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Application of deep learning model in Operating data analysis of vacuum pressure equipment

Lei Zhang[1], *Bingding Li*[1], *Lingtao Kong*[1] *and Junxi Han*[2,*]

[1] Power Workshop, Baoji Cigarette Factory, China Tobacco Shaanxi Industrial Co., Ltd., Baoji 721013, Shaanxi, China
[2] Baoji Cigarette Factory, China Tobacco Shaanxi Industrial Co., Ltd., Baoji 721013, Shaanxi, China

SUMMARY: *Aiming at the problems of strong multivariable coupling, obvious control lag, scattered abnormal symptoms and difficult to identify by traditional methods in the operation process of environmental control equipment in vacuum rehumidification section, this paper takes K3-K4 (ZK-120) combined air conditioning unit of Baoji Cigarette Factory as the object. Relying on the temperature and humidity, pressure difference, valve opening, inverter current, frequency and power data collected by PLC, PROFINET communication and central control monitoring link, a deep learning analysis model combining timing feature extraction, attention enhancement and multi-dimensional feature fusion is constructed. The model takes operation state identification and key variable trend prediction as dual task outputs, which can describe the dynamic correlation between temperature and humidity regulation, fan load change and actuator response in a continuous time window. Experimental results show that the Accuracy, Recall and F1 of the proposed model in the state recognition task reach 95.8%, 94.6% and 94.9%, respectively. The RMSE and MAE of the model in the trend prediction task are 0.118 and 0.087, respectively, and the average amount of warning advance reaches 2.9 hours. The research shows that the deep learning method can effectively improve the accuracy and foresight of the operation data analysis of vacuum pressure equipment, and provide computational support for equipment early warning, operation and maintenance decision-making and stable operation.*

KEYWORDS: *Constrained PPO algorithm; Virtual entrepreneurship simulation; Risk control decision; Reinforcement learning*

1 Introduction

In the production process of cigarette silk, the vacuum moisture return link has higher requirements on the air state and the running stability of the equipment. Small fluctuations in temperature, humidity, air volume, valve opening, chilled water, steam and other parameters will affect the continuity of the process environment, and further conduct to the equipment load distribution, energy consumption level and abnormal occurrence probability. Combined with the existing information of Baoji cigarette factory, it can be known that the K3-K4 unit serving the vacuum moisture return area of the large silk line belongs to the ZK-120 combined air conditioning unit, which takes on the task of returning air, cooling, heating and humidification. On the system side, a data acquisition and control system combining PLC,

*baojihanjunxi@126.com
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sensors, frequency converters, touch screens and remote monitoring in the central control room has been formed, which can continuously record workshop temperature and humidity, return air and mixed air status, filter pressure difference, valve opening, frozen water and steam parameters, and inverter current, voltage, frequency and power and other operating information. It can be seen that the operation process of vacuum pressure equipment has a relatively complete data basis, which also provides realistic conditions for subsequent deep learning analysis [1].

However, from the perspective of engineering practice, the operation data of vacuum pressure equipment is not a simple univariate time series. Firstly, the heat and humidity load of the workshop will change dynamically with the production cycle, seasonal environment and process state. Second, there is obvious coupling between the cooling valve, heating valve, humidifying valve and fan frequency; Third, filter blockage, steam pressure fluctuation, valve failure, abnormal inverter and other faults are often not instantaneous outbreaks, but gradually appear in the form of slow drift, local deviation and multivariate linkage. Although the existing control logic adopts the strategy of combining feedback, division and selection to complete constant temperature and humidity and interlocking protection, its core is still biased towards real-time control, and the identification of potential anomalies in advance and the deep mining of trend changes under complex working conditions are still insufficient.

Concerning the fault diagnosis and prediction of HVAC and related industrial equipment, existing studies have shown that methods based on rules, thresholds or traditional machine learning have certain practicability in specific scenarios, but the generalization ability and feature expression ability of the model are still limited when facing high-dimensional, non-stationary and strong time-series dependence data [2, 3]. In recent years, convolutional neural network, LSTM, autoencoder, Transformer and interpretable deep learning methods have been gradually introduced into equipment fault diagnosis, state recognition and predictive maintenance tasks, showing higher potential in multi-source signal modeling, long-term dependence capture and abnormal pattern extraction [4, 5]. This shows that the introduction of deep learning methods into the operation data analysis of vacuum pressure equipment is not only feasible in method, but also in line with the development trend of industrial field from "empirical judgment" to "data-driven".

Based on this, this paper constructs a deep learning analysis model that integrates timing feature extraction, attention enhancement and multi-dimensional feature dynamic representation for the operation scenario of vacuum rehydration related equipment, so as to realize the identification of equipment running status and the prediction of key operating trends. The research focus is not to replace the original control system, but to mine the potential correlation in multivariate operation information based on the data formed by the existing PLC and industrial communication architecture, improve the timeliness of abnormal perception, the accuracy of state discrimination and the intelligent level of operation analysis, so as to provide computational support for the stable operation, fault early warning and maintenance decision of vacuum pressure equipment.

2 Analysis of operating data characteristics of vacuum pressure equipment

2.1 Data source and collection method

The research object of this paper is the environmental control unit of the vacuum rehumidifying section of the big silk line in Baoji cigarette Factory. The corresponding K3-K4 unit is a ZK-120 combined air conditioning unit, which mainly assumes the tasks of air return, refrigeration, heating and humidifier regulation in this area, and has strong continuous operation characteristics and multi-parameter coupling characteristics [6, 7]. Field data show that the unit is equipped with 90kW+37kW motor, and the air volume, cooling capacity and steam humidifier capacity are at a high level, which determines its operation data has the characteristics of more sampling points, rapid state change and long control chain.

From the perspective of acquisition mode, the system has formed a more complete industrial data acquisition architecture. The bottom layer is composed of workshop temperature and humidity sensor, outdoor fresh air temperature and humidity sensor, return air and mixed air temperature and humidity sensor, differential pressure sensor, temperature and pressure sensor, etc. In the control layer, SIEMENS S7-1500 PLC was used, and the inverter transmitted the operating parameters through the PROFINET bus. The TP1500 touch screen was used to complete the man-machine interaction in the field. This structure enables the device operation information to be continuously aggregated according to the path of "sensor/actuator -- PLC -- industrial communication -- upper monitoring", providing a stable source of data input for subsequent deep learning modeling [8, 9].

In terms of specific data content, the system collects digital state and analog parameters at the same time. The digital quantity mainly includes the running state, fault state, automatic state and interlocking state of the return fan. The simulated quantities cover the temperature and humidity of the workshop, the temperature and humidity of the return air, the state after the meter cooler, the pressure difference of the filter, the opening of the air valve and the water vapor valve, the temperature and pressure of the chilled water supply and return, and the internal current, voltage, frequency, active power and running time of the frequency converter. This kind of data contains not only the electrical information on the equipment side, but also the heat and humidity information on the process environment side, which can reflect the operation process and dynamic changes of the vacuum pressure equipment more completely.

2.2 Analysis of running data characteristics

The operating data of vacuum pressure equipment has obvious multi-source coupling characteristics, and is not the result of linear change of a single measurement point. Combined with the field monitoring content, the system continuously records the temperature and humidity of the workshop, the state of return air and mixed air, the pressure difference of the filter, the parameters of chilled water and steam, the opening degree of the valve, and the current, frequency and power of the frequency converter [10, 11]. These variables affect each other in the same control cycle, and jointly reflect the load change of the unit, the air treatment state and the response process of the actuator. As shown in Figure 1, the operation data of vacuum pressure equipment is not an independent signal separated from each other, but a compound data structure composed of environmental status data, equipment operation data, actuator data and event alarm data, which has obvious linkage relationship and hierarchical transmission characteristics.

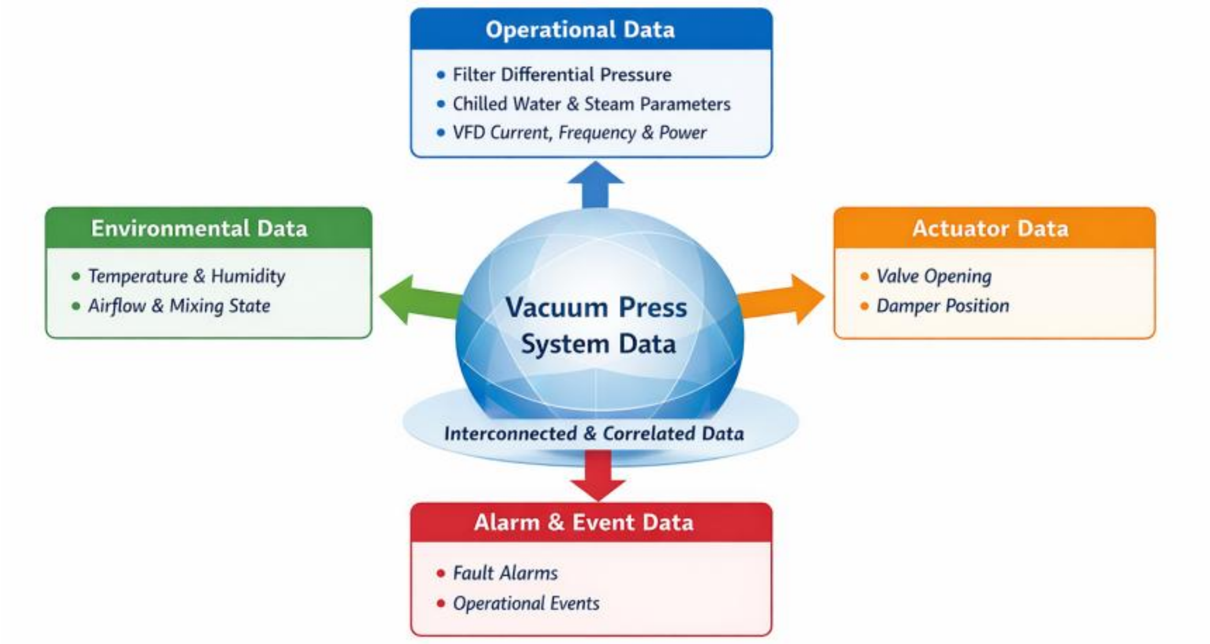

Figure 1: Schematic diagram of the operation data characteristics of vacuum pressure equipment

From the perspective of time domain characteristics, this kind of data has the characteristics of continuous sampling, slow drift and short time mutation. Changes in production load, external environment and process cycle can cause synchronous adjustment of air supply temperature and humidity, fan frequency and valve opening. Therefore, in the process of computer analysis, it is usually necessary to use sliding time Windows to extract statistical features such as mean value, standard deviation, rate of change, peak difference and number of limit overruns to describe the smoothness of equipment operation and adjustment sensitivity [12, 13]. For fan current, frequency conversion frequency and pressure difference signals, frequency domain analysis can be further carried out to identify periodic oscillations, local abnormal wave peaks and potential mechanical load fluctuations, so as to improve the ability to distinguish abnormal states [14]. In addition, this kind of operation data also has significant non-stationarity and nonlinearity. Because the system belongs to the large lag control object, the temperature change will linkage relative humidity, and humidity adjustment will reverse affect the meter cooling valve and humidification valve output; Once the filter is blocked, the steam pressure fluctuates, the valve response is slow, or the inverter is abnormal, the relevant signals are often not isolated mutations, but gradually appear in a multivariate linkage manner. Traditional analysis methods based on fixed thresholds or shallow features are difficult to fully depict such complex mapping relationships, so it is more necessary to use deep learning models that can deal with long-term dependencies, feature coupling and nonlinear relationships to carry out operational data analysis [15, 16].

2.3 Data preprocessing methods

The operating data of vacuum pressure equipment come from temperature and humidity sensor, differential pressure detection unit, valve feedback, frozen water and steam parameter collection point, and internal parameters of frequency converter uploaded by PROFINET bus. Because the sampling frequency, dimensional range and fluctuation intensity of different measurement points are not consistent, if they are directly input into the model without sorting, it is easy to amplify the noise interference, weaken the time series correlation feature, and affect the state recognition and trend prediction results. Therefore, data cleaning, normalization transformation and missing correction should be completed before modeling.

In the data cleaning stage, continuous variables such as temperature and humidity, differential pressure, current and frequency are jointly processed by the sliding mean and 3σ criterion to identify sensor instantaneous jitter, abnormal spikes and communication disturbances. For discrete signals such as fan fault, valve state switching and interlocking alarm, the original jump characteristics are retained to avoid distortion of the working condition boundary caused by excessive smoothing. Considering the presence of filter blockage, communication anomaly, inverter alarm and valve feedback anomaly in the field, the abnormal samples cannot be simply deleted, but should be marked in combination with the alarm records to retain the fault evolution information.

The normalization process is mainly oriented to the unified expression of multi-source heterogeneous variables. Temperature and humidity, pressure, current, power, and valve opening are quite different in numerical scale; in this paper, Z-score standardization is used for continuous variables and numerical coding is used for switching and state quantities. At the same time, for the missing values caused by short-time communication interruption or individual sensors out of step, linear interpolation, forward filling or local estimation methods based on the relationship between adjacent measurement points are selected according to the change rate of variables. As shown in Table 1, different types of data are not completely consistent on the preprocessing path. This hierarchical processing method is more in line with the characteristics of industrial field data, and is more conducive to the subsequent deep learning model to extract stable and computable time series representation.

Table 1: Operation data preprocessing strategy of vacuum pressure equipment

Data Type	Typical Variables	Main Problems	Preprocessing Methods
Environmental state data	Workshop temperature, relative humidity, supply/return air temperature and humidity	Jitter, short-term spikes, inconsistent scales	Moving average, 3σ anomaly detection, Z-score normalization
Equipment operation data	Current, voltage, frequency, active power, differential pressure	Noise interference, large differences in fluctuation amplitude	Denoising and smoothing, anomaly truncation, normalization
Actuator data	Cooling valve, heating valve, humidification valve, air damper opening	Feedback lag, partial missing values	Forward filling, linear interpolation, interval constraints
Event state data	Fault alarms, manual/automatic status, interlock status	Discrete jumps, mixed categories	State encoding, time alignment, label retention

3 Design of operating data analysis model of vacuum pressure equipment based on deep learning

3.1 Overall framework design of the model

Aiming at the characteristics of vacuum pressure equipment operation data with many variables, strong coupling, obvious time delay and long abnormal evolution process, this paper constructs a general framework of deep learning model for industrial time series analysis. The framework does not separate from the field control system, but builds on the existing PLC, automatic control instrument, PROFINET communication and central management workstation data foundation. The information of workshop temperature and humidity, return air and mixed air status, filter pressure difference, valve opening, frozen water and steam parameters, and inverter current, frequency, power and other information are integrated into the analysis link, so as to realize the continuous processing from multi-source acquisition, feature extraction to state recognition and trend prediction. Field data show that the vacuum moisture return area of Baoji cigarette factory corresponds to K3-K4 (ZK-120) unit, and the system has the ability of real-time recording, alarm display, historical query and remote control, which provides a stable data interface and application scenario for model deployment.

As shown in Figure 2, the model is generally composed of an input layer, a temporal feature extraction layer, an attention enhancement layer, a multi-dimensional feature fusion layer, and a dual-task output layer. The input layer receives the pre-processed continuous variables, state quantities and alarm labels, and organizes them into a multivariate time window sequence according to a uniform time step. The temporal feature extraction layer is responsible for capturing the local fluctuations and long-term dependence in temperature and humidity regulation, fan load change, valve response and working condition switching. The attention enhancement layer assigns higher weights to the key time slices and key variables to weaken the interference of redundant signals on the discrimination results. The multi-dimensional feature fusion layer compresses the environment side, equipment side, actuator side and event side features into computable dynamic representations, which are used to describe the current operating conditions and potential abnormal trends of the unit.

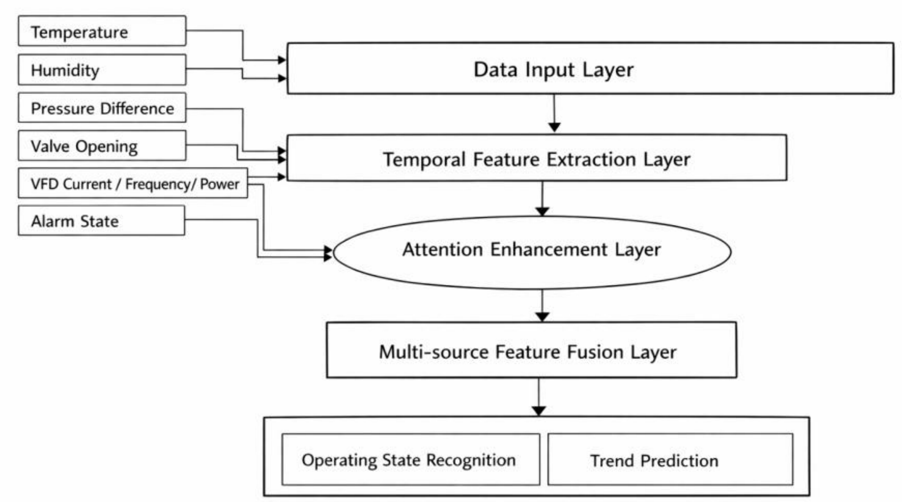

Figure 2: Overall framework of deep learning-based operating data analysis model for vacuum pressure equipment

The design basis of the framework and the field control mechanism correspond to each other. The existing system adopts the control law of "feedback + distance + selection". The temperature control loop acts on the heating valve and the meter cooling valve, the humidity control loop acts on the humidification valve and the meter cooling valve, and the air supply state point will reverse affect the fan frequency regulation. At the same time, the system itself belongs to the large lag object, and there is a continuous coupling relationship between temperature and relative humidity. Traditional methods can only deal with local parameter deviations, while the deep learning model can identify these linkage patterns on a longer time scale, which is more suitable for describing the dynamic changes of the operating state of vacuum pressure equipment. At the output end, this paper sets the model as a dual-task structure of "state recognition + trend prediction" : on the one hand, it determines whether the equipment is in a normal, mild abnormal or fault warning state, and on the other hand, it predicts the short-term change trend of the air supply state, fan load or key control quantity, so as to provide a basis for operation and maintenance and parameter optimization. This framework not only absorbs the modeling advantages of deep learning in equipment fault diagnosis and predictive maintenance, but also maintains a direct correspondence with the vacuum moisture recovery process scenario, so it has good engineering adaptability.

3.2 Time series feature extraction module

The operation process of vacuum equipment is essentially a multi-variable coupling time series evolution process. The field system continuously collects the temperature and humidity of the workshop, the return air and mixed air state, the filter pressure difference, the opening of the meter cooling valve and humidification valve, the frozen water and steam parameters, and the current, voltage, frequency and active power of the frequency converter. At the same time, there is an obvious linkage between temperature and relative humidity, and the air valve, water vapor valve and fan frequency participate in the regulation together, so that the system shows the characteristics of large lag, strong coupling and non-stationary. Therefore, the time series feature extraction module cannot only focus on the measured value at a single time, but needs to capture the local fluctuation, step correlation and condition transfer information from continuous time Windows. The field data also show that the system belongs to the large lag control object, and there is a clear control mapping relationship between the air supply state point (T,ϕ) and the fan frequency, the air enthalpy value and the air valve opening. Let the m-dimensional operational feature vector collected at time t be:

$$x_t = [T_t, \phi_t, \Delta P_t, v_t^c, v_t^h, v_t^m, f_t, I_t, P_t, \cdots] \in \mathbb{R}^m \tag{1}$$

where, T_t and ϕ_t respectively represent temperature and relative humidity, ΔP_t is pressure difference, v_t^c, v_t^h, v_t^m respectively represent the opening of gauge cooling valve, heating valve and humidifying valve, f_t, I_t and P_t respectively represent the frequency, current and power of frequency conversion. A sliding window of length L is used to construct the input sequence:

$$X_t = [x_{t-L+1}, x_{t-L+2}, \dots, x_t] \in \mathbb{R}^{L\times m} \tag{2}$$

This representation can extend a single point observation to a short-term running segment, which provides a basis for the subsequent network to extract dynamic trends. In the specific implementation, this paper adopts a two-level timing extraction structure of "one-dimensional convolution + gated recurrent unit". The convolutional layer scans the local changes along the time axis and is used to identify short-period patterns such as frequent valve regulation, fan load fluctuation, and sudden pressure difference rise, which is expressed as

$$z_t^{(k)} = \sigma\left(\sum_{i=0}^{s-1} W_i^{(k)} x_{t-i} + b^{(k)}\right) \tag{3}$$

where s is the width of the convolution kernel and $W_i^{(k)}$ is the parameter of the KTH convolution kernel. The convolution output is then fed into the LSTM unit to retain the state memory on long time scales:

$$h_t = \mathrm{LSTM}(z_t, h_{t-1}, c_{t-1}) \tag{4}$$

Here, h_t is the hidden state and c_t is the memory unit. This structure is not simply stacking network layers, but uses convolution to extract local disturbance features, and then uses LSTM to describe the long-term dependence between temperature and humidity drift, steam fluctuation and fan frequency adjustment. Corresponding to the operation scenario of vacuum pressure equipment, the output of this module is not static features, but dynamic representations with temporal context. It can compress the progressive anomalies such as "gradual increase of filter resistance - fan current change - air supply state deviation", or the regulation chain such as "steam pressure fluctuation - humidification valve compensation - humidity recovery" into a calculable hidden vector, which provides a more stable input for subsequent attention enhancement and state recognition. Combined with the field monitoring and control logic, this time series extraction method is more in line with the real operation mechanism of vacuum pressure equipment, and can better reflect the advantages of deep learning models in complex industrial data analysis.

3.3 Attention mechanism enhancement module

In the operation scenario of vacuum pressure equipment, although the timing feature extraction module can retain the continuous change information of variables such as temperature and humidity, differential pressure, current, frequency, and valve opening, the contribution of different measurement points to the state discrimination is not constant. When the equipment is in stable condition, some signals only show small fluctuations. Once the disturbance of heat and humidity load in the workshop is enhanced, or the filter resistance is increased, the steam pressure fluctuates, and the valve response is slow, what really determines the state change is often only a few time slices and a few key variables. Combined with the field control logic, the system carried out feedback, division and selection control around the temperature and humidity of the workshop. The meter cold valve was affected by the temperature loop and the humidity loop at the same time, and the fan frequency was closely related to the air supply state point (T,ϕ), which meant that there were significant primary and secondary differences and cross-variable dependence within the input sequence. If all features are treated with equal weight, the model is easily disturbed by redundant fluctuations, which weakens the sensitivity of anomaly recognition.

Based on this, this paper introduces an attention mechanism enhancement module after the temporal feature extraction layer to adaptively weight key moments and key variables. Let the hidden state sequence output by the previous module be:

$$H = [h_1, h_2, \dots, h_T], \quad h_t \in \mathbb{R}^d \tag{5}$$

Then, for the feature vector of t at any time, the query vector, key vector and value vector are constructed respectively:

$$q_t = W_q h_t, k_t = W_k h_t, v_t = W_v h_t \tag{6}$$

Here, W_q, W_k and W_v are trainable parameter matrices. Through this linear mapping, the original time-series features are projected into a representation space that is more suitable for correlation calculation, which provides a basis for subsequent capture of long-term dependencies. In the weight allocation stage, the module uses the scaled dot product method to calculate the correlation strength between different moments, and normalizes it to the attention weight by Softmax:

$$\alpha_{tj} = \frac{\exp\left(q_t k_j^T / \sqrt{d}\right)}{\sum_{j=1}^{T} \exp\left(q_t k_j^T / \sqrt{d}\right)} \tag{7}$$

$$c_t = \sum_{j=1}^{T} \alpha_{tj} \, v_j \tag{8}$$

where, α_{tj} represents the degree of attention at time t to time j, and c_t is the weighted context feature. Unlike normal weighted averaging, there is no preset rule, but the model automatically learns which time slices are more important during training. For example, when the filter pressure difference continues to rise and the fan current rises synchronously, the module will increase the weight of the relevant time period; When steam supply fluctuations cause humidity regulation to swing frequently, features related to humidification valve opening and supply air humidity deviation will also be preferentially retained.

Considering that the data of vacuum pressure equipment not only have key segments in the time dimension, but also have contribution differences in the feature dimension, this paper further adopts the gated fusion method to couple the original time series representation and the attention enhanced representation:

$$\tilde{h}_t = \beta_t \odot c_t + (1 - \beta_t) \odot h_t \tag{9}$$

Here, β_t is the gating coefficient and $\odot$ denotes element-wise multiplication. The purpose of this processing is to avoid that the attention results completely replace the original dynamic information, but to strengthen the expression of key abnormal symptoms while preserving the basic running contour. In the case of vacuum equipment, this mechanism is especially suitable for identifying "slow drift" anomalies, because many faults do not immediately trigger shutdown, but first appear as continuous symptoms such as increased temperature and humidity control deviations, increased valve regulation frequency, increased power fluctuations, and increased local alarms.

3.4 Multi-dimensional feature fusion and dynamic representation

The operation process of vacuum equipment is not determined by a single signal. As far as the field system is concerned, the input data includes at least four types of sources: first, the environmental side information such as workshop temperature and humidity, return air state, mixed air state and air enthalpy value; Second, current, voltage, frequency, active power, differential pressure and shaft temperature and other equipment side information; Three is the gauge cold valve, heating valve, humidification valve and new exhaust mixing valve opening and other actuator information; Fourth, inverter fault, temperature and humidity overrun, valve feedback deviation and interlocking shutdown and other event information. The data show that the system itself is a large lag object, and there are obvious feedback, interval and selection relationships between temperature, humidity, air volume and valve action. If only relying on a certain type of characteristics for discrimination, it is often difficult to completely describe the state transition process under vacuum moisture return conditions.

Based on this, after the time series feature extraction and attention enhancement, this paper further constructs a multi-dimensional feature fusion layer to map the representation vectors from different sources into a unified feature space. Let the representations of ttt at time for environment side, device side, actuator side and event side be zte, ztd, ztc and zta, respectively, then the dynamic fusion weight can be expressed as:

$$\lambda_t = \mathrm{Softmax}\left(W_f[z_t^e \| z_t^d \| z_t^c \| z_t^a] + b_f\right) \tag{10}$$

Here, ‖ denotes vector concatenation, and $\lambda_t = [\lambda_t^e, \lambda_t^d, \lambda_t^c, \lambda_t^a]$ reflects the importance of the four types of features in the current working condition. Furthermore, the fusion feature is defined as:

$$f_t = \lambda_t^e z_t^e + \lambda_t^d z_t^d + \lambda_t^c z_t^c + \lambda_t^a z_t^a \tag{11}$$

The resulting f_t is no longer a simple splicing result, but a comprehensive representation that is dynamically adjusted with the change of the operating state.

As shown in Figure 3, the multi-source input is aggregated and concatenated with the attention enhanced representation of the previous stage to form a high-level dynamic vector for state recognition and trend prediction. This treatment is more suitable for vacuum pressure equipment scenarios than fixed weighting or direct series. The reason is that the dominant factors corresponding to the same workshop humidity deviation are not consistent under different backgrounds: when the filter pressure difference continues to rise and the fan current rises synchronously, the equipment side characteristics and the event side characteristics should account for higher weights. When the steam pressure fluctuation causes frequent modification of the humidification valve, the characteristics of the actuator and the environmental side are more worthy of attention. The dynamic fusion layer can automatically learn this "state-feature contribution" relationship during training, so as to compress the local symptoms scattered at different measurement points into a more stable and discriminative running representation.

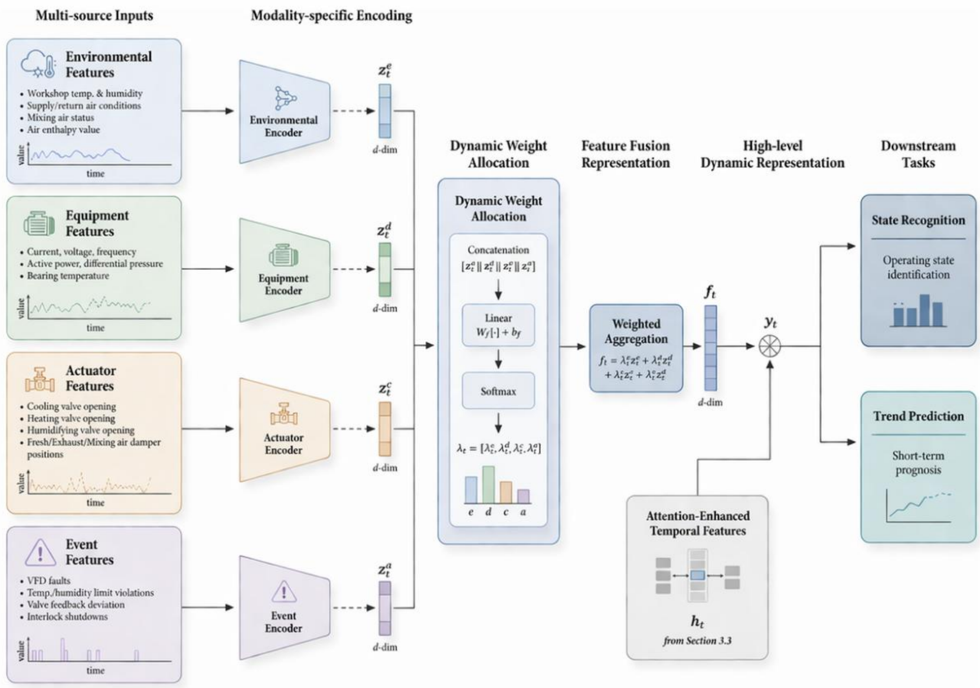

Figure 3: Flow chart of multidimensional feature fusion and dynamic representation of vacuum pressure equipment

From the perspective of engineering application, the significance of multi-dimensional feature fusion and dynamic representation module is not only to improve the accuracy of the model, but also to unify the field control logic, alarm information and equipment trajectory into the same computing framework. In this way, the model can not only identify complex anomalies such as air supply state deviation, motor load anomaly and valve response hysteresis, but also provide a continuous, compact and updatable input basis for subsequent operation state recognition and short-term trend prediction, making the deep learning analysis results closer to the real operation mechanism of vacuum pressure equipment.

3.5 Operation state identification and trend prediction model construction

After the completion of temporal feature extraction, attention enhancement, and multi-dimensional feature fusion, the model needs to transform the high-level dynamic representation into a discriminative result that can directly serve the production operation. Combined with the monitoring object and alarm system of the field system, it can be seen that the vacuum pressure equipment has discrete state information such as the running state of the return fan, the fault state of the frequency converter, the action of the fire valve, the alarm of the antifreeze switch, and the running current of the motor exceeding the limit. At the same time, continuous variables such as temperature and humidity of the workshop, the return air state, the valve opening, the filter pressure difference, the frequency, the current and the power are continuously recorded. Since these signals not only reflect the current working condition, but also imply the subsequent offset trend, the output layer is designed as a dual-task structure of "state recognition + trend prediction" to complete the operation state discrimination and short-term prediction of key indicators at the same time. Let the dynamic representation of the output of the multidimensional feature fusion module at time t be $f_t \in \mathbb{R}^{d_f}$, then the shared representation layer can be written as:

$$u_t = \sigma(W_s f_t + b_s) \tag{12}$$

Here, W_s and b_s are shared layer parameters, and $\sigma(\cdot)$ represents the nonlinear activation function. The role of this layer is not simply to increase the depth of the network, but to compress the environmental side, equipment side, actuator side and event side features into a discriminative unified representation, so that the model can depict the implicit connection between temperature and humidity regulation, fan load change and valve action in the same space. Field control data show that the system belongs to a large lag object, and there is a continuous coupling relationship between temperature, humidity, enthalpy value, air volume and fan frequency, so this shared representation is more suitable to undertake state transition information under complex working conditions.

In the state recognition branch, this paper uses the Softmax classifier to output the probability distribution of the device in normal, early warning or fault states:

$$\hat{y}_t = \mathrm{Softmax}(W_c u_t + b_c) \tag{13}$$

where $\hat{y}_t$ is the state class probability vector. The "early warning" here does not mean that the shutdown fault has occurred, but refers to the continuous increase in filter resistance, the decline in air supply, the abnormal current drop, the expansion of temperature and humidity deviation, and the frequent communication failure, which have not yet completely failed but have revealed abnormal symptoms. The descriptions of filter differential pressure alarm, insufficient air supply, motor overload, abnormal motor temperature rise, and inverter alarm in the training material also provide a basis for the label construction of such intermediate states. In the trend prediction branch, the model gives continuous value estimates for critical running quantities in the future period:

$$\hat{r}_{t+\tau} = W_r u_t + b_r \tag{14}$$

Here, $\hat{r}_{t+\tau}$ represents the prediction result at time τ in the future, which can correspond to core indicators such as supply air temperature, relative humidity, fan frequency, differential pressure or power. These variables were chosen because the field control logic is already focused on the air supply state point, air enthalpy value, and fan frequency, and filter resistance, steam pressure, and valve response continue to influence the trajectory of these quantities through the control link.

The value of this dual-task structure is that it combines "is it abnormal now" and "how will it change" into the same computational framework. The classification results can serve for fault alarm and operation classification, and the regression results can provide a basis for parameter pre-tuning, maintenance scheduling and energy consumption optimization. Compared with the model that only does single fault identification, the operation state identification and trend prediction model constructed in this paper is more in line with the field characteristics of continuous operation, slow drift and multivariate linkage of vacuum pressure equipment, and also makes the dynamic characteristics formed in the previous section truly fall into the executable engineering output.

4 Experimental simulation and result analysis

4.1 Experimental Environment and Data set Construction

The experiment is completed on an industrial data analysis workstation with GPU acceleration. The operating system is Ubuntu 20.04, the programming language is Python 3.10, and the deep learning framework is PyTorch. The data processing and visualization are implemented in NumPy, Pandas, and Matplotlib, respectively. Considering that the operating data of vacuum pressure equipment has the characteristics of multivariate, long time window and continuous iterative training, the experimental environment is equipped with multi-core CPU, independent graphics card and large memory to ensure the stability of sliding sample construction, model training and parameter optimization. Such a combination of software and hardware not only meets the parallel computing requirements of temporal network, but also facilitates the subsequent comparison algorithm reproduction experiments.

The data set construction does not rely on a single measurement point, but is organized for the complete control link of the vacuum rehydration related unit. According to the field data, the bottom layer of the system is composed of temperature and humidity sensor, differential pressure sensor, valve feedback unit, frozen water and steam parameter collection point, and internal communication parameters of the inverter. The upper layer realizes status display, history inquiry, alarm filing and remote control through S7-1500 PLC, PROFINET bus, TP1500 touch screen and central management workstation. Therefore, in this paper, variables such as workshop temperature and humidity, return air temperature and humidity, mixed air and meter cooling state, filter pressure difference, valve opening, temperature and pressure of chilled supply and return water, steam supply parameters, and inverter current, voltage, frequency, power, and running time are uniformly included in the sample construction scope, and reorganized into multivariate time series samples according to a fixed time step.

In the label construction, this paper combines real-time alarm records and operation and maintenance knowledge to label the state of the sample. In addition to the normal working conditions, the abnormal scenes such as inverter fault, air supply temperature and humidity overrun, motor operating current overrun, water vapor valve feedback deviation, fire valve action, filter differential pressure alarm and insufficient humidification amount are mainly retained, so that the data set covers both the continuous adjustment process and the typical fault evolution process. As shown in Table 2, the data set of this study is composed of four types of information: environment side, equipment side, actuator side and event side, which is closer to the real operation mechanism of vacuum pressure equipment and provides a more complete data basis for subsequent state identification and trend prediction.

Table 2: Composition of the experimental data set

Data Category	Main Source	Typical Variables	Function
Environmental data	Temperature–humidity sensors, air duct measuring points	Workshop temperature and humidity, supply/return air temperature and humidity, mixed air temperature and humidity, post-cooling-coil temperature and humidity	Characterize the process environment and air handling status
Equipment-side data	Variable-frequency drive communication parameters, pressure and temperature sensors	Current, voltage, frequency, power, operating time, differential pressure, supply/return water temperature and pressure	Reflect equipment load and operating intensity
Actuator-side data	Valve and air damper feedback units	Cooling valve opening, heating valve opening, humidification valve opening, fresh/return/mixed air damper opening	Describe the control response process
Event-side data	Alarm archives, operating status records	VFD faults, temperature/humidity limit violations, current limit violations, valve feedback deviation, fire damper actuation	Support state label construction and anomaly identification

4.2 Evaluation index setting

In order to keep the experimental results consistent with the "dual task" output structure constructed in the previous section, this paper divides the evaluation indicators into two categories: running state recognition indicators and trend prediction indicators. Considering that the vacuum pressure equipment contains not only discrete states such as frequency converter fault, air supply temperature and humidity overrun, current overrun, valve feedback deviation, but also continuous output variables such as temperature and humidity, frequency, power, pressure difference, etc., a single index is difficult to completely reflect the model performance, so it is necessary to evaluate from two levels: classification effect and numerical fitting error.

In the running state recognition task, this paper uses accuracy, precision, recall and F1 value as the core indicators. Accuracy is used to measure the proportion of correct judgments made by the model as a whole and is defined as:

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{15}$$

Here, TP, TN, FP and FN denote true, true negative, false positive and false negative examples, respectively. Considering that early warning samples and fault samples are usually less than normal samples in actual operation, it is easy to cover up the insufficient identification of minority classes by only using accuracy. Therefore, precision and recall are further introduced:

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{16}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{17}$$

$$\mathrm{F}_1 = \frac{2 \times \mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{18}$$

The synthesis reflects the ability of the model to identify abnormal states. For vacuum pressure equipment, a low recall means that potential anomalies are missed, while a low precision results in too many false positives, both of which are detrimental to field operation decisions.

In the trend prediction task, this paper mainly evaluates the short-term prediction effect of key variables such as supply air temperature and humidity, fan frequency, pressure difference and power, and chooses the root mean square error and mean absolute error as the evaluation basis. The expressions are respectively:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\hat{\mathrm{y}}_\mathrm{i} - \mathrm{y}_\mathrm{i})^2} \tag{19}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}|\hat{\mathrm{y}}_\mathrm{i} - \mathrm{y}_\mathrm{i}| \tag{20}$$

where y_i is the true value, $\hat{\mathrm{y}}_\mathrm{i}$ is the predicted value, and N is the number of samples. RMSE is more sensitive to large deviations, which is suitable for testing the responsiveness of the model to sudden fluctuations. MAE is more intuitive to reflect the average prediction error level. The combination of the two indexes can comprehensively evaluate the accuracy of the model in describing the dynamic change process of vacuum pressure equipment.

4.3 Comparison of algorithm choices

In order to objectively test the effectiveness of the model in the operation data analysis of vacuum pressure equipment, the experiment set up comparison algorithms around the two tasks of "operation state identification" and "trend prediction". The reason for the sub-task comparison is that the field data simultaneously contains discrete state information such as frequency converter fault, fire valve action, air supply temperature and humidity overrun, motor current overrun and other discrete state information. Time series variables such as workshop temperature and humidity, filter pressure difference, valve opening, frequency conversion frequency, current and active power are also continuously recorded. The two types of tasks are different in output form and modeling emphasis, and it is difficult to accurately judge the advantage boundary of the proposed method if only a single reference model is used.

In the part of running state recognition, support vector machine and decision tree are selected as the traditional comparison algorithms. Support vector machine (SVM) is suitable for small and medium scale and high dimensional feature classification problems. It can nonlinearly divide the preprocessed features such as temperature and humidity, pressure difference, current and valve feedback deviation. The decision tree has a clear structure, which is easy to observe the splitting relationship between different alarm variables and state labels, and has certain interpretability. These two categories of methods are retained because they are representative in industrial state recognition and can be used as the base reference for deep learning models.

In the part of trend prediction, ARIMA and single-layer LSTM are selected as comparison models in this paper. ARIMA is mainly used to test the fitting ability of traditional statistical time series methods to continuous variables such as supply air temperature and humidity, fan frequency, pressure difference and power. Single-layer LSTM can capture a certain degree of time dependence, which can be used as a basic baseline for deep time series prediction. Due to the continuous coupling between temperature and humidity, enthalpy-value, air volume and fan frequency in the field system, and non-stationary disturbances caused by filter resistance changes, steam fluctuations and valve action hysteresis, the comparison of the proposed model with ARIMA and LSTM can more intuitively reflect the role of multi-dimensional feature fusion and attention enhancement in the analysis of complex working conditions.

4.4 Display and analysis of experimental results

Under the unified data division, the same preprocessing process and the same label system, the running state recognition comparison experiment of the proposed model, SVM and DT is carried out. The status label is constructed according to the field alarm and operation logic, which mainly covers three categories: normal operation, early warning state and fault state. The early warning state mainly corresponds to the samples that have not triggered the interlocking shutdown but have shown abnormal symptoms, such as the continuous rise of filter pressure difference, the expansion of valve feedback deviation, the air supply temperature and humidity close to the upper limit, and the abnormal fluctuation of inverter related parameters. This setting is consistent with the system's existing functions of differential pressure detection, valve opening feedback, inverter fault monitoring and history recording.

As shown in Table 3, the proposed model achieves 95.8%, 94.6% and 94.9% in the three indicators of Accuracy, Recall and F1, respectively, which are significantly higher than those of SVM and DT. The reason is not only that the number of network layers increases, but also that the temporal feature extraction and attention enhancement mechanism constructed in the previous section can extract more discriminative dynamic patterns from multi-source sequences such as temperature and humidity, pressure difference, frequency, current and valve opening. When the system has progressive anomalies such as "filter resistance rise - fan load rise - air supply state deviation", the traditional model can only identify local deviations. However, the proposed model can preserve the time dependence relationship and the coupling relationship between variables at the same time, so the identification results are more stable.

Table 3: Results of operation status identification of different algorithms

Algorithm	Accuracy / %	Precision / %	Recall / %	F1 / %
Proposed model	95.8	95.2	94.6	94.9
SVM	87.4	86.1	84.8	85.4
DT	89.1	88.3	86.5	87.4

At the same time, for the key continuous variables such as supply air temperature, supply air relative humidity, fan frequency and filter pressure difference, this paper further compares the short-term prediction performance of different models. The reason why this group of indicators is selected is that the on-site control system automatically adjusts around the air supply state point, fan frequency, water vapor valve opening and filter resistance changes, and saves the corresponding historical query data. These quantities can reflect both the current operating level and the early exposure of problems such as steam pressure fluctuations, insufficient humidification efficiency and elevated ventilation resistance.

As shown in Table 4, the RMSE and MAE of the proposed model are 0.118 and 0.087, respectively, which are significantly lower than those of ARIMA and single-layer LSTM. At the same time, the average warning advance of the proposed model reaches 2.9 hours, which is higher than that of the other two groups of comparison models. This shows that under the dataset and experimental Settings constructed in this paper, the multi-dimensional feature fusion and dual-task output structure not only improve the numerical fitting accuracy, but also enhance the ability to perceive the abnormal evolution process in advance. For vacuum equipment, increasing the warning time has direct engineering significance, because problems such as blocked filters, low steam pressure, and slow valve action are usually not instantaneous failures, but rather go through a slow, observable migration process.

Table 4: Comparison of trend prediction results of different algorithms

Algorithm	RMSE	MAE	Average Early Warning Lead Time / h
Proposed model	0.118	0.087	2.9
ARIMA	0.294	0.221	0.8
Single-layer LSTM	0.183	0.136	1.7

From the prediction trajectory, Figure 4 shows the trend of RMSE variation of different models when the prediction step size increases. It can be seen that as the step size increases from 1 to 12, the errors of the three methods all rise, but the curve of the proposed model is lower and fluctuates less as a whole, indicating that it has stronger adaptability to long-term dependence and working condition migration. Especially under the condition of high humidity load fluctuation and steam supply disturbance, the error expansion of the proposed model can still maintain a relatively gentle increase, while the error expansion of the traditional statistical model is more obvious.

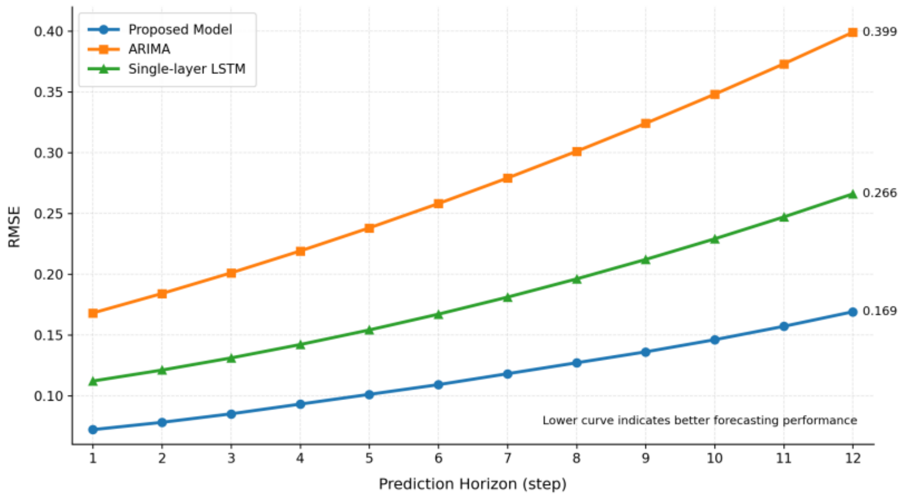

Figure 4: RMSE variation curves of each algorithm under different prediction step sizes

In order to further investigate the robustness of the model, supplementary experiments are carried out under different training sample sizes and different working conditions. Figure 5 shows that as the proportion of training samples increases from 20% to 100%, the recognition accuracy of the proposed model continues to rise and tends to be stable around 80%, indicating that it can gradually learn a more complete operating mode with the increase of data volume, and there is no obvious performance oscillation due to sample expansion. In contrast, SVM and DT have a smaller boost and are more susceptible to local feature distribution changes in complex operating conditions.

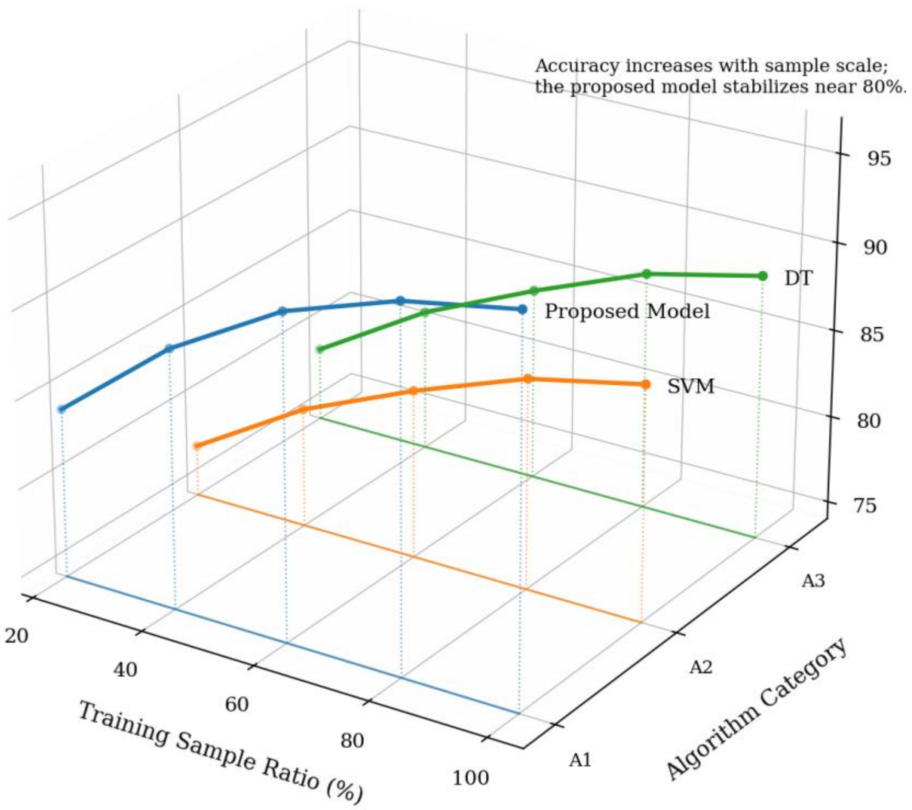

Figure 5: Variation curves of state recognition accuracy of each algorithm under different proportions of training data

In the experiment of working condition change, three scenarios of high humidity disturbance, rising filter pressure difference and steam pressure fluctuation were simulated. The results show that the state recognition accuracy decline of the proposed model is controlled within 3% in the three types of scenarios, and the increment of trend prediction RMSE is also kept at a low level. This is consistent with the control mechanism of the field system: temperature and humidity regulation, fan frequency regulation, water vapor valve range control and alarm interlock together constitute a strong coupling operation link. Only by capturing the information of environment side, equipment side and actuator side at the same time, the model can maintain stable discrimination ability under changing working conditions.

5 Conclusion

In this paper, a deep learning analysis framework consisting of timing feature extraction, attention mechanism enhancement, multi-dimensional feature fusion and dual-task output is constructed around the problems of multi-source monitoring data that are difficult to express uniformly, strong coupling of operating states, scattered abnormal symptoms and time-delay. Based on the vacuum moisture return related unit of Baoji Cigarette factory, the system modeling of the operation process of vacuum pressure equipment is carried out by using the industrial data link formed by PLC, PROFINET communication, temperature, humidity and pressure difference sensors, valve feedback unit, inverter operating parameters and historical records of central control platform. The results show that the proposed method can better integrate the information of environment side, equipment side, actuator side and event side, and extract the dynamic operation features with discriminative power under complex operating conditions. The experimental results show that the proposed model achieves good performance in the task of running state recognition, with the Accuracy, Recall and F1F_1F1 reaching 95.8%, 94.6% and 94.9%, respectively, which are better than traditional methods such as SVM and DT. In the trend prediction task, the RMSE and MAE of the model are 0.118 and 0.087, respectively, which show a lower error level than ARIMA and single-layer LSTM, and the average amount of warning advance reaches 2.9 hours. This shows that the proposed method can not only distinguish the normal, early warning and fault states more accurately, but also make a more stable prediction of short-term changes in key operating quantities such as supply air temperature and humidity, fan frequency, pressure difference and power. Combined with the experimental results of different data scales and working condition disturbances, the model still maintains good adaptability in scenarios such as sample increase and high humidity, increase in pressure difference, and steam fluctuation, and the decline of state recognition accuracy is controlled within a small range, indicating that it has certain robustness and engineering application potential. Of course, there is still room for improvement in this paper. The current research data are mainly from the vacuum retidal related units in a single plant, and the cross-equipment migration ability and cross-scene generalization ability of the model still need to be further verified. At the same time, deep models are still higher than traditional methods in terms of training cost, parameter scale, and online deployment efficiency. Subsequent research can combine transfer learning, model lightweight and incremental update mechanism to further improve the adaptability of the model under different equipment, different seasons and different load conditions, and incorporate operation and maintenance logs, maintenance records and long-term process beat information into the analysis link, promoting the operation data analysis of vacuum pressure equipment from experimental verification to field closed-loop application.

Corresponding author

HAN Junxi Intermediate Engineer, Material Supply Section, Baoji Cigarette Factory, China Tobacco Shaanxi Industrial Co., Ltd., Baoji 721013, Shaanxi, China E-mail: baojihanjunxi@126.com

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