipped with eight sets of natural gas compression and injection systems, each consisting of a 4000 kW four-cylinder natural gas compressor unit and a companion forced-draft air-cooling tower. Each air-cooling tower adopts a combined primary and secondary cooling configuration, employing a 180-2ZF type air-cooled heat exchanger with dual-fan forced-draft cooling. Each fan has a rated power of 56 kW and an impeller diameter of 4572 mm, with a total design airflow rate of 18,722 m³/min.

In routine gas injection operations, the two-stage series configuration constitutes the fundamental and normal operating mode of the compressor unit and the air-cooling system. Natural gas first enters the primary compression cylinder for boosting, and the high-temperature gas after compression is then sent to the primary cooler of the air-cooling system for temperature reduction. After being cooled, the gas enters the secondary compression cylinder for further boosting to the final discharge pressure, and subsequently passes through the secondary cooler of the air-cooling system to be cooled to the specified outlet temperature. The two-stage series compression enables the discharge pressure to reach nearly 30 MPa, satisfying the high-pressure injection requirement of the underground reservoir. In this process, the primary and secondary coolers of the air-cooling system remain in continuous operation and are arranged in series according to the compression sequence. The primary cooler undertakes inter-stage cooling, while the secondary cooler performs final deep cooling, ensuring precise control of the outlet temperature to meet the process requirements at each compression stage and the final discharge.

The two-stage series configuration achieves a rational distribution of the thermal load between the two coolers through the synergistic action of stepwise boosting and stepwise cooling, effectively eliminating the problem of excessive load concentration in a single stage. Meanwhile, the graded and progressive pressurization and cooling process helps reduce the thermal differential stress and mechanical impact imposed on the compression and heat-exchange equipment, which helps extend the service life of the equipment. The cooling performance of the air-cooling system is directly related to the reliability and safety of the gas injection system, while its energy consumption level constitutes a critical factor affecting the overall economic efficiency of the gathering station.

2.2. Energy Consumption Mechanism of the Cooling System

The operational energy consumption of the gas injection compressor cooling system is primarily concentrated in the fan system. During fan operation, electrical energy is converted into mechanical energy that drives the impeller to rotate, achieving cooling of the natural gas through forced air convective heat transfer. In engineering practice, fan energy consumption can be directly characterized by shaft power. According to the fundamental theory of fans, the shaft power N can be expressed by Equation (1).

$$N \propto \frac{QP}{\eta} \quad (1)$$

where Q is the air flow rate (m^3/s), representing the volume of air delivered per unit time; P is the total pressure (Pa), representing the pressure provided by the fan to overcome the total system resistance; η is the fan efficiency.

For a continuously operating cooling system, the system resistance characteristics remain relatively stable over a given operating period, and the variation in equipment efficiency within the normal operating range is also limited. Therefore, the regulation of fan energy consumption can be simplified to the control of air flow rate Q . On this basis, the present study identifies the following two air flow regulation methods, thereby enabling direct control of shaft power.

(1) Rotation Speed Regulation Method

This method achieves precise control of the impeller rotational speed by varying the operating frequency of the fan drive motor through a variable frequency drive. According to the fan affinity laws [23], the volumetric flow rate of the fan is proportional to the

rotational speed, while the shaft power is proportional to the cube of the rotational speed, as expressed in Equations (2) and (3), respectively.

$$\frac{Q_1}{Q_2} = \frac{n_1}{n_2} \quad (2)$$

$$\frac{P_1}{P_2} = \left(\frac{n_1}{n_2}\right)^2 \quad (3)$$

Combining Equations (2) and (3), the quantitative relationship between fan shaft power and rotational speed can be derived as shown in Equation (4). This relationship indicates that fan power consumption decreases at a cubic rate with decreasing rotational speed, revealing the significant advantage of rotational speed regulation in fan energy saving.

$$\frac{N_1}{N_2} = \left(\frac{n_1}{n_2}\right)^3 \quad (4)$$

The above equations quantitatively describe the effect of rotational speed regulation on fan energy consumption. In actual engineering practice, factors such as variations in fan efficiency and transmission losses typically result in actual energy savings slightly lower than the theoretically calculated values; nevertheless, the energy-saving trend revealed by the cubic relationship in Equation (4) still provides significant engineering guidance. Combined with the technical advantages of variable frequency speed control—namely, mature and reliable technology, high control precision, and wide regulation range—rotational speed regulation constitutes the primary technical pathway for achieving energy efficiency optimization in air-cooling systems.

(2) Blade Pitch Angle Regulation Method

Blade pitch angle regulation adjusts the airflow angle of attack by altering the blade installation angle, thereby modifying the aerodynamic characteristics of the fan. Increasing the blade pitch angle enhances the lift characteristics and shifts the performance curve upward, enabling the fan to generate a higher pressure head and greater flow rate at the same rotational speed. Unlike rotational speed regulation, the energy consumption characteristics of pitch angle regulation exhibit an approximately linear or quadratic relationship, which cannot achieve the cubic energy-saving benefit unique to rotational speed regulation. Consequently, its energy-saving effect is considerably lower than that of rotational speed regulation.

In summary, rotational speed regulation, by virtue of its cubic energy-saving characteristic, represents the core technical pathway for energy efficiency optimization in air-cooling systems; blade pitch angle regulation, with its limited energy-saving effect, can serve as an auxiliary control measure under over-temperature conditions. The subsequent control strategy of this paper is founded upon this theoretical basis, establishing a hierarchical regulation system with rotational speed regulation as the primary approach and pitch angle regulation as the supplementary measure.

3. Data-Driven Prediction Model for Outlet Temperature of Cooling System

Accurate acquisition of the outlet temperature is the fundamental prerequisite for quantitative performance evaluation and dynamic operational regulation of the air-cooling system. However, due to the complexity of field operating conditions, manually recorded data are often incomplete and fail to cover the full range of operating conditions. To comprehensively evaluate the operational status of each unit under full operating conditions, it is necessary to employ a prediction model to reasonably infer the outlet temperatures for va-

cant operating conditions. To this end, this chapter constructs a deep neural network (DNN) integrated with an adaptive sample selection mechanism to predict the outlet temperature of the air-cooling system, enabling effective imputation of missing operating-condition data and thereby providing full-condition data support for subsequent performance evaluation and control strategy development.

3.1. Historical Operating Data Processing for the Gas Injection Compressor Air-Cooling System

This study focuses on the eight compressor units and their associated air-cooling systems at the Chongqing Xiangguosi Underground Gas Storage Gathering Station. Historical monitoring data were obtained from equipment operation and maintenance records, covering the period from 2022 to 2025. For the operating parameters (e.g., inlet pressure, discharge pressure, inlet gas temperature, and compressor cylinder discharge temperature), six samples were collected daily between 03:00 and 23:00 at a fixed sampling interval of 4 h, and their average was used as the daily operating parameter for subsequent modeling. The routine operational parameters (e.g., average ambient temperature, daily gas throughput, and loading time) were recorded once per day. A total of 29,790 raw records were obtained for the eight units. To ensure the generalization performance and output reliability of the subsequent prediction model, a series of outlier identification criteria was established during data preprocessing to identify anomalous and missing data caused by factors such as on-site sensor signal interference and incomplete equipment maintenance records. These problematic data accounted for approximately 23.27% of the total data volume, and 22,858 valid records were retained after processing.

- (1) Operating-condition consistency criterion. The primary compressor suction pressure is adopted as the benchmark for operating-condition classification. Based on the statistical analysis of historical data, its normal operating range is determined to be 5–10 MPa. Data records falling outside this range are identified as anomalies and are accordingly discarded.
- (2) Statistical distribution criterion. Based on the 3σ rule, zero values and data points deviating by more than three times the global standard deviation are treated as outliers. Depending on the data characteristics, these are either replaced by the mean value of the same date or removed directly.
- (3) Physical plausibility criterion. Based on the thermodynamic coupling between the compressor unit and the inter-stage cooling system, data records that violate fundamental physical laws are corrected or removed. A typical criterion is as follows: if the discharge temperature of the secondary compressor cylinder is lower than the unit outlet temperature, indicating that the secondary air cooler has failed to achieve effective heat exchange, the corresponding record is corrected or eliminated to ensure that the data truthfully reflect the equipment operating status. For such anomalies, the following correction and rejection criteria are established: (i) if the anomaly is a single point or lasts for no more than two consecutive sampling points, and the adjacent data are stable, it is regarded as a transient disturbance and corrected by linear interpolation; (ii) if the anomaly persists for three or more consecutive sampling points, or the proportion of abnormal data for the same unit during the same period exceeds 5%, it is regarded as an irreparable systematic error and is directly rejected.

Based on the above criteria, outliers in the historical operational data can be effectively identified and processed, providing a reliable data foundation for the subsequent development and training of the prediction model. Notably, the above data processing and modeling are performed on a unit-by-unit basis. Although the eight units are of the same type and share the same operating mode, they differ in commissioning date, cumulative operating hours, and maintenance history. The operating records of each unit therefore

constitute an independent dataset, on which a separate prediction model is trained. Accordingly, each unit's performance degradation is captured and learned by the model as a unit-specific data feature, rather than being conflated across units.

3.2. Outlet Temperature Prediction Model Based on Deep Neural Network with Adaptive Sample Selection Mechanism

Although the historical operational dataset obtained in Section 3.1 is free of anomalies and exhibits clear trending characteristics, it still suffers from large data volume and complex distribution patterns. Conventional machine learning-based regression methods are often inadequate for capturing the deep-level features of the data, thereby failing to achieve prediction accuracy of engineering significance. To address this issue, the present study proposes a prediction method that integrates a DNN with an adaptive training sample optimization mechanism, combined with a data correlation analysis approach based on HTRI simulation, to achieve high-precision prediction of the unit outlet temperature.

3.2.1. Correlation Analysis of Key Parameters Based on HTRI Simulation

To ensure the validity of the input variables for the outlet temperature prediction model, it is necessary to identify the key operating parameters that exhibit strong correlation with the unit outlet temperature. Given the complex operating conditions and strong nonlinearity of the air-cooling system data, this paper proposes a correlation analysis method based on HTRI simulation. This method leverages the industrial-grade heat-transfer experimental data and thermodynamic models embedded in the HTRI software (Version 7.0) to rapidly identify strongly correlated parameters. In the HTRI software, the required input parameters include air velocity, mass flow rate, and heat exchanger inlet and outlet temperatures and pressures [24]. To evaluate the accuracy and reliability of the HTRI model, several operating conditions of Unit 1 in 2024 were selected. Table 1 compares the HTRI-simulated outlet temperatures with the corresponding measured values. The maximum relative error between the simulated and measured values is 2.11%, indicating good agreement between the simulation results and field measurements. This provides a reliable basis for the subsequent correlation analysis of key parameters using the HTRI model. The control variable method is adopted herein, keeping all parameters except than the evaluated one at their benchmark values, with the benchmark operating conditions listed in Table 2.

Table 1. HTRI performance validation.

Date	Actual Outlet Temperature/°C	Simulated Temperature/°C	Temperature Deviation/°C	Relative Error
24 June 2024	47.88	48.89	−1.01	2.11%
25 June 2024	48.77	49.14	−0.37	0.76%
27 June 2024	47.12	46.72	0.4	0.85%
1 July 2024	50.68	51.27	−0.59	1.69%
4 July 2024	51.3	52.31	−1.01	1.97%

Table 2. Baseline parameters for HTRI simulation conditions.

Parameter	Flow Rate (kg/s)	Air Velocity (m/s)	Air Cooler Inlet Gas Temperature (°C)	Discharge Pressure (MPa)	Ambient Temperature (°C)
Baseline value	14	6.8	65 °C	19	25 °C

This study focuses on analyzing the relationships between four variables—inlet pressure, ambient temperature, discharge pressure, and volumetric flow rate—and the outlet

temperature. According to thermodynamic theory, the inlet pressure is directly related to the discharge temperature of the secondary compressor cylinder, and the volumetric flow rate is linearly related to the mass flow rate. Therefore, in the HTRI simulations, the inlet gas temperature and mass flow rate of the air cooler for the second-stage compressor cylinder are used as substitute input parameters. The variation trends of outlet temperature with respect to different operating parameters are shown in Figure 1. The results indicate that all four variables exhibit a significant positive correlation with the outlet temperature. Accordingly, they are identified as strongly correlated variables and incorporated as input features for the subsequent prediction model.

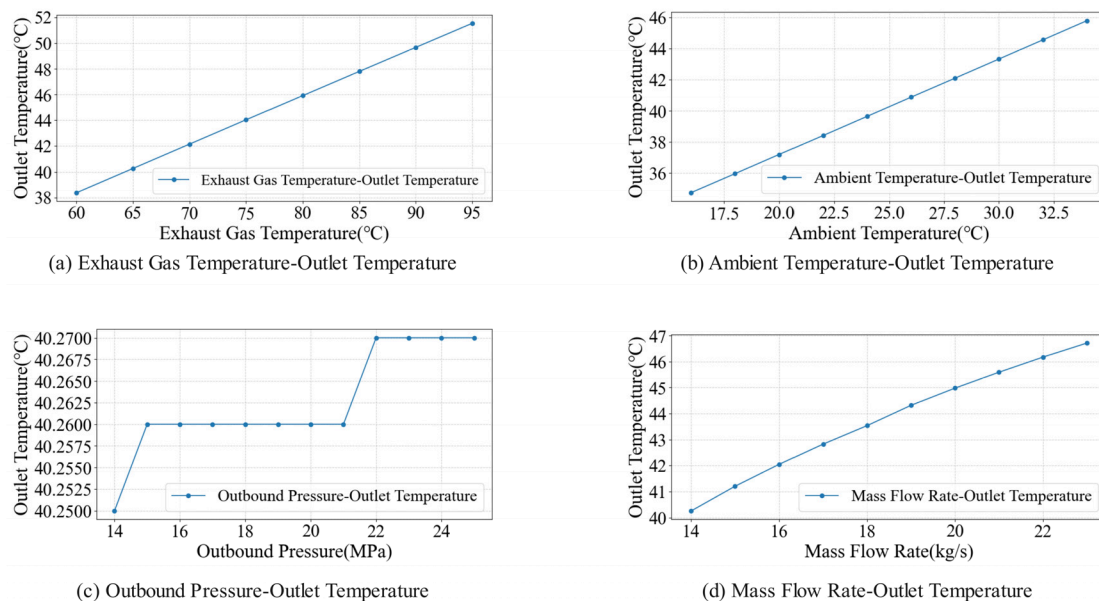


Figure 1. HTRI simulation curves of outlet temperature versus key operating parameters.

3.2.2. Deep Neural Network-Based Outlet Temperature Prediction Model

The DNN is a type of feedforward neural network with a multi-layer hierarchical architecture, consisting of a large number of interconnected neurons. Through multiple hidden layers, the network progressively extracts and transforms input features, enabling complex nonlinear mapping from input variables to output targets. The DNN typically adopts a fully connected architecture, with information transmission and feature transformation between layers accomplished via nonlinear activation functions, thereby effectively learning deep patterns in high-dimensional data. The DNN architecture adopted in this paper is illustrated in Figure 2.

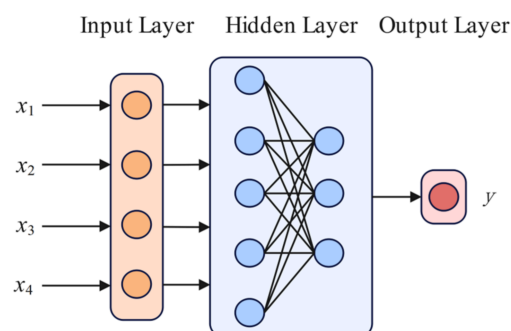


Figure 2. Deep neural network prediction model architecture.

The output of the l -th layer, a^l is given by:

$$a^l = \sigma(z^l) = \sigma(W^l a^{l-1} + b^l) \quad (5)$$

where a^l is the output of the l -th layer, W^l is the matrix of linear coefficients for the l -th layer, and b^l is the bias of the l -th layer.

The DNN is flexible in application and suitable for prediction tasks involving various nonlinear complex systems; however, it is prone to overfitting. To mitigate such risks, L2 regularization [25] and an adaptive learning rate decay strategy are introduced during network construction. The modified loss function and learning rate of the DNN are given by Equations (6) and (7), respectively:

$$J_{L2}(w) = J(w) + \lambda \|w\|_2^2 \quad (6)$$

where $J(w)$ is the loss function, $\|w\|_2$ is the L2 norm, and λ is the regularization strength hyperparameter—the larger its value, the greater the penalty imposed by regularization.

$$lr(epoch) = lr_0 \times \gamma^{\frac{epoch}{T}} \quad (7)$$

where lr_0 is the initial learning rate, epoch is the number of training epochs, and γ is the decay factor, set to 0.7 in this study.

By introducing the above techniques, the typical deficiencies of traditional DNN models in architectural design and training procedures can be effectively compensated, significantly enhancing the model's generalization capability and prediction accuracy. The implementation workflow of the optimized DNN is shown in Figure 3.

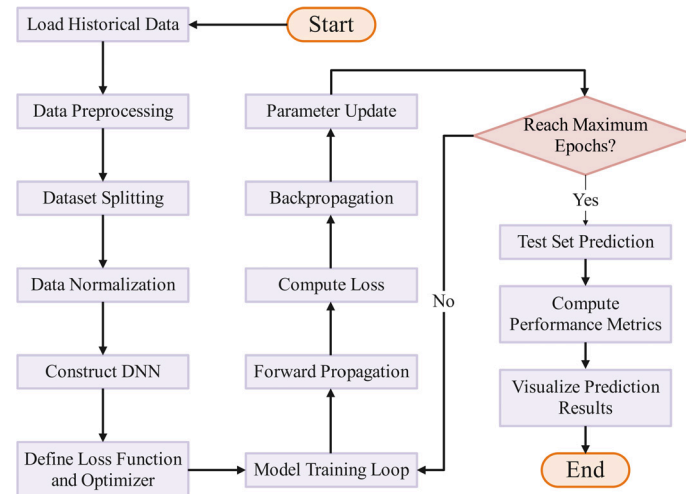


Figure 3. Deep neural network prediction workflow.

3.2.3. Adaptive Sample Selection Mechanism

Conventional neural networks typically adopt random sampling for dataset partitioning. However, the random approach often fails to comprehensively represent the overall data distribution and carries a non-negligible risk of omitting key feature regions or over-aggregating within specific intervals. To address this issue, the present study proposes an adaptive sample selection mechanism that progressively screens a subset of samples with high information density and strong representativeness from the sample pool through an intelligent selection strategy, thereby effectively improving the prediction accuracy and generalization capability of the model. The evaluation metrics adopted by the adaptive selection mechanism are as follows.

- (1) Uncertainty estimation metrics. Uncertainty estimation encompasses two methods: gradient uncertainty and query-by-committee voting.

(i) Gradient uncertainty. This method evaluates uncertainty by adding small random perturbations to the input samples and observing the magnitude of variation in the prediction results [26]. A larger variation indicates higher gradient sensitivity of the model to the sample, implying stronger uncertainty. Let the original unlabeled sample be x_i , and let the sample after adding Gaussian noise is:

$$x'_i = x_i + \varepsilon \cdot N(0, 1) \quad (8)$$

where ε is the perturbation magnitude, set to 0.01 in this study.

The gradient uncertainty is then mathematically expressed as:

$$\text{grad_uncert}(x_i) = |\hat{y}(x_i) - \hat{y}(x'_i)| \quad (9)$$

(ii) Query-by-committee (QBC) voting mechanism. This method constructs a committee of multiple models and uses the degree of prediction disagreement among the committee members to measure the uncertainty of a sample. The greater the disagreement among members, the higher the informational value of that sample. Let the committee consist of C models (taking $C = 3$ in this study), and let the prediction of the c -th model on sample x_i be $\hat{y}_c(x_i)$. Then:

$$\text{QBC}(x_i) = \frac{1}{C} \sum_{c=1}^C |\hat{y}_c(x_i) - \bar{\hat{y}}(x_i)| \quad (10)$$

where $\bar{\hat{y}}(x_i)$ is the mean prediction of the committee, expressed as:

$$\bar{\hat{y}}(x_i) = \frac{1}{C} \sum_{c=1}^C \hat{y}_c(x_i) \quad (11)$$

- (2) Diversity metric. A sample diversity score is adopted to measure the diversity of samples, ensuring that the selected samples adequately cover different regions of the input feature space and avoid redundancy [27]. In Euclidean space, the greater the distance between an unlabeled sample and the labeled samples, the higher its diversity.

Assuming the labeled sample set is $X_{\text{labeled}} = \{x_1^L, \dots, x_k^L\}$, and the unlabeled sample is x_i^U , the Euclidean distance between them is expressed as:

$$\text{dist}(x_i^U, x_j^U) = \sqrt{\sum_{d=1}^D (x_i^U - x_j^U)^2} \quad (12)$$

The similarity between the two samples is then given by:

$$\text{diversity}(x_i^U) = \text{mindist}(x_i^U, x_j^U) \quad (13)$$

- (3) Expected model change (EMC). EMC is used to evaluate the expected contribution of an unlabeled sample to the model parameter update once it is incorporated into the training set. A larger expected contribution indicates higher potential value of the sample for model training, which should therefore be prioritized for labeling [28]. The sample contribution is calculated as:

$$\text{EMC}(x_i^U) = |\hat{y}(x_i^U) - \bar{\hat{y}}| \quad (14)$$

where $\hat{y}_i$ is the predicted output for the unlabeled sample, and the computed value—the larger it is, the more prominent the role of the sample.

- (4) Score normalization and weighted fusion. After the above metrics (1)–(3) are computed, each score needs to be normalized and fused with weighted averaging to obtain a final comprehensive evaluation index for guiding sample screening and optimization.

(i) Score normalization. Normalization is a prerequisite for weighted fusion, aiming to map scores of different magnitudes to the $[0, 1]$ interval to eliminate the influence of dimensional differences on the fusion result. The min-max normalization method is adopted. Let the raw score be s , the normalized expression is:

$$s'_i = \frac{s_i - \min(s)}{\max(s) - \min(s)} \quad (15)$$

(ii) Weighted fusion strategy. A weighted summation method is employed to integrate the various scoring results, with weight allocation as shown in Table 3. Among them, gradient uncertainty receives the highest weight (0.4), as it directly reflects the model's cognitive blind spots regarding the sample, contributing most significantly to improving prediction robustness under complex multi-condition scenarios. The diversity metric is assigned the second-highest weight (0.3), aiming to ensure that the training samples cover different regions of the input feature space, thereby avoiding redundancy and local overfitting—particularly important for storage facility operational data characterized by seasonal injection–withdrawal cycles and significant load fluctuations. EMC is weighted at 0.2, and is used to evaluate the potential impact of samples on model parameter optimization, focusing on the selection of critical samples. QBC receives the lowest weight (0.1), mainly serving as a supplementary validation for uncertainty estimation, given its relatively high computational cost and certain informational overlap with gradient uncertainty. The above weight allocation follows the principle of “higher contribution, higher weight,” balancing model generalization performance with training efficiency.

Table 3. Weights for scoring metrics in the adaptive sample selection mechanism.

Scoring Metric	Gradient Uncertainty	Diversity	EMC	QBC
Weight	0.4	0.3	0.2	0.1

Based on the weight allocation in Table 3 and the computed scores, the final comprehensive score for each sample is:

$$\text{combined}(x_i^U) = 0.4s'_{\text{grad}} + 0.3s'_{\text{diversity}} + 0.2s'_{\text{EMC}} + 0.1s'_{\text{QBC}} \quad (16)$$

According to the comprehensive score obtained from Equation (16), candidate samples are ranked in descending order. In each iteration, a certain number of top-ranked samples are selected and added to the training set, and the model is retrained. As the iteration proceeds, the training samples progressively concentrate toward high-information-density regions, and the model's prediction accuracy under critical operating conditions improves iteratively. The selection process terminates upon reaching the preset performance target. Specifically, a composite early stopping criterion is defined as follows: (i) the number of iterations exceeds 20 and the number of labeled samples reaches the preset target sample size; (ii) the MAPE on the validation set is adopted as the evaluation metric, and the model accuracy is considered to have plateaued when the improvement in the average MAPE over the most recent five iterations relative to the previous five iterations is less than 2%; (iii) the

current MAPE exceeds the historical best MAPE by 5%, indicating possible overfitting or performance degradation. When all of the above conditions are satisfied, the preset performance target is deemed reached, and the active learning loop is terminated, as the model is unlikely to achieve significant improvement from newly added samples. The overall workflow is shown in Figure 4.

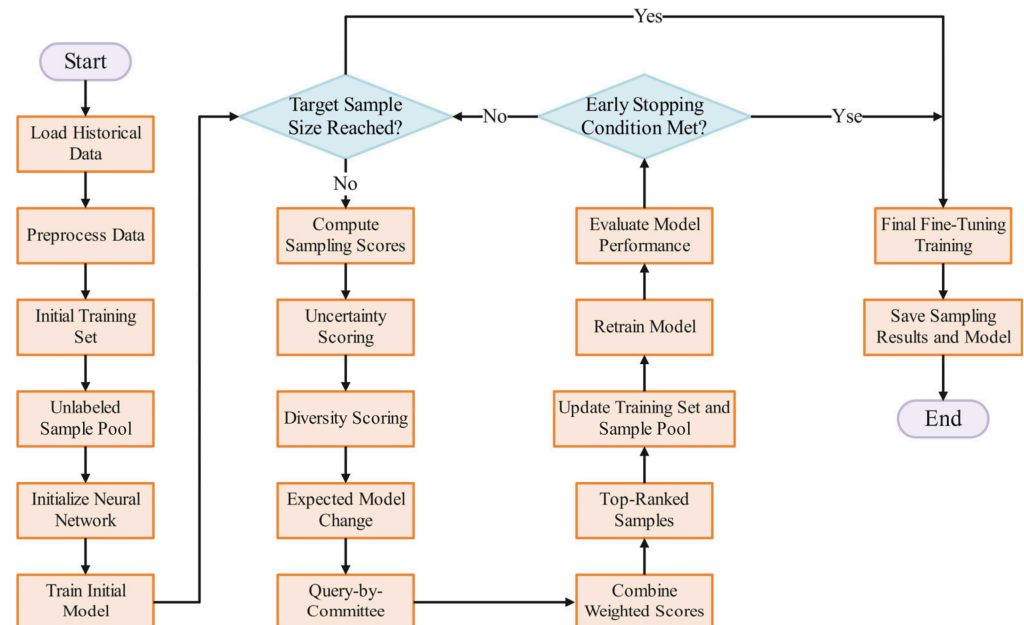


Figure 4. Execution workflow of the adaptive sample selection mechanism.

3.3. Model Training and Comparative Validation of Prediction Performance

Based on the historical operational dataset processed in Chapter 2 and the parameter correlation analysis results in Section 3.1, the inlet pressure, discharge pressure, ambient temperature, and volumetric flow rate are used as input variables, with the unit outlet temperature as the output variable. These are imported into the adaptive sample selection–DNN framework constructed in Section 3.2, with the dataset partitioned into training and test sets at a ratio of 7.5:2.5. The key training hyperparameters are listed in Table 4. These hyperparameters were selected primarily based on the characteristics of the prediction task and the convergence behavior of the training process. The model has four input variables and one output variable, which constitutes a low-dimensional regression problem. For such a problem, two hidden layers are sufficient to capture the nonlinear mapping between the operating parameters and the outlet temperature; further increasing the network depth would provide only marginal improvement in representational capacity while increasing the risk of overfitting. The two hidden layers contain 128 and 64 neurons, respectively, followed by one output neuron, forming a 128–64–1 architecture. This progressive reduction in layer width compresses the feature dimension while preserving sufficient representational capability and avoiding parameter redundancy. In terms of training behavior, a batch size of 32 provides a balance between gradient estimation stability and computational efficiency. An initial learning rate of 0.01 with a decay factor of 0.7 applied every 50 epochs enables the learning rate to decrease progressively during training, allowing rapid convergence in the early stage and finer convergence toward the optimum in the later stage. Overall, these settings achieve a favorable balance among model capacity, convergence speed, and generalization ability while keeping the network compact.

Table 4. Hyperparameter settings for DNN model training.

Parameter	Setting Value
Maximum number of epochs	400
Batch size	32
Initial learning rate	0.01
Number of network layers	3
Number of neurons	128-64-1
Optimizer	Adam
Activation function	RELU

This study adopts the root mean square error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2) as evaluation metrics for model prediction performance, calculated according to Equations (17)–(19), respectively.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (17)$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \frac{|y_i - \hat{y}_i|}{y_i} \quad (18)$$

$$R^2 = \frac{\sum (y_i - \bar{y})^2}{\sum (y_i - \hat{y}_i)^2} \quad (19)$$

where y_i is the true value of the sample, $\bar{y}$ is the mean value of the samples, and $\hat{y}_i$ is the predicted value obtained from the prediction model.

To comprehensively validate the effectiveness of the proposed method, Random Forest, K-nearest neighbors (KNN), BP neural network, and convolutional neural Network (CNN) are selected as benchmark models for comparison. Taking Compressor Unit No. 5 as an example, the prediction performance comparison of each model is shown in Table 5. The fitting curves between predicted values and actual values for all eight air-cooling units are presented in Figure 5.

Table 5. Performance metrics comparison of different prediction models.

Metric	Random Forest	KNN	BP Neural Network	CNN	Proposed Method
RMSE	1.8476	1.9604	1.5001	1.7918	1.1794
MAPE	2.82%	3.19%	2.55%	3.01%	1.87%
R^2	0.9463	0.9395	0.9646	0.9495	0.9774

As shown in Table 5 and Figure 5, the proposed method achieves the best prediction performance among all benchmark models, with the lowest RMSE and MAPE of 1.1794 and 1.87%, respectively, and an R^2 of 0.9774. The predicted values are highly consistent with the actual values in terms of trend. The above results indicate that the proposed method exhibits good adaptability and consistency across different equipment units, with prediction accuracy meeting engineering application requirements. It can thus provide reliable data support for subsequent imputation of missing operating-condition data and energy consumption control analysis of the cooling system.

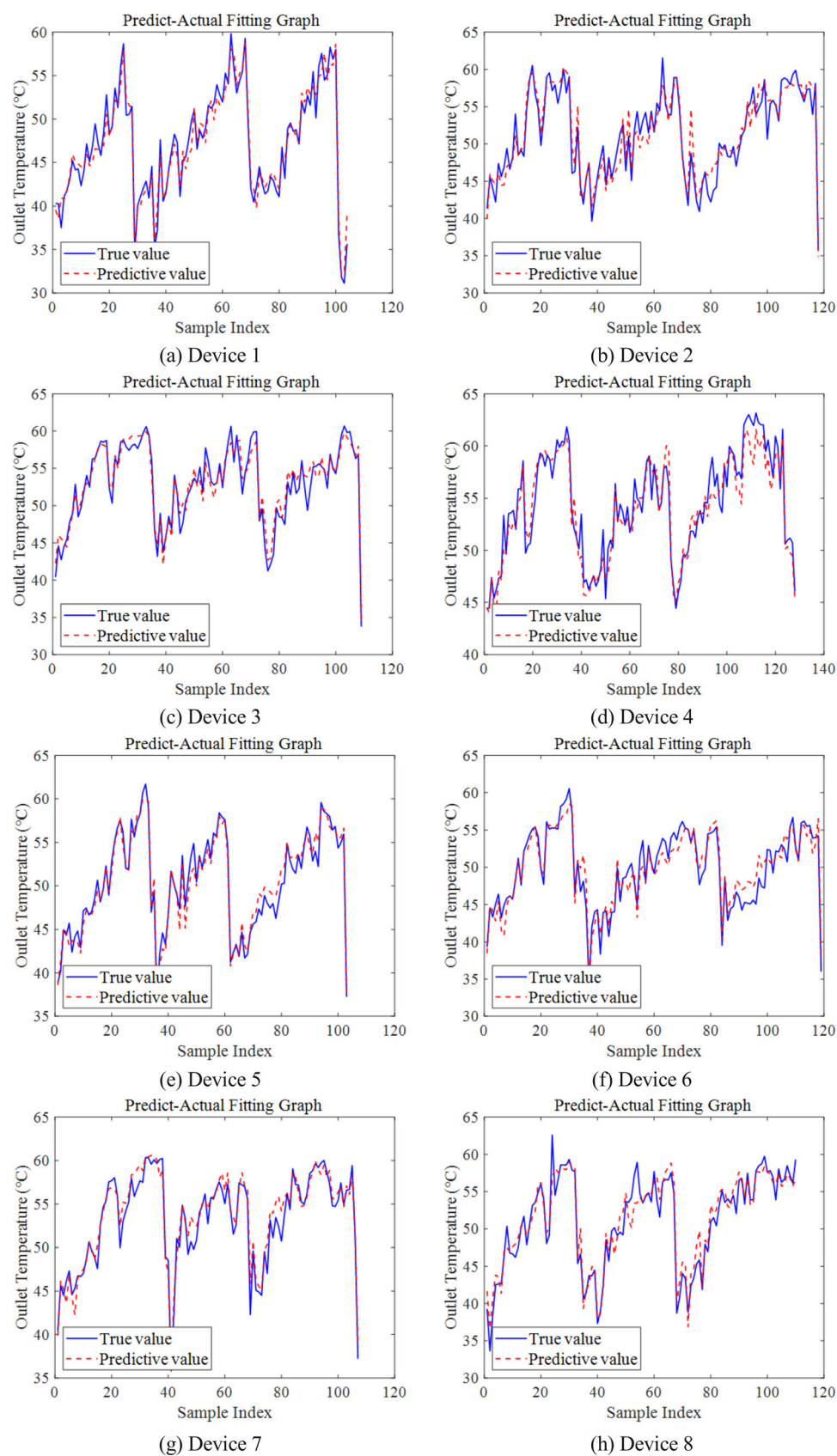


Figure 5. Fitting curves of predicted vs. actual values for the proposed outlet temperature prediction model.

4. Hierarchical Regulation Strategy for Air-Cooling System Based on Thermal Margin

In field operations, injection compressor air-cooling systems commonly suffer from a lack of effective performance evaluation means, poor adaptability to varying conditions, and high energy consumption due to overcooling. Traditional empirical regulation methods can hardly balance process safety and energy saving. To address this, based on the actual operating characteristics of the eight injection compressor air-cooling units at the Chongqing Xiangguosi UGS injection station, this section adopts thermal margin as the core quantitative indicator and, using the outlet temperature prediction model established in Section 3.3, constructs a hierarchical and precise regulation strategy that jointly considers process safety and energy saving.

4.1. Heat Transfer Performance Evaluation of Air-Cooling System Based on Thermal Margin

The operating status of an air-cooling system is usually evaluated directly by the outlet natural gas temperature. However, this temperature indicator alone cannot quantify the cooling margin relative to the process safety limit under current operating conditions. The absence of this key information weakens the effectiveness of regulation decisions under varying conditions. To address this, we define a dimensionless thermal margin φ to quantify the current safety margin of the air-cooling system, expressed as Equation (20).

$$\varphi = \frac{T_0 - T_{\text{Out}}}{T_0} \times 100\% \quad (20)$$

where T_0 is the process-allowed outlet temperature threshold, taken as 50 °C according to the field operating specification, and T_{Out} is the actual outlet natural gas temperature of the air-cooling system. This indicator uses 0 as the critical value. A positive φ indicates that the current operating temperature is below the safety threshold, with a larger value meaning a higher cooling surplus. A negative φ indicates an over-temperature risk, which can be directly used for quantitative regulation of fan speed in subsequent steps.

Traditional heat transfer performance evaluation methods mostly rely on accurate mechanistic models and numerous prior parameters. In engineering applications, they suffer from high computational cost and difficulty in obtaining time-varying parameters, making them unsuitable for large-scale performance evaluation across multiple units. To address this, we propose a performance evaluation method based on historical operating data with condition-zoned analysis. By dividing the operating data into standardized condition intervals, we calculate the thermal margin of each unit within similar condition subsets and rank them accordingly, thus achieving accurate evaluation of the heat transfer status of the air-cooling system.

To achieve comparable evaluation and quantitative ranking of the heat transfer performance of the eight compressor-supporting cooling units under identical conditions, the historical operating data must first be divided into standardized condition zones. This ensures that all units are compared under the same boundary conditions, eliminating the interference of condition differences on performance evaluation. From the perspective of heat transfer mechanism analysis, the heat transfer performance of an air-cooling system is mainly determined by two core boundary conditions: (i) the hot-side medium condition, which determines the total system heat load, characterized by the natural gas processing flow rate; and (ii) the cooling-side ambient condition, which determines the reference temperature difference for heat transfer, characterized by the ambient temperature. Although inlet pressure and outlet pressure can indirectly affect the heat transfer process through their influence on the air cooler inlet temperature, the eight units share the same injection system pressure condition. The pressure parameters among units are highly overlapping

with little inter-unit difference, and thus are not suitable as the primary control dimensions for condition differentiation. Therefore, this paper selects ambient temperature and volumetric flow rate as the core dimensions for condition zoning. Because thermal margin is a relative quantity rather than an absolute temperature level, comparing it across units within the same operating-condition zone effectively suppresses the influence of constant systematic bias in each unit's temperature sensors on the evaluation results. Consequently, the resulting ranking accurately reflects the degradation of each unit's heat-transfer performance. Based on the parameter distribution ranges of the historical operating data from the eight units, we discretize these two dimensions using uniform interval steps. Each sub-interval corresponds to a specific ambient temperature range and flow rate range. The core boundary conditions of samples within each interval can be regarded as approximately consistent, and thus are classified as the same operating condition. This constructs a standardized condition-zone system applicable to all units. The specific zoning step sizes are given in Table 6.

Table 6. Parameters for two-dimensional condition zoning.

Condition Zoning Variable	Range	Step Size
Ambient temperature/ $^{\circ}\text{C}$	10–35	2.5
Volumetric flow rate/ (m^3/s)	15–24	0.75

After condition zoning is completed, the thermal margin ϕ of each unit is calculated within each sub-interval as the quantitative indicator for heat transfer performance evaluation. Since the air cooler inlet temperature is strongly correlated with ambient temperature, and the two-dimensional condition zoning in this study has effectively constrained both dimensions, the fluctuations of inlet temperature and natural gas processing flow rate within the same sub-interval are both limited. As a result, the difference in heat load input on the hot side among units remains small. Therefore, within the same condition zone, the variation in thermal margin among different units mainly reflects the degradation of their own heat transfer performance (e.g., tube bundle fouling, fan performance deterioration), rather than changes in ambient temperature or processing flow rate.

Due to field operational constraints, historical data cannot cover all predefined condition zones. Missing samples in some zones compromise the comprehensiveness of performance evaluation. To address this, we use the DNN prediction model for air cooler outlet temperature established in Section 3 to fill the missing data. Direct manual sampling cannot adequately cover the parameter fluctuation range within a zone with limited sample size, and sparse or uneven sampling points may cause large deviations and randomness in zone performance estimation. Therefore, we adopt Monte Carlo sampling to handle the missing zones. This method performs batch random sampling within the condition zone and obtains statistically meaningful performance estimates, effectively avoiding accidental errors from single-point predictions and fitting the needs of zone-level performance evaluation in this study. A stratified sampling strategy is employed, covering both the pressure dimension and the operating-condition dimension. For the pressure dimension, since the eight units share the same injection system pressure and the pressure distribution characteristics are consistent across all operating conditions, a unified sampling is performed over the global pressure distribution range. This ensures a consistent baseline for multi-unit comparison and reflects the average performance over the entire cycle. For the operating-condition dimension, ambient temperature and volumetric flow rate are the zoning dimensions, and sampling is performed respectively within the parameter ranges of the corresponding missing zones. The sampled data are input into the DNN prediction

model to calculate the statistical thermal margin values for each missing zone, thereby completing the data filling process.

After filling the thermal margin values for the missing condition zones of each unit, the mean thermal margin of each unit within each condition zone is used as the ranking basis. By comparing the mean thermal margins of different units within the same condition zone, quantitative evaluation and ranking of the cooling system heat transfer performance for each unit can be achieved. Taking a typical condition (ambient temperature range [15, 17.5) °C, volumetric flow rate range $[15.75, 17.25) \times 10^4 \text{ m}^3/\text{s}$) as an example, the final performance ranking results are shown in Table 7. The optimal performance ratios of the cooling systems for all units under full operating conditions are shown in Table 8. Here, the optimal performance ratio refers to the proportion of condition zones in which a given unit ranks first in thermal margin among all effective condition zones. A higher ratio indicates that the unit exhibits better heat transfer performance under most operating conditions.

Table 7. Example of heat transfer performance ranking for each unit under typical operating conditions.

Ambient Temperature–Volumetric Flow Rate Condition Zone	[15.75, 16.5)	[16.5, 17.25)
[15, 17.5)	4 < 8 < 7 < 5 < 2 < 1 < 3 < 6	4 < 8 < 7 < 5 < 2 < 1 < 3 < 6
[17.5, 20)	4 < 8 < 7 < 5 < 2 < 1 < 3 < 6	4 < 8 < 7 < 5 < 2 < 3 < 1 < 6
[20, 22.5)	4 < 8 < 7 < 5 < 1 < 6 < 2 < 3	4 < 2 < 8 < 7 < 5 < 3 < 1 < 6
[22.5, 25)	4 < 8 < 7 < 5 < 2 < 3 < 6 < 1	8 < 7 < 5 < 6 < 3 < 4 < 1 < 2
[25, 27.5)	2 < 8 < 7 < 6 < 4 < 5 < 3 < 1	8 < 5 < 7 < 4 < 6 < 3 < 2 < 1
[27.5, 30)	7 < 2 < 5 < 1 < 8 < 4 < 6 < 3	2 < 7 < 8 < 3 < 5 < 6 < 4 < 1
[30, 32.5)	3 < 2 < 1 < 7 < 5 < 8 < 4 < 6	2 < 3 < 1 < 5 < 7 < 8 < 6 < 4

Table 8. Statistics of optimal performance ratio for each unit under full operating conditions.

Unit No.	Times Ranked First	Optimal Rate (%)
1	23	16.1
2	8	5.6
3	3	2.1
4	4	2.8
5	9	6.3
6	57	46.9
7	8	5.6
8	21	14.7

The results in Table 8 show that the cooling equipment of Unit No. 6 has the highest optimal performance ratio, reaching 46.9%, which accounts for nearly half of all condition zones. Unit No. 1 (16.1%) and Unit No. 8 (14.7%) rank next. Although their ratios are significantly lower than that of Unit No. 6, they still maintain a clear advantage over the remaining units.

4.2. Construction of Mapping Relationship Between Thermal Margin and Fan Speed Based on HTRI Simulation

In Section 4.1, the performance evaluation and selection of each unit's cooling system were accomplished through comparison and ranking of thermal margins among multiple units under the same condition zone. However, for a single air-cooling system in actual operation, multiple parameters such as ambient temperature, natural gas processing flow rate, and operating pressure continuously fluctuate, resulting in complex and variable heat transfer conditions. Therefore, a quantitative basis for fan speed regulation that adapts to all operating scenarios is still needed to achieve dynamic matching between

cooling capacity and heat load. To address this, on the basis of the thermal margin φ defined above, we further propose a hierarchical fan speed regulation method based on thermal margin grading. This method first builds a numerical model of the air cooler using HTRI Xchanger Suite software (Version 7.0), taking the air cooler structural parameters, natural gas inlet conditions, and ambient parameters as inputs. Through batch simulations, the outlet temperatures under typical conditions covering the full parameter range are obtained. A quantitative mapping relationship between thermal margin intervals and recommended regulation speeds is then established, forming a standardized hierarchical regulation database. This provides theoretical support for subsequent energy-saving regulation strategy formulation and field engineering applications.

4.2.1. Hierarchical Fan Speed Regulation Strategy Under Normal Operating Conditions

Using the thermal margin φ as the classification indicator, and based on the thermal margin calculation results from historical operating data, the operating states of the cooling system are divided into six categories as shown in Table 9, covering normal cooling, multiple cooling margin levels, and over-temperature states. The first five categories belong to normal operating conditions that satisfy process requirements, i.e., $\varphi > 0$. To ensure the representativeness and generalizability of the simulation results, multiple operating samples covering different condition ranges are selected within each normal-state interval. The selection principles are as follows. Within the value ranges of ambient temperature, gas pressure, and gas flow rate, extreme points and several intermediate levels are selected, and cross-combinations of different levels of each parameter are covered, so that the samples fully reflect the fluctuation range of all parameters. Meanwhile, within each thermal margin interval, the φ values of the selected samples are kept discretely distributed. Taking the 0–5% interval as an example, samples with φ close to 1%, 2%, 3%, 4%, and 5% are selected to ensure that the thermal margin is covered as evenly as possible within the interval. This selection approach takes into account the distribution characteristics of both the key operating parameters and the thermal margin, ensuring that the sample set input into HTRI is sufficiently representative within the condition space.

Table 9. Classification of operating states based on thermal margin intervals.

Operating State No.	Thermal Margin Interval
1	0–5%
2	5–10%
3	10–15%
4	15–20%
5	>20%
6	<0

For each selected typical operating sample, wind speed sweep simulations are performed using HTRI. With other operating parameters held constant, the external air velocity across the fan is gradually reduced from the rated value of 6.8 m/s, and the corresponding natural gas outlet temperature is calculated, until the outlet temperature reaches the process limit of 50 °C. The air velocity at this point is recorded as the critical safe velocity for the sample under the current operating condition. At this velocity, fan power consumption is minimized while the process limit is satisfied, making it the optimal regulation target under that condition. To cover the full regulation range, the sweep starts from the rated velocity of 6.8 m/s and extends downward to 1 m/s, with six discrete levels: 6 m/s, 5 m/s, 4 m/s, 3 m/s, 2 m/s, and 1 m/s. Through the above simulations, a mapping database between the external air velocity of the air cooler and outlet temperature is constructed, covering various operating states and their corresponding condition combinations.

For each operating state, the critical safe velocities obtained from the condition samples are analyzed statistically. It is found that within each operating state, the critical safe velocities are concentrated in a finite continuous range. Further statistical summarization is performed on the distribution of critical velocities within each range, and the values are converted to percentages relative to the rated velocity. After boundary rounding and reserving a safety margin, the corresponding relationship between each thermal margin interval and the recommended air velocity regulation range is established. Taking the thermal margin interval of 15–20% as an example, the simulated critical safe velocities range from 3 m/s to 5 m/s, corresponding to 44.1–73.5% of the rated velocity. To balance operational reliability and improve engineering convenience, this range is rounded to 50–75% of the rated velocity. Similarly, for the interval with $\varphi > 20\%$, the simulated critical safe velocities range from 1 m/s to 3 m/s, corresponding to 14.7–29.4% of the rated velocity. After rounding, this range is preliminarily recommended to be 20–40% of the rated velocity. In the HTRI simulation modeling, the external air velocity is used as the calculation variable. Under fixed blade pitch angle conditions, the air velocity is linearly proportional to the fan speed. Therefore, the regulation conclusions derived from the simulation analysis in terms of air velocity are equivalent to the corresponding fan speed regulation, and the two are consistent at the control level. Based on the above full-range statistical analysis, a hierarchical mapping relationship between thermal margin intervals and recommended fan speed regulation ranges is finally established, as shown in Table 10.

Table 10. Hierarchical mapping relationship between thermal margin intervals and recommended fan speed regulation ranges.

Thermal Margin Interval	Recommended Speed Regulation Range	Theoretical Energy Saving Rate
0–5%	90–100%	0–27.1%
5–10%	75–90%	27.1–57.8%
10–15%	50–75%	57.8–87.5%
15–20%	40–50%	87.5–93.6%
>20%	20–40%	93.6–99.2%

It should be noted that the recommended range of 20–40% of rated speed is a theoretical lower limit derived solely from heat transfer performance considerations. In actual operation, however, a fan has an inherent stable operating envelope. Prolonged operation at extremely low speeds near this theoretical lower limit may cause aerodynamic instability, insufficient torque, and inadequate lubrication. Specifically, aerodynamic instability may cause the fan to enter surge conditions; insufficient torque may reduce the motor's driving capability; and inadequate lubrication may impair bearing oil film formation, thereby accelerating equipment wear. Therefore, when formulating field energy-saving control strategies, the actual fan speed boundary should be determined according to the minimum continuous stable operating speed specified by the fan manufacturer or the safe lower limit obtained through field measurements. For example, if the field-verified minimum safe speed is 30% of the rated speed, the control range for the $\varphi > 20\%$ interval can be revised to 30–40% of the rated speed. This adjustment preserves most of the energy-saving potential while helping ensure the long-term reliability and safety of fan operation. The above description reflects the steady-state correspondence between air velocity and outlet temperature; the actual fan speed can be selected within the recommended range according to the real-time variation in thermal margin.

Based on the corrected thermal margin–speed hierarchical mapping presented above, and combined with HTRI multi-condition simulations and validation against historical operating data, this study further evaluates the expected benefits of the proposed strategy

in terms of energy-saving rate. When the thermal margin falls within the ranges of 0–5%, 5–10%, 10–15%, 15–20%, and >20%, the recommended speed is adjusted to 90–100%, 75–90%, 50–75%, 40–50%, and 30–40% of the rated speed, respectively (constrained by a 30% minimum safe operating speed). The corresponding theoretical energy-saving rates are 0–27.1%, 27.1–57.8%, 57.8–87.5%, 87.5–93.6%, and 93.6–97.3%, respectively. These values are estimated from the ideal fan shaft-power relationship $P \propto N^3$, without accounting for motor/VFD efficiency, fan efficiency degradation, variations in system resistance, or control losses. Therefore, the actual energy-saving rate is expected to be lower than these theoretical values. Taking a typical high-margin condition (ambient temperature 30 °C, volumetric flow rate 20 m³/s, thermal margin > 20%) as an example, while ensuring safe and stable fan operation, the proposed strategy recommends reducing the fan speed to 30–40% of the rated value. According to the cubic relationship between fan shaft power and speed, the shaft power decreases to 2.7–6.4% of the rated power, and the expected energy-saving rate can still reach 93.6% or above. The above results indicate that the proposed strategy has significant energy-saving potential and engineering feasibility while satisfying the 50 °C process limit.

4.2.2. Emergency Regulation Strategy with Coordinated Fan Speed and Blade Angle Adjustment Under Over-Temperature Conditions

For different condition samples corresponding to the over-temperature operating states of the air cooler, the air velocity level is gradually increased from the rated value, and stepwise simulations are performed using HTRI software. The results are shown in Figure 6. The simulation results indicate that the cooling effect of velocity adjustment is directly related to the degree of over-temperature. For mild over-temperature with ϕ between −3% and 0, increasing the air velocity from the rated 6.8 m/s to 9–10 m/s is sufficient to bring the outlet temperature below the process limit. For moderate over-temperature with ϕ around −5% to −10%, the air velocity needs to be increased to 11–12 m/s to bring the outlet temperature back to the allowable range. For severe over-temperature with ϕ down to −10% to −20%, even further increasing the air velocity can hardly reduce the outlet temperature to below the limit, and the cooling effect tends to saturate. It can be seen that under over-temperature conditions, the regulation strategy relying solely on speed increase has obvious efficiency limitations. As the over-temperature degree intensifies, the marginal benefit of speed regulation diminishes, while fan power consumption increases significantly with rising speed. Both the economic efficiency and the reliability of regulation decrease accordingly.

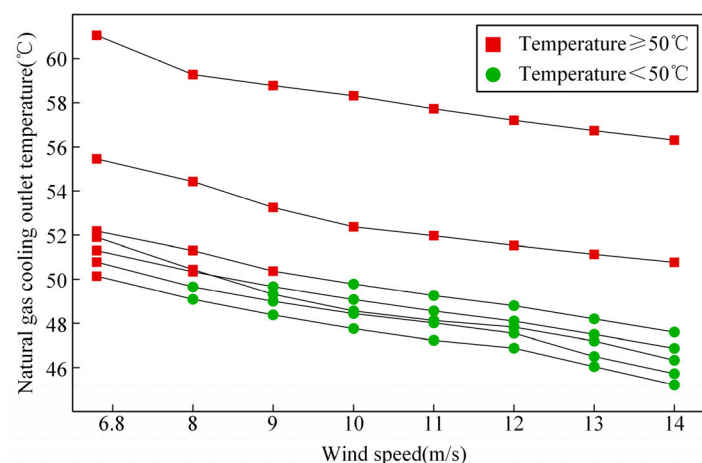


Figure 6. Natural gas outlet temperature of the air cooler under different air velocity settings.

To address this, we propose an emergency regulation strategy that coordinates fan speed and blade pitch angle adjustment to meet the heat transfer demands under different degrees of over-temperature. Taking the thermal margin evolution of a single unit within one injection cycle as an example, as shown in Figure 7, the thermal margin shows a gradual decreasing trend as the injection process proceeds. At the early injection stage, the thermal margin is relatively abundant. A smaller blade pitch angle can be set to allow the fan to operate at a lower aerodynamic load, reducing power consumption while reserving room for subsequent adjustment. At this stage, speed regulation is the primary control means, with moderate speed reduction under the premise of meeting heat transfer demand. As the injection enters the middle stage, the thermal margin gradually narrows. The blade pitch angle can be appropriately increased to improve the fan's aerodynamic performance at the same speed, thereby slowing down the rate of speed increase required. When the thermal margin continues to decline and an over-temperature trend appears, the system activates a hierarchical emergency strategy. The first-level response is to increase the fan speed to the rated value, as an initial measure to quickly suppress temperature rise. If the outlet temperature still cannot be controlled within the safety limit, the second-level response is activated, i.e., increasing the blade pitch angle to enhance cooling effect. Through coordinated adjustment of speed and blade pitch angle, this method can effectively control over-temperature risk while avoiding excessive increase in fan power consumption, balancing both regulation safety and economic efficiency.

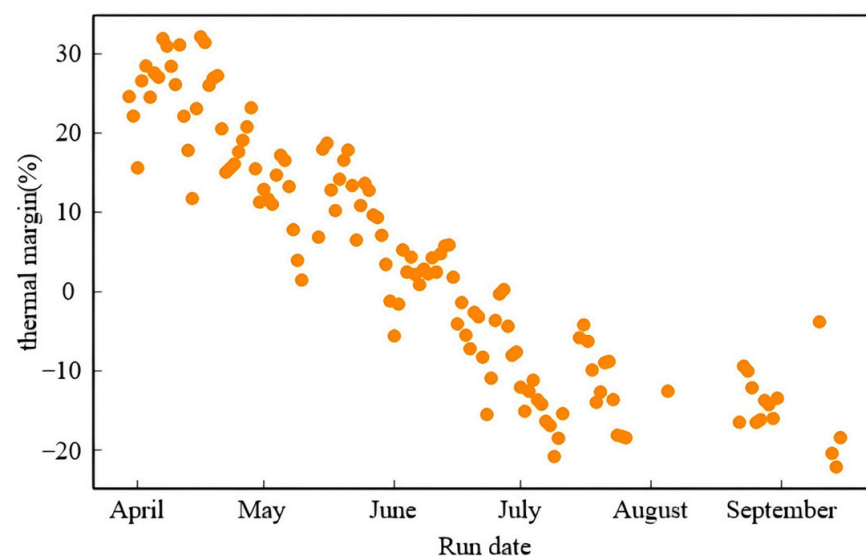


Figure 7. Evolution of thermal margin over time for a single unit within one injection cycle.

4.3. Collaborative Implementation Procedure for Equipment Selection and Speed Regulation

Section 4.1 completed the performance evaluation and selection of each unit's cooling system through thermal margin comparison and ranking. Section 4.2 established the hierarchical mapping relationship between thermal margin intervals and fan speed, providing a quantitative basis for speed regulation. On this basis, this section further integrates equipment selection, operating state identification, and speed regulation into a unified execution procedure, forming a progressive regulation strategy for engineering applications. The specific implementation of the procedure is illustrated in Figure 8.

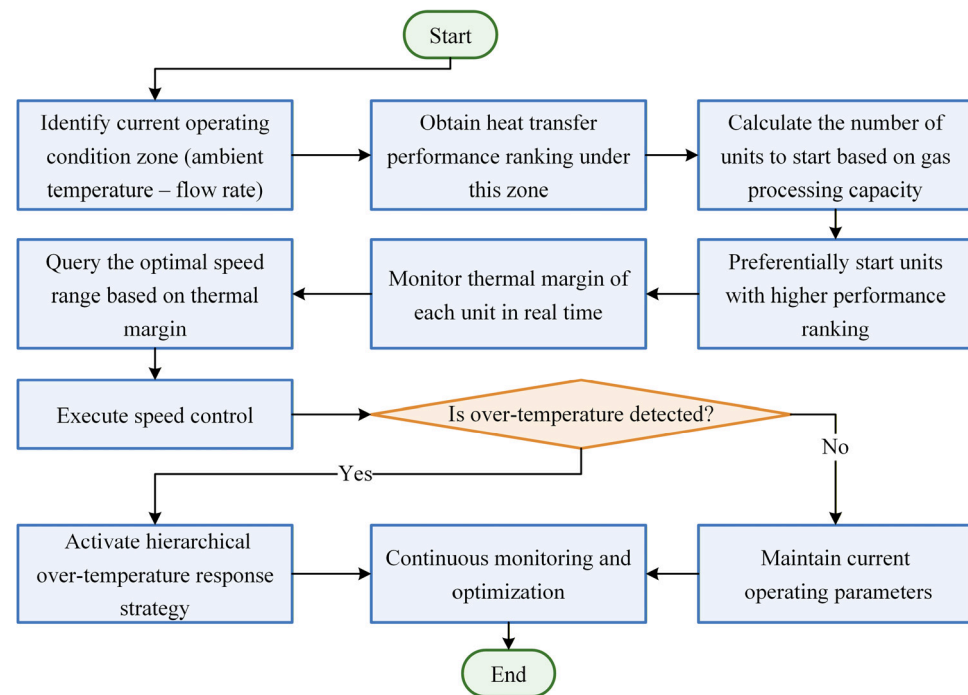


Figure 8. Implementation procedure of the hierarchical regulation strategy.

- (1) Operating condition identification: By real-time monitoring of ambient temperature and process gas flow rate, the current operating point is located in the pre-constructed two-dimensional condition zoning table (Table 6), and the corresponding condition zone is determined.
- (2) Unit group start-stop optimization: Based on the actual gas processing capacity of the current injection system and the rated processing capacity of a single cooling system, the number of units to be put into operation is determined. According to the performance ranking results, the unit combination with better heat transfer performance within the current condition zone is preferentially put into operation.
- (3) Single-unit speed dynamic optimization: The outlet temperature of each cooling system is monitored in real time and the thermal margin is calculated. The recommended speed range is obtained from the hierarchical mapping table (Table 10). When φ is in a relatively high interval, the fan speed is preferentially reduced to tap energy-saving potential. When φ approaches the critical value, the speed is maintained or slightly increased to ensure safety margin, forming a dynamic regulation mechanism based on real-time safety margin.

To verify the advantages of the proposed hierarchical collaborative strategy in dynamic processes, this section takes the on-site conventional manual control at the Xiangguosi underground gas storage as a reference and conducts a comparative analysis from two dimensions: overshoot suppression and dynamic transition process. The on-site conventional control highly depends on manual experience: when an operator finds from temperature monitoring that the outlet temperature exceeds the threshold, the only measure is to manually reduce the compressor throughput to lower the system heat load. This mode has two inherent bottlenecks in dynamic transition processes: action lag and inability to adjust quantitatively.

- (1) Comparative analysis of overshoot. Due to the inherent lag of “perception–decision–execution” in on-site conventional manual control, when an operator detects an over-temperature condition and begins to reduce the gas throughput, the outlet temperature has already exhibited significant positive overshoot. Moreover, because

manual reduction of gas throughput cannot be quantified, operators usually cut the throughput excessively to prevent further temperature rise. This causes the heat load to drop sharply and instantaneously, thereby triggering reverse overshoot. Such behavior is highly unfavorable to smooth control of the air cooler outlet temperature. In contrast, the hierarchical regulation strategy proposed in this paper relies on the DNN prediction model to predict the trend of operating condition evolution in advance. It generates an assessment of the thermal margin before the temperature approaches the critical value and performs quantitative and smooth adjustment of the fan speed through a variable frequency drive. Since fan speed changes continuously and steplessly, the heat removal rate can be dynamically matched with the system heat generation rate. Therefore, the overshoot can be significantly suppressed within a very small range, and both positive and reverse overshoot are avoided.

- (2) Comparison of dynamic transition processes. Under the manual gas throughput reduction control mode, operators can only adjust the gas throughput in a stepwise manner based on experience, and each adjustment requires waiting for the response of the system thermal inertia. As a result, the entire regulation process is extremely long. Operators often need to repeatedly adjust between “cooling down” and “preventing overcooling”, and the system temperature oscillates around the safety boundary for a long time. The dynamic transition process lacks a clear convergence direction. In contrast, the proposed strategy establishes a quantitative mapping relationship between thermal margin intervals and recommended speed ranges, transforming complex dynamic regulation into deterministic interval control. When the operating condition changes abruptly, the system can directly output the recommended speed range according to the real-time thermal margin, and the fan variable frequency actuator responds rapidly. Simulation validation based on historical operating data shows that, compared with on-site conventional manual control, the proposed strategy significantly shortens the settling time of the outlet temperature. The outlet temperature can quickly and smoothly converge within the safety boundary, demonstrating better dynamic response quality.

The above comparison demonstrates that the proposed hierarchical collaborative strategy significantly outperforms the on-site conventional manual control in both overshoot suppression and dynamic transition acceleration. This advantage stems from the synergistic combination of the feedforward information provided by the prediction model and the continuous stepless regulation capability of variable frequency speed control. It provides a more reliable means of dynamic control for the safe and energy-efficient operation of the air-cooling system in underground gas storage.

5. Conclusions

This study investigated the eight parallel injection compressor air-cooling systems at the Chongqing Xiangguosi UGS facility. To address the limitations of conventional regulation methods in temperature prediction, performance evaluation, and energy regulation, an integrated refined regulation method was proposed that combines outlet temperature prediction, heat transfer performance evaluation, and hierarchical fan speed control. The main conclusions are as follows.

- (1) A DNN model was developed for predicting the outlet temperature of the air-cooling system. Training samples with high information density were dynamically screened using joint evaluation criteria based on gradient uncertainty and diversity metrics. For all eight units, the proposed model achieved lower RMSE and MAPE than the benchmark models, including RF, KNN, BP neural network, and CNN. These results

indicate that the proposed modeling framework effectively improves prediction accuracy under multi-condition operation.

- (2) A performance evaluation framework was established for the air-cooling system, with thermal margin as the core indicator. Through two-dimensional condition zoning based on ambient temperature and natural gas volumetric flow rate, combined with Monte Carlo sampling for data filling, objective performance ranking of multiple cooling systems under identical baseline conditions was achieved. The evaluation results show that Unit No. 6 had the highest optimal performance ratio of 46.9% across all condition zones, followed by Unit No. 1 and Unit No. 8. This ranking provides a quantitative basis for prioritized unit selection in multi-unit parallel scenarios.
- (3) A quantitative mapping relationship between thermal margin and fan speed was established through HTRI multi-condition simulations. For over-temperature conditions, a hierarchical regulation strategy coordinating fan speed and blade pitch angle was proposed, forming a three-level progressive regulation procedure that covers condition zone identification, prioritized unit start-stop, and dynamic speed optimization. Evaluations based on HTRI simulations and historical data show that as thermal margin increased from 0–5% to >20%, the recommended fan speed decreased from 90–100% to 30–40% of the rated value, and the theoretical energy-saving rate increased from 0–27.1% to 93.6–97.3%. Under a typical high-margin condition (30 °C, 20 m³/s, >20%), the expected energy-saving rate exceeded 93.6%.
- (4) The proposed hierarchical collaborative regulation strategy was compared with the conventional on-site control strategy based on manual reduction of gas throughput. The results of HTRI simulations and historical backtesting indicate that the proposed strategy outperformed the conventional strategy in suppressing outlet temperature overshoot and shortening the dynamic transition time. It also reduced fan energy consumption through on-demand regulation based on the quantitative mapping between thermal margin and fan speed while satisfying the 50 °C process limit.

The proposed method provides a safe and energy-efficient operational pathway for the air-cooling system at the Xiangguosi UGS facility and a methodological reference for similar multi-unit parallel heat exchange systems under strongly time-varying conditions. Its broader application may be most appropriate for stations with multiple parallel air coolers equipped with variable-frequency fans; otherwise, adaptation or simplification to start-stop or opening-based control may be required. For new stations, retraining the DNN with local data and recalibrating it using HTRI are recommended, and sufficient historical data are desirable for adaptive sample selection and model reliability. The minimum fan speed should also be carefully re-determined according to the fan model, bearing transmission, and manufacturer specifications. Given that continuous gas injection currently limits on-site testing, the present validation mainly relies on historical backtesting and HTRI multi-condition simulations. Future work will proceed in two directions: (i) advancing from offline modeling to online adaptation, in which real-time data are used to update model parameters and refine regulation rules; and (ii) conducting on-site trials during low-load windows through a progressive strategy, beginning with a single closed-loop pilot on one representative air cooler to collect actual fan power and economic benefit data. Once safety and reliability are verified, the strategy can be gradually extended to all eight parallel units to further demonstrate its engineering value.

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