1 Appendix A

Non-stationary characteristics pose a significant obstacle to the safe and stable operation of complex industrial processes, with traditional safety control methods often overlooking these factors, making it difficult to adapt to changing operating conditions. To address above issue, this paper proposes a scheme for safety control of non-stationary complex industrial processes based on a resiliently time-varying dynamic Bayesian network (RTV-DBN). This method is based on a vector autoregressive model, which extracts the temporal variation features among multiple variables, dynamically updating the RTV-DBN model structure and parameters to ensure that it can accurately describe the dynamic changes in industrial processes. For non-stationary processes, a global detection model for non-stationary characteristics of industrial processes is constructed, using difference guidance to remove non-stationarity. In addition, a RTV-DBN model is established using global information to capture the causal relationships among multiple variables from the time-varying process and identify potential abnormal operating conditions. The temporal data is projected into a finite-dimensional space, and learning the structure and parameters of the RTV-DBN model, probability density functions are used to accurately locate abnormal time slices and determine the process variables causing the abnormal conditions. Finally, the effectiveness of the proposed method is validated in coal preparation processes.

2 Appendix B

Existing safety control methods for non-stationary complex industrial processes can be categorized into model-based methods, knowledge-driven methods, and data-driven methods. Model-driven methods are based on physical and chemical principles, with strong model interpretability, suitable for specific process operations [1–3]. For nonlinear and non-stationary processes, modeling is challenging, and updating and maintaining models is difficult. Model-driven approaches find it hard to adapt to rapidly changing conditions [4]. Knowledge-driven methods leverage expert knowledge and experience, with clear rules and transparent reasoning processes, suitable for known conditions and fault types [5]. Establishing and maintaining a rule base is a major challenge for knowledge-driven approaches, as they cannot handle new, unknown failures and have limited capability to manage complex nonlinear relationships [6,7]. Data-driven methods can handle large volumes of data, capture complex patterns and nonlinear relationships, are highly adaptable, and can be applied to various process operations [8–10]. Nevertheless, they rely on large amounts of high-quality data, are difficult to interpret and understand, and have low sensitivity to newly emerging faults and conditions [11, 12]. Methods purely based on models or knowledge, data-driven approaches have limited capabilities in the face of anomalies in non-stationary complex industrial processes. This paper constructs a knowledge-data dual-driven visual graph model guided by industrial knowledge to describe the causal topological structure of non-stationary complex industrial processes. The Bayesian network(BN) is a probabilistic graph model widely used by combining graph theory and probability theory. Li H and Wang F addressed the issue of insufficient abnormal data in the gold hydrometallurgy thickening process and proposed a safety control modeling method based on Bayesian network transfer learning for the thickening process of gold hydrometallurgy [13]. Hao Yan, Shiji Song et al. addressed the problem of data scarcity in the flotation process and proposed an operational adjustment modeling approach based on Bayesian network transfer learning for new flotation processes under scarce data. Through transfer learning of structure and parameters, the decision-making accuracy of new processes is improved [14]. Hao Yan et al. introduced a Bayesian network method based on transfer learning to address small data problems under abnormal conditions in magnesium smelting processes [15]. Dynamic Bayesian Network (DBN) is an extension of BN, which is a probabilistic graphical model specifically to handle temporal data that changes over time. By combining graph structures and probability theory, DBNs can effectively represent and reason about the complex dependencies and uncertainties in temporal data. In the areas of complex industrial process fault detection and decision support, DBN demonstrate unique advantages and broad application prospects [16]. Huimin Wang and Qi Huang proposed a Dynamic Bayesian Network Control Strategy for Modeling Grid-Connected Inverter Stability to address the dynamic stability issue of grid-connected inverters in distributed generation systems [17]. D. Codetta-Raiteri and L. Portinale proposed an innovative method for designing and implementing fault detection, identification, and recovery (FDIR) for autonomous spacecraft, such as

Mars rovers, using dynamic Bayesian networks [18]. Tong Q and Gernay T proposed a framework to measure the resilience of facilities in the process industry susceptible to cascading accidents, using DBNs to model scenarios of potential spatial and temporal cascading accident evolution, considering the uncertainty in the evolutionary paths during accident escalation [19]. Nevertheless, Existing safety control methods mainly focus on stationary temporal data and are predominantly grounded in linear models with the assumption of independent and identically distributed (IID) data. This restricts their ability to handle the intricate control problems of non-stationary processes. In real-world industrial settings, processes frequently display non-stationary traits. Their properties and behaviors evolve dynamically over time. The dynamic aspect means that data in non-stationary processes have temporal correlations and thus do not meet the IID assumption. To address the safety control problem of non-stationary processes, this paper establishes a Resilient Time-Varying Dynamic Bayesian Network (RTV-DBN) model for multi-level and multi-dimensional decision-making. This model adaptively handles non-stationary sequential data, dynamically adjusting its structure and parameters to reflect real-time process changes, ensuring the safe and stable operation of industrial process. First, field data is collected to construct a detection model for non-stationary characteristics, using the Augmented Dickey-Fuller (ADF) test to assess process stationarity. If non-stationarity is detected, differencing is employed. Stabilized and original stationary data are then integrated for correlation analysis, enhancing decision-making accuracy during anomalies. Next, a RTV-DBN model is established to capture causal relationships in time-varying processes and identify potential abnormalities. Temporal data is projected into a finite-dimensional space, and after learning the model's structure and parameters, the probability density function is used to pinpoint abnormal time slices and identify the variables causing anomalies. Finally, abnormal data is input as evidence into the dynamic Bayesian network to reason decision-making schemes that eliminate abnormal conditions, which are converted into robust control actions. The effectiveness of this method is validated in dense medium coal preparation and flotation processes. The contributions of this paper are summarized as follows:

- A novel safety control framework for non-stationary industrial processes is proposed based on a RTV-DBN, effectively addressing the challenges posed by frequent abnormal conditions and dynamic changes in complex process environments. Unlike traditional methods that overlook temporal variations, the RTV-DBN dynamically adapts to changing conditions by updating its structure and parameters, enabling robust abnormal condition detection and control.
- A knowledge-data guided RTV-DBN modeling approach is developed, which integrates global non-stationarity detection, temporal variation feature extraction, and causal structure learning to capture time-evolving causal relationships among process variables and accurately identify potential abnormal conditions.
- Extensive validation through real-world simulation cases in dense medium coal preparation and coal slurry flotation processes demonstrates the effectiveness and robustness of the proposed method in improving process safety and stability under non-stationary conditions.

3 Appendix C

3.1 ADF Test

The ADF test is a statistical test used to detect the presence of a unit root in temporal data [20]. The presence of a unit root indicates that the time series data is non-stationary, meaning its mean, variance, and autocorrelation structure change over time. The stationarity of a time series is a fundamental assumption in many statistical and econometric models, making the ADF test highly significant in time series analysis. The ADF test determines the stationarity of a time series by testing for the presence of a unit root in the model. It is an extension of the Dickey-Fuller test, accommodating more complex situations, including higher-order autocorrelation structures in the time series. The ADF test improves the reliability of the test by introducing lagged difference terms to eliminate higher-order autocorrelation in the series.

The ADF test is based on one of the following three model forms:

1.Without a constant term and without a time trend.

$$\Delta y_t = \alpha y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + {}_t \tag{1}$$

2.With a constant term but without a time trend.

$$\Delta y_t = \mu + \alpha y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + {}_t \tag{2}$$

3.With a constant term and a time trend.

$$\Delta y_t = \mu + \lambda t + \alpha y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + {}_t \tag{3}$$

where, Δy_t represents $y_t - y_{t-1}$, which is the first difference of the time series; y_{t-1} is the lagged value of the time series; μ is the constant term; λt is the time trend term; α is the most important coefficient in the ADF test, used to determine the existence of a unit root; β_i are the coefficients of the difference terms, used to eliminate higher-order autocorrelation in the series; p is the lag order.

The data in the dense medium coal preparation and coal slurry flotation process often exhibit a mean value and a non-zero time trend due to the changes in the properties of the raw coal and the systematic drift of the operating environment. After multiple experimental tests, this paper ultimately selects the third ADF test mode. The steps of the ADF test are divided into four steps:1. Select the appropriate model form based on the characteristics of the time series; 2. Use the least squares method to estimate the parameters in the model;3. Calculate the ADF statistic, which is the estimated divided by its standard error; 4. Compare the calculated ADF statistic with the corresponding critical value. The critical values are obtained from the Dickey-Fuller distribution table. If the ADF statistic is smaller than the critical value, the null hypothesis is rejected, indicating that the time series is stationary; if the ADF statistic is greater than the critical value, the null hypothesis cannot be rejected, indicating that the time series is non-stationary.

3.2 Resiliently Time-Varying Dynamic Bayesian Network Structure and Parameter Learning

A BN is composed of a DAG consisting of nodes and directed edges, where each node represents a random variable, and the directed edges represent the conditional dependencies between these variables. A DBN is an extension of a BN, which specifically deals with temporal data and dynamic systems [21]. It combines the time dependency characteristics of hidden Markov models (HMM) and state-space models, thus enabling the representation and reasoning of probabilistic relationships that change over time. In a DBN, a set of random variables X is represented as $X = \{X_i\}[T]_{i=1\ldots n}$, where $X_i[t]$ is the random variable at time step t. Define a network structure G, where this network structure represents the dependencies between variables at the same and adjacent time steps [22]. The dependencies in G allow for connections between variables at adjacent time steps, represented as $\mathrm{Pa}(Xi[t]) \subset \{X[t-1], X[t]\}$. This process assumes that the transition process follows a first-order Markov property, where all conditional dependencies are assumed to be stationary. Therefore, the dependencies between variables in the dynamic Bayesian network over time are as follows:

$$P(X_t|X_{t-1}, \theta_t) = \prod_{i=1}^{n} P(X_{t,i}|\mathrm{Pa}(X_{t,i}), \theta_t) \tag{4}$$

Nevertheless, in actual complex industrial processes, industrial processes are mostly dynamic and non-stationary. Therefore, this paper proposes a RTV-DBN. This network is an extended DBN model specifically designed to handle non-stationary complex processes with dynamically changing time series data and structures. This model combines the advantages of BN and DBN, capable of adaptively processing non-stationary temporal data with dynamically changing structures. RTV-DBN can dynamically adjust the network structure, network topology, and parameters based on the changes in temporal data, thereby better capturing the dependencies in the system at different time points. By dynamically adjusting the structure and parameters over time, RTV-DBN can adapt to the system's different modes of behavior at different times. Between time points t and $t+1$, let $X_i[t]$ and parameters $\Theta_i[t]$ represent the nodes at time point t, and let the conditional dependencies between the nodes be represented by $G[t]$. Then the parents of node $X_i[t]$ can be defined as [23–25]:

$$\mathrm{Pa}(X_i[t]) = \{\mathrm{Pa}_d(X_i[t]), \Theta_i[t]\} \tag{5}$$

where, $Pa_d(X_i[t])$ represents the non-parameter parent nodes of node $X_i[t]$, which are the set of data nodes adjacent to $X_i[t]$.

To describe the dynamic changes in parameters and structure, this paper introduces two transition models: one for parameter transitions and one for structural transitions.

Assuming the parameter $\Theta_i[t]$ is independent and follows a Gaussian process, then:

$$\Theta_i[t+1] \sim GP(\mu_i, K_i) \tag{6}$$

where, μ_i is the mean function, and K_i is the covariance function, describing the smooth changes of the parameter over time.

To justify the Gaussian process (GP) assumption for parameter transitions, we note that the temporal evolution of parameters in non-stationary industrial processes often exhibits smoothness and continuity, which aligns well with the properties of GP models. The GP framework allows for flexible modeling of non-linear trends and uncertainty in time-evolving parameters. The covariance function K_i is modeled using a squared exponential kernel:

$$K_i(t, t\prime) = s^2 Exp\left(-\frac{(t-t\prime)}{2\ell^2}\right) \tag{7}$$

where s^2 is the signal variance controlling the amplitude of fluctuations, and ℓ is the length-scale hyperparameter controlling temporal smoothness. These hyperparameters are selected via cross-validation on a held-out validation set, maximizing the marginal likelihood of observed data under the GP prior.

For structural transitions, the Markov assumption is adopted due to its simplicity and effectiveness in modeling systems with memoryless transitions between discrete states. This assumption is widely used in dynamic Bayesian networks and enables tractable inference of structure evolution over time.

Assuming the changes in structure $G[t]$ can be represented as a discrete-time Markov process, then:

$$P(G[t+1]|G[t]) = \prod_{i,j} P(e_{ij}[t+1]|e_{ij}[t]) \tag{8}$$

where, $e_{ij}[t]$ represents the directed edge between nodes i and j at time t. $P(e_{ij}[t+1]|e_{ij}[t])$ describes the transition probability of edge e_{ij} from time t to time $t+1$.

In summary, the RTV-DBN combined transition probability distribution can be represented as:

$$\begin{aligned} &P(\Theta[t+1], G[t+1]|\Theta[t], G[t]) = \\ &P(\Theta[t+1]|\Theta[t])P(G[t+1]|G[t]) \end{aligned} \tag{9}$$

where, $P(\Theta[t+1]|\Theta[t])$ represents the parameter transition process, and $P(G[t+1]|G[t])$ represents the structure transition process.

4 Appendix D

The stationarity of an complex industrial process refers to a time series where the mean and variance do not change over time, representing a long-term stable relationship. Nevertheless, most complex industrial processes are non-stationary. Non-stationary complex industrial processes typically exhibit characteristics where parameters and structures change over time due to factors such as disturbances and operational condition switches. These factors cause continuous changes in system states and parameters, making it difficult for a single fixed model to accurately describe and assess system behavior, thereby affecting control performance and decision accuracy. Proposing a reliable safety control scheme for non-stationary processes is crucial to ensuring the safe and stable operation of industrial processes.

Table 1 Measurement Variables in the Dense Medium Coal Preparation Process

Container	Nodes Physical Meanings	Nodes	Nodes States
Double Deck Screen	Output Flow Rate (t/h)	B	1: $Normal$, 2: $AbnormalSmall$, 3: $AbnormalLarge$
Single Deck Screen	Output Flow Rate (t/h)	C	1: $Normal$, 2: $AbnormalSmall$, 3: $AbnormalLarge$
Mixing Tank	Slurry Density (kg/m^3)	E	1: $Normal$, 2: $AbnormalSmall$, 3: $AbnormalLarge$
Dense Medium Cyclone	Medium Density (kg/m^3)	F	1: $Normal$, 2: $AbnormalSmall$, 3: $AbnormalLarge$
Correct Medium Tank	Medium Density (kg/m^3)	K	1: $Normal$, 2: $AbnormalSmall$, 3: $AbnormalLarge$
Dense Medium Cyclone	Overflow Ash Content (%)	H	1: $Normal$, 2: $Abnormal$

Table 2 Operational Variables in the Dense Medium Coal Preparation Process

Container	Nodes Physical Meanings	Nodes	Nodes States
Raw Bunker	Coal input (t/h)	A	1: $Normal$, 2: $AbnormalSmall$, 3: $AbnormalLarge$
Dense Medium Cyclone	Intervention pressure (Pa)	G	1: $Normal$, 2: $AbnormalSmall$, 3: $AbnormalLarge$

4.1 Analysis of Dense Medium Coal Preparation and Coal Slurry Flotation Processes

Dense medium coal preparation is a commonly used coal washing method that separates coal and gangue using a dense medium suspension, aiming to improve coal quality and reduce impurity content. The basic principle is to exploit the density differences between coal and gangue. Through the flotation action of the dense medium suspension, coal with a smaller density floats on the surface of the suspension, while gangue with a larger density sinks to the bottom, thus achieving the separation of coal and gangue. The process flow diagram of dense medium coal preparation is shown in Figure 1. The main equipment includes a dense medium cyclone, a double deck screen, a single deck screen, a mixing tank, a magnetic separator, a gangue desliming screen, a correct medium tank. In the analysis case presented in this paper, the dense medium coal preparation process includes 6 measurement variables and 2 operational variables, with detailed variable allocations shown in Tables 1 and 2.

In the dense medium coal preparation process, the raw coal is first crushed and screened to remove large pieces of coal and gangue, ensuring a uniform particle size of the coal entering the separation process. The pre-treated coal enters the dense medium separator, where, in the dense medium suspension, coal with a smaller density float to the surface while gangue with a larger density sinks to the bottom. The clean coal floating on the surface and the gangue sinking to the bottom are separately subjected to dewatering using dewatering screens, removing the surface suspension liquid to obtain clean coal and gangue. Finally, a magnetic separator is used to recover magnetite powder from the suspension, which is then reintroduced into the suspension for recycling. With technological advancements and increasing environmental requirements, the development trend of dense medium coal preparation is moving towards automation and intelligence. The adoption of automated and safety control technologies is crucial for improving separation efficiency and ensuring the safe and stable operation of industrial processes.

The coal slurry flotation process is a method that achieves separation by exploiting the differences in density and surface chemical properties between coal and mineral impurities. The flotation method utilizes the different wettability of coal and impurities in water. By adding flotation reagents, coal particles attach to air bubbles and float to the surface of the water, thereby separating coal from mineral impurities. The basic principle of flotation is based on the different wettability of coal and mineral impurities in water. Coal has strong hydrophobicity, while most mineral impurities are hydrophilic. By adding flotation reagents, the surface properties of coal particles are altered to become more hydrophobic, making it easier for them to attach to air bubbles and float to the surface along with the bubbles. The process flow diagram of the flotation process is shown in Figure 2. The main equipment includes: Ore Slurry Pre-Processor, Thickener, Flotation cell, raw bunker, reagent addition system, and others. Detailed variable allocations are shown in Tables 3 and 4.

In the coal slurry flotation process, the raw coal is first crushed and screened to reduce the coal particle size and remove large impurities, ensuring that the coal particle size meets flotation requirements. The pre-treated coal is then further ground and mixed into a slurry to increase the surface area and improve flotation effectiveness. During the slurry preparation process, coal powder is mixed with water to form a slurry. At this stage, regulators are added to adjust the pH of the slurry to enhance the flotation performance of the mineral surfaces. Suitable flotation reagents are then selected based on the properties of the coal and impurities. The most critical step is flotation, where the slurry is fed into a

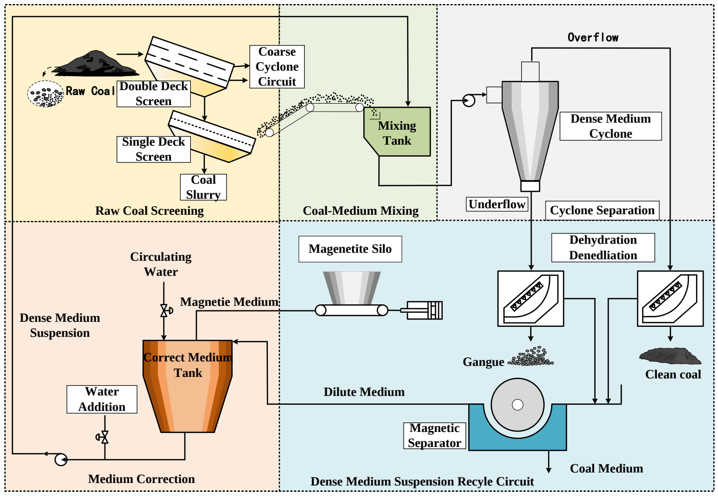


Figure 1 Dense medium coal preparation process flow diagram.

Table 3 Measurement Variables in the Slurry Flotation Process

Container	Nodes Physical Meanings	Nodes	Nodes States
Ore Slurry Pre-Processor	Medium Density (kg/m^3)	N	$1\colon Normal, 2\colon AbnormalSmall, 3\colon AbnormalLarge$
Thickener	Medium Density (kg/m^3)	M	$1\colon Normal, 2\colon AbnormalSmall, 3\colon AbnormalLarge$
Flotation cell	Overflow Ash Content (%)	S	$1\colon Normal, 2\colon Abnormal$

flotation cell. In the flotation cell, mechanical agitation and air injection generate numerous bubbles, and the froth product floating to the surface is collected through a froth trough. The froth product obtained from flotation needs to be dewatered to obtain the final clean coal product. If abnormalities occur during the flotation process, they can lead to economic losses and even serious consequences such as injuries or fatalities.

4.2 Resiliently Time-varying Dynamic Bayesian Network Modeling

Methods based solely on data or expert knowledge are difficult to adapt to the highly dynamic, multivariable, time-varying, and strongly coupled nature of non-stationary complex industrial production processes. To address the safety control issues of non-stationary complex industrial processes, this paper designs a decision model based on a RTV-DBN. The RTV-DBN decision model combines data-driven and mechanism knowledge for modeling, making it a hybrid model driven by both data and knowledge. When data is abundant, the model can automatically adjust parameters through learning; when data is scarce, prior knowledge can be used to supplement and ensure the model's effectiveness. It can also be updated in real-time to adapt to changes in non-stationary processes. By dynamically adjusting model parameters and structure, it accurately reflects the state changes of the system over different periods, ensuring precise description and prediction of the system state. RTV-DBN can handle complex dependencies among multiple variables simultaneously, which is particularly important when dealing with multivariable coupling issues in complex industrial processes, as multiple process variables often influence and relate to each other. The model captures long-term trend changes and sudden abnormal conditions in industrial processes when dealing with time-varying characteristics of process parameters and structure, making the model more flexible and accurate. RTV-DBN inherently have the advantage of handling uncertainty, quantifying, and managing it through probability distributions.

Table 4 Operational Variables in the Slurry Flotation Process

Container	Nodes Physical Meanings	Nodes	Nodes States
Raw Bunker	Coal input (t/h)	A	$1\colon Normal, 2\colon AbnormalSmall, 3\colon AbnormalLarge$
Thickener	Underflow flow (m^3/h)	L	$1\colon Normal, 2\colon AbnormalSmall, 3\colon AbnormalLarge$
Flotation cell	Stirring speed (rad/min)	P	$1\colon Normal, 2\colon AbnormalSmall, 3\colon AbnormalLarge$

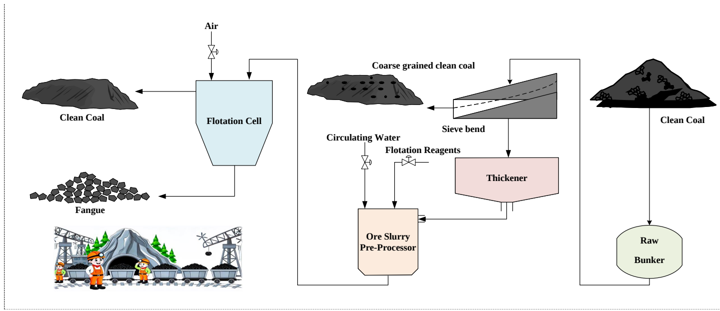


Figure 2 Coal slurry flotation process flow diagram.

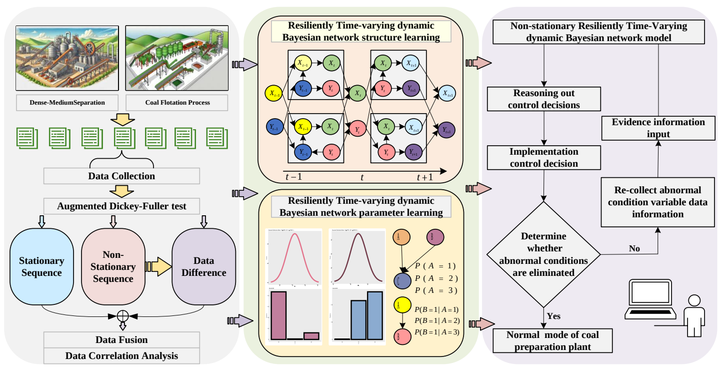


Figure 3 Safety control model for non-stationary complex industrial processes based on RTV-DBN.

In RTV-DBN, uncertainty is described through conditional probability distributions, effectively dealing with randomness and noise in industrial processes. As shown in Figure 3, to achieve anomaly detection and decision reasoning in non-stationary complex industrial processes, the main process of the RTV-DBN model is divided into three parts:1. Data Preprocessing: Analyze and process the collected field data. Use the ADF square root algorithm to test the stationarity of the data. If the data is non-stationary, apply differencing to stabilize the data. Merge the stabilized data with the original stationary data. After data fusion, perform correlation analysis to assess the relationships and dependencies between different variables. 2. RTV-DBN Structure Learning and Parameter Learning: Construct a network structure that reflects the causal relationships among industrial process variables, capturing the dependency changes of the system over different periods. Accurately locate abnormal time slices based on the learned structure and parameters, and determine the process variables causing the anomalies. The stationary temporal data is projected into a finite-dimensional space and fed into the RTV-DBN. After learning the structure and parameters of the RTV-DBN model, probability density functions are used to precisely locate abnormal time slices and identify the process variables responsible for the abnormal conditions. Structure learning is based on an resiliently net regression approach, where a temporally weighted Gaussian kernel function is employed to sparsely model the dynamic dependencies among variables. Significant connections are selected via L1 regularization, and a directed acyclic graph (DAG) is constructed accordingly. Parameter learning is divided into static and dynamic components. The static parameters are initialized using weighted maximum likelihood estimation. The dynamic parameters are updated recursively using a particle filtering algorithm, which incorporates a forgetting factor and M-estimation to handle non-stationary data. Additionally, KL divergence is utilized to monitor model drift and trigger structure adaptation when necessary.3. Decision Reasoning: Use the abnormal data as evidence input into the model to reasoning decision schemes that can eliminate abnormal conditions, and convert the decision schemes into robust control operations applied to the coal preparation process. The specific steps are as follows:

Step 1: Data Collection

Gather data from industrial processes, this involves collecting various temporal data representing different process related variables.

Step 2: Stationarity Testing with ADF
Apply the ADF test to the collected temporal data. This test assesses whether the data is stationary. Stationary data has constant statistical properties over time. If the data fails the ADF test, it is non-stationary and requires further processing.
Step 3: Handling Non-stationary Data
For non-stationary data identified in Step 2, use differencing techniques. This typically involves subtracting consecutive data points to transform the non-stationary data into a stationary sequence. The goal is to make the statistical properties of the data stable over time.
Step 4: Data Fusion
Fusion the stabilized non-stationary data with the original stationary data. This creates a combined dataset that contains all relevant information about the industrial process variables in a consistent format for further analysis.
Step 5: Data Correlation Analysis
Perform correlation analysis on the fusion dataset. This analysis helps identify the relationships between different variables in the industrial process. By calculating correlation coefficients, we can determine which variables move in tandem and how strongly they are related, providing insights into the process dynamics.
Step 6: RTV-DBN Structure Learning
Conduct structure learning for the RTV-DBN. Analyze the time-varying relationships between variables in the processed data. Use algorithms to determine the causal connections between variables at different time steps. This step builds the network structure that represents the process's dynamic behavior.
Step 7: RTV-DBN Parameter Learning
After establishing the network structure in Step 6, estimate the parameters of the RTVDBN model. Calculate probabilities associated with the relationships between variables. These parameters quantify the strength and nature of the causal relationships in the network, enabling accurate predictions.
Step 8: Abnormal Detection with RTV-DBN
Input the online abnormal data phenomenon variables into the established RTVDBN model as evidence. The model uses its learned structure and parameters to perform probabilistic inference. Through this process, it determines the specific time slices when anomalies occur in the industrial process and identifies the variables causing these abnormal conditions.
Step 9: Control Scheme Reasoning
Based on the anomaly detection results from Step 8, the RTVDBN model reasons out control schemes. These schemes are designed to eliminating the identified abnormal conditions and bring the industrial process back to normal operation.
Step 10: Control Scheme Implementation
Implement the control schemes in the industrial process. Monitor the process to check if the abnormal conditions are eliminated. If the anomalies are resolved, the process switches to normal working mode. If not, return to Step 8, input new online data as evidence, and repeat the process of anomaly detection, control scheme reasoning, and implementation until the abnormal conditions are successfully addressed.

5 Appendix E

Due to changes in environmental conditions, disturbances, and operational condition switches, both the dense medium coal preparation process and the coal slurry flotation process exhibit non-stationarity. The non-stationarity and time-varying nature of industrial processes lead to continuous changes in system states and parameters, making it difficult for a single fixed model to accurately describe and assess system behavior, thereby affecting control performance and decision accuracy. Relying solely on expert knowledge or data-driven methods to solve abnormal conditions introduces significant uncertainty, increasing the difficulty of modeling and making control decisions. Therefore, using the dense medium coal preparation process and the coal slurry flotation process as examples, this paper designs a safety control decision model based on resiliently time-varying dynamic Bayesian networks. This section will take the coal preparation process as an example to carry out experimental verification of the method proposed in Appendix D on the laboratory simulation platform. The simulation platform is shown in Figure 8. There are 10,000 pieces of data respectively in both the dense medium coal preparation process and the coal slurry flotation process, and the data sampling frequency is at the minute level.

5.1 Stationarity Testing and Analysis of the Coal Preparation Process

To explore the stationarity of the coal preparation process, this subsection employs the ADF square root test method to perform stationarity testing on the coal preparation process. If a time series is non-stationary, it means its statistical properties change over time. The presence of a unit root is one of the main reasons for the non-stationarity of a time series. The ADF test method constructs a hypothesis test to determine whether a time series contains a unit root. The original hypothesis is that a unit root exists, indicating the data is non-stationary; the alternative hypothesis is that a unit root does not exist, indicating the data is stationary. Understanding the stationarity of data in the coal preparation process is crucial for establishing effective control strategies and improving separation efficiency. In the coal preparation process, key variables such as density and flow rate may fluctuate over time, and such fluctuations can lead to process control instability and reduced separation efficiency. Experiments show that key variables in the coal preparation process exhibit non-stationarity. Automatic control systems based on traditional control methods may not effectively adapt to these changes, leading to a decline in control performance.

This paper conducts ADF tests on the time series data in the coal preparation process to identify non-stationary process variables, thereby providing a reliable basis for further data processing and control strategy adjustments. In the dense medium coal preparation process, the non-stationary variables are the raw coal feed rate into the raw bunker (A), the double deck screen discharge flow rate (B), the single deck screen discharge flow rate (C), the cyclone medium density (F), the dense medium cyclone inlet pressure (G), and the dense medium cyclone overflow ash content (H). In the coal slurry flotation process, the non-stationary variables are the thickener underflow flow rate (L), the thickener medium density (M), the slurry pretreatment device medium density (N), and the flotation cell stirring speed (P).

The trend in non-stationary data can interfere with the decision-making capability of models and easily lead to overfitting. Converting the non-stationary process into a stationary process has significant benefits for control decision-making. This not only improves the accuracy and robustness of predictive models, but also simplifies the computation and analysis processes. By removing the non-stationarity of the data, the interpretability and operability of the data are enhanced, and the sensitivity and reliability of the control strategy are improved. After performing non-stationarity testing using the above method, this paper adopts data differencing to convert the non-stationary data process into a stationary one. On the basis of stationary data, any abnormal points deviating from stationarity can be more easily detected, which helps to timely identify and handle abnormal situations in the coal preparation process, and allows learning a more robust and adaptive time-varying dynamic Bayesian network structure and parameters.

5.2 Control Decision-making and Reasoning in the Coal Preparation Process

To validate the effectiveness of the modeling method proposed in Appendix D, this subsection conducts an online application verification of the RTV-DBN modeling method. The experimental validation is divided into two processes. The quality indicators selected for the two processes in this article are the ash content of the cyclone overflow (node H) and the ash content of the flotation cell overflow (node S). The detailed information about the abnormalities of the two quality indicators is shown in Table 5.

Table 5 Abnormal Information of Quality Indicators

Variable	Range	Types of Abnormal	Process Impact
H	10%–11%	anomaly: larger (>11%) anomaly: smaller (<10%)	Decline in the quality of clean coal, increased equipment wear
S	6%–6.6%	anomaly: larger (>6.6%) anomaly: smaller (<6%)	Decline in the quality of clean coal, reduced economic benefits, loss of flotation tailings

Process One: Dense Medium Coal Preparation Process.

Due to the complexity of the production environment, the dense medium coal preparation process exhibits characteristics of a non-stationary complex industrial process, such as multivariable, time-varying, and strongly coupled properties. The RTV-DBN model can adapt to parameters and structures that change over time, which is crucial for handling the non-stationary characteristics of the coal preparation process. The model captures the causal relationships between variables and presents these relationships in a graphical form, providing intuitive support for control decisions. After removing the non-stationarity of the data, the RTV-DBN model is trained with the data to uncover the causal relationships behind the data and determine the dynamic dependencies between nodes. As time progresses, the model can update these dependencies in real-time, reflecting the real-time state changes in the coal preparation process. When an anomaly is detected in a key variable or its dependencies, timely adjustments can be made to ensure the safe and stable operation of the coal preparation process. The network structure of the dense medium coal preparation process is shown in Figure 4.

Table 6 Conditional Probability Table for Overflow Ash Content H in the Dense Medium Coal Preparation Process

	B					1				
	C		1			2			3	
	G	1	2	3	1	2	3	1	2	3
!!Hpt¡	1	0.1768	0.2039	0.2305	0.1658	0.0305	0.1481	0.2257	0.2318	0.0885
	2	0.8232	0.7961	0.7695	0.8342	0.9695	0.8519	0.7743	0.7682	0.9115
	B					2				
	C		1			2			3	
	G	1	2	3	1	2	3	1	2	3
!!Hpt¡	1	0.1304	0.3076	0.1639	0.0806	0.1039	0.2336	0.1779	0.1636	0.0314
	2	0.8696	0.6924	0.8361	0.9194	0.8961	0.7664	0.8221	0.8364	0.9686
	B					3				
	C		1			2			3	
	G	1	2	3	1	2	3	1	2	3
!!Hpt¡	1	0.2972	0.2428	0.3014	0.3639	0.2468	0.3651	0.0714	0	0.2901
	2	0.7028	0.7572	0.6986	0.6361	0.7542	0.6349	0.9286	1	0.7099

Table 7 Dense Medium Coal Peparation Process Control Variable Adjustment Strategy

case	A	B	C	E	F	G	K
1	-	↑	-	-	↓	↓	-
2	-	-	↑	-	-	↓	-
3	-	↑	↑	-	↓	↓	-
4	↑	-	-	-	-	↓	-

As shown in Figure 4, the dynamic changes and causal relationships between variables in the dense medium coal preparation process are clearly evident. The structure in Figure 4 contains a total of 8 variables, and there are 50 time slices in total to display the dynamic changes of the causal structure. Over time, the structure and edges of the graph are updated in real-time. After learning the RTV-DBN structure for the dense medium coal preparation process, parameter learning is conducted by providing the conditional probability table (CPT) for each node, which forms the basis for reasoning control schemes. When an abnormal condition occurs in the coal preparation process, the probability density function is used to reasoning the abnormal time slice. Then, the conditional probability distribution is used to identify the variables causing the abnormal condition, reasoning the state of each variable at the current moment, and derive the optimal safety control scheme. Table 6 shows the conditional probability table for the quality variable overflow ash content H during an abnormal condition in the dense medium coal preparation process. The CPT is used to describe the probabilities of the quality variable (H) taking different values under different combinations of values of other relevant variables. Among them, variables B, C, and G have three different value states, namely Normal, Abnormal Small, and Abnormal Large. In the dense medium coal preparation process, the abnormality of the dense medium cyclone overflow ash content (H), a quality variable, has a strong causal relationship with variables B, C, and G. Process variable status 1 indicates normal, 2 indicates an abnormally small value, and 3 indicates an abnormally large value. In the reasoning, the abnormal evidence state is set to 1.

After completing the parameter learning of the RTV-DBN and determining the time slices when anomalies occur in the dense medium coal preparation process, the desired quality indicators and state values of the variables are input into the local network structure for reasoning, obtaining the posterior probabilities of the operational nodes. Based on the principle of maximizing the posterior probability, the decision adjustment scheme for the dense medium coal preparation process is derived, as shown in Table 7, where four process cases are selected for validation. In the table, '$\uparrow$' means that the value of the operating variable is increased, '$\downarrow$ ' means that the value of the operating variable is decreased, and '-' means that the value of the operating variable is unchanged. Excessive inlet pressure will increase the turbulence intensity inside the dense medium cyclone, leading to poorer particle separation. Finer particles and ash may be carried into the overflow, resulting in increased overflow ash content. High inlet pressure Requires higher pump power, which increases energy consumption and operating costs. Additionally, the increased load on the pump may lead to intensified wear and tear on the pump and pipes.

Table 8 CPT FOR OVERFLOW ASH CONTENT S IN THE COAL SLURRY FLOTATION PROCESS

	L	1			2			3		
	N	1	2	3	1	2	3	1	2	3
!!t¡	1	0.3182	0.0217	0.2571	0.1233	0	0.1126	0.5391	0.4379	0.2063
	2	0.6818	0.9783	0.7429	0.8767	1	0.8874	0.4609	0.5621	0.7937

To validate the effectiveness of the RTV-DBN modeling method and the case adjustment strategies, the four cases mentioned above were simulated on the dense medium coal preparation process simulation platform shown in Figure 8. After the occurrence of abnormal conditions, the overflow ash content of the dense medium cyclone was observed to determine whether it could return to the normal range. As shown in Figure 5, based on the guidance of on-site operators, the threshold for the premium ore grade in the dense medium coal preparation process is set to 0.11. When the threshold was exceeded, it was used as evidence input into the established RTV-DBN model to reasoning control schemes. As can be seen from Figure 5(a), in each case study, when an abnormal condition occurred, the control schemes reasoning using the proposed model in this paper could quickly eliminate the anomaly, ensuring the safe and stable operation of the non-stationary dense medium coal preparation process. Compare the proposed RTV-DBN method with the DBN-based methods and the methods proposed in References [13] and [14].By observing the BNTLS model, the DBN model, and the BNTLOAM model, as shown in Figure 5(b), Figure 5(c), and Figure 5(d), the algorithm proposed in this paper is significantly superior to the other three models in terms of eliminating abnormal working conditions. In addition, as shown in Table 10, in the safety control of the dense medium coal preparation process, the abnormal reasoning efficiency of the algorithm in this paper reaches 98.25%, which is better than the other three models, and the method proposed in this paper can handle dynamic processes.

Process Two: Coal Slurry Flotation Process.

In the coal slurry flotation process, the operating environment and various parameters frequently change, causing significant fluctuations in operating conditions, which severely affect product quality and production efficiency. Coal slurry flotation is a typical non-stationary industrial process influenced by various production environments and operating parameters. Its stability is crucial for ensuring production safety and improving economic benefits. Achieving safe control of the coal slurry flotation process is essential to ensure safe and stable operations. The safety control decision-making and reasoning process for the coal slurry flotation process relies on the RTV-DBN model to effectively manage abnormal conditions and improve product quality. The RTV-DBN model is an enhanced method of the traditional Bayesian network, capable of handling time series data and the temporal dynamics between variables. This network extends the Bayesian network to handle time-related data by introducing time slices. Using the model established in Appendix D, the coal slurry flotation process data is processed. After stabilizing the process, the RTV-DBN is used to uncover the causal relationships between variables and learn the

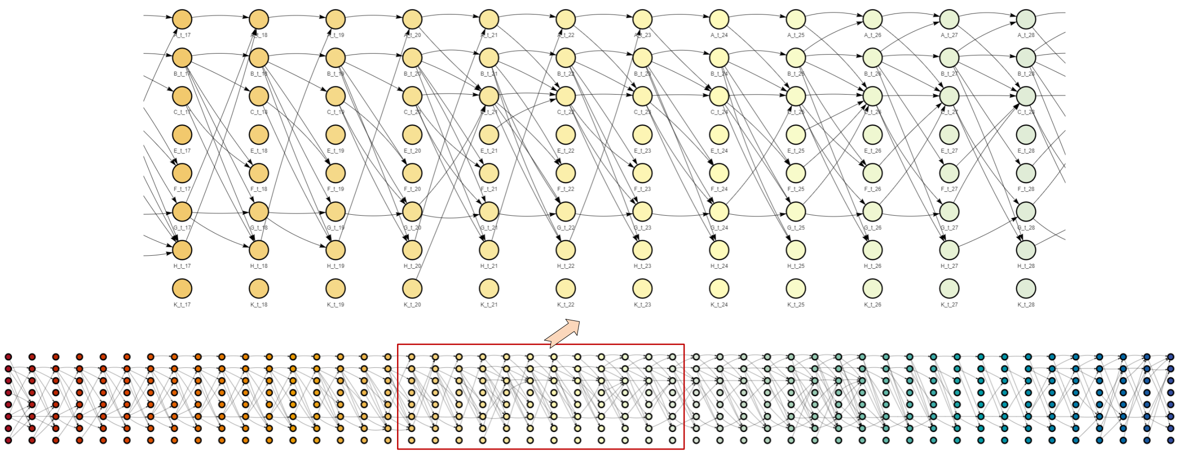


Figure 4 RTV-DBN structure for the dense medium coal preparation process.

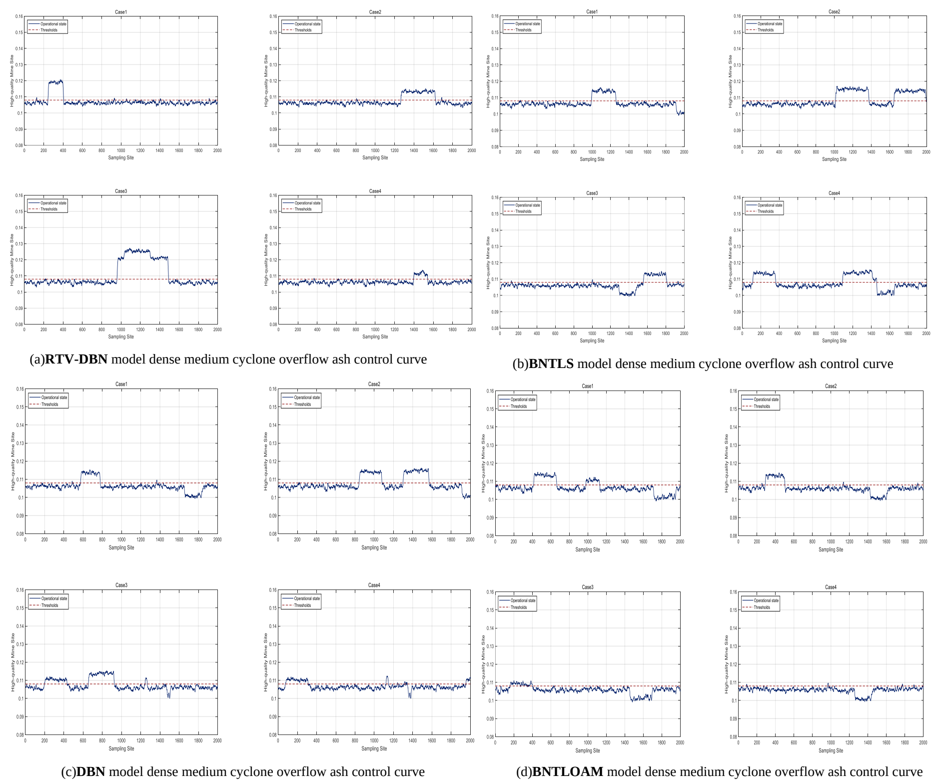


Figure 5 Curve of dense medium cyclone overflow ash content changes after implementing control schemes.

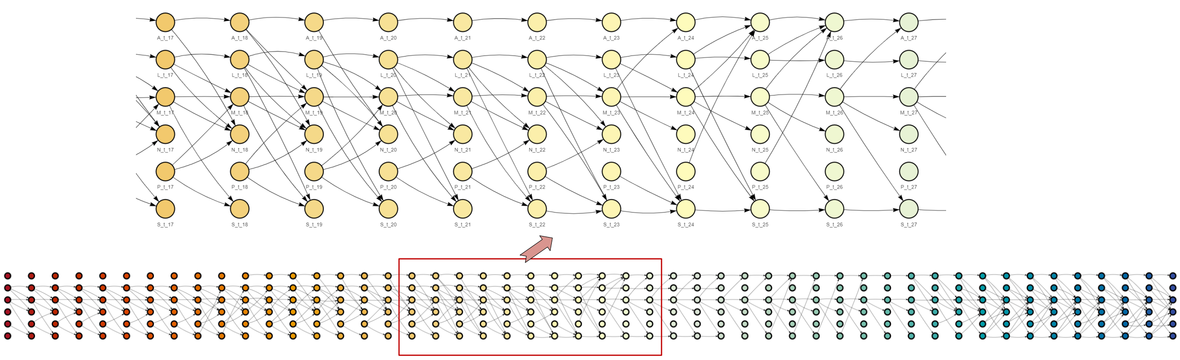


Figure 6 RTV-DBN structure for the coal slurry flotation process.

network structure of the flotation process. The structure in Figure 6 contains a total of 6 variables, and there are 50 time slices in total to display the dynamic changes of the causal structure.

By adjusting the network parameters through learning algorithms, the model can accurately reflect the actual process. When an abnormal condition occurs, forward reasoning is performed to estimate the probability distribution of the current state, identify the time slice when the anomaly occurs, and determine the control variables causing the anomaly. Based on the anomaly detection results, a decision scheme is reasoning to adjust the control variables, ensuring the safe and stable operation of the coal preparation process. Table 8 shows the CPT for the quality variable overflow ash content S during an abnormal condition in the coal slurry flotation process. Process variable 1 indicates normal, 2 indicates an abnormally low value, and 3 indicates an abnormally high value. In the reasoning process for the coal slurry flotation, the abnormal evidence state is set to 2.

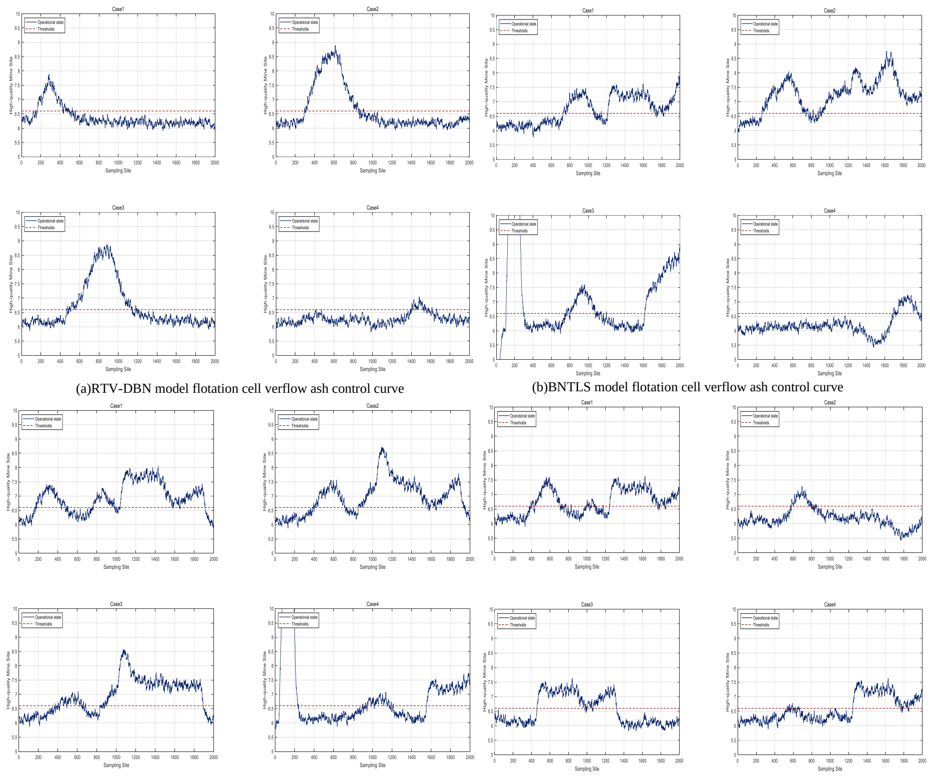
Table 9 Adjustment Strategy for Control Variables in the Slurry Concentration Flotation Process

case	A	L	M	N	P
1	↓	↑	-	↑	↓
2	↓	-	↑	-	-
3	↓	↓	↓	-	↓
4	-	-	↑	-	-

Table 10 Model Comparison

Model	**Process**	**Adapt dynamics**	**Reasoning accuracy rate**
BNTLS	Dense medium coal preparation	×	93.8%
	Coal slurry flotation		95.1%
BNTLOAM	Dense medium coal preparation	×	96.2%
	Coal slurry flotation		97.0%
DBN	Dense medium coal preparation	✓	95.0%
	Coal slurry flotation		96.2%
RTV-DBN	Dense medium coal preparation	✓	98.5%
	Coal slurry flotation		99.8%

After completing parameter learning, the abnormal evidence state in the coal slurry flotation reasoning process is input into the local network structure for reasoning. The reasoning process yields the



(a)RTV-DBN model flotation cell verflow ash control curve (b)BNTLS model flotation cell verflow ash control curve

(c)DBN model flotation cell verflow ash control curve (d)BNTLOAM model flotation cell verflow ash control curve

Figure 7 Curve of flotation cell overflow ash content changes after implementing control schemes.

decision adjustment scheme for the coal slurry flotation process, as shown in Table 9. Four cases were selected to verify the effectiveness of the model and control schemes in the coal slurry flotation process. In the table, "↓" indicates an increase in the adjustment direction, "↑" indicates a decrease in the adjustment direction, and "-" indicates no change. For example, if the stirring speed of the flotation cell is too high, it will increase the turbulence intensity in the liquid, causing bubbles to break easily. Bubble breakage reduces the number of bubbles and the surface area of the bubbles in the flotation process, thereby reducing the contact opportunities between mineral particles and bubbles, leading to abnormal conditions. In this case, the stirring speed of the flotation cell needs to be reduced.

To validate the effectiveness of the control schemes for the coal slurry flotation process, this paper simulated the above four cases on the simulation platform shown in Figure 8. After the occurrence of abnormal conditions, the overflow ash content of the flotation cell was observed to determine whether it could return to the normal range. As shown in Figure 7(a), based on the guidance of on-site operators, the threshold for the premium ore grade in the coal slurry flotation process is set to 6.6. When the threshold was exceeded, it was used as evidence input into the established resiliently time-varying dynamic Bayesian network model to reasoning control schemes. If the anomaly is not eliminated, the phenomenon variable data of the abnormal condition is re-collected and used as evidence input into the model to reasoning new control schemes until the anomaly is eliminated. In addition, the method RTV-DBN proposed in this paper is compared with the BNTLS model, the DBN model, and the BNTLOAM model, as shown in Figure 7(b), Figure 7(c), and Figure 7(d), with the overflow ash content of the flotation cell as the quantitative index. The comparative methods, the BNTLS model, are from Reference [13], and the BNTLOAM model is from Reference [14]. The algorithm proposed in this paper is significantly superior to the other three models in eliminating the abnormality of the overflow ash content of the flotation cell. When an abnormality occurs in the industrial process, the method proposed in this paper can eliminate the abnormality in a timely manner. Among all the comparison experiments, the BNTLS model has the worst effect. When facing the abnormal working conditions of the non-stationary process, it can barely eliminate the abnormality only in Case 4. In addition, as shown in Table 10, in the safety control of

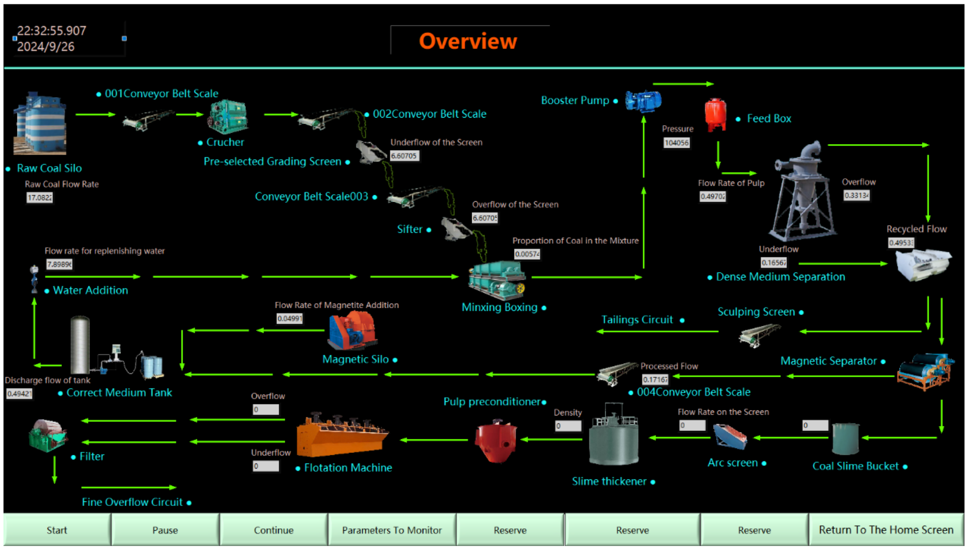


Figure 8 Coal preparation full-process simulation platform.

the coal slurry flotation process, the abnormal reasoning efficiency of the algorithm in this paper reaches 99.8%, which is better than the other three models, and the method proposed in this paper can handle dynamic processes.

6 Appendix F

This paper addresses the issue of frequent abnormal operating conditions caused by the non-stationary characteristics of complex industrial processes and proposes a safety control method for non-stationary complex industrial processes based on RTV-DBN. The model uses a VAR model to describe the temporal dynamics between multiple variables. By dynamically adjusting the model structure and parameters, it reflects process changes in real time, ensuring an accurate representation of process behavior. Data from a coal preparation plant is collected, and the ADF square root algorithm is used to test the stationarity of the coal selection process. For non-stationary process data, a differencing method is employed to remove non-stationarity, and the stationary data is fused with the original stationary data for correlation analysis. This helps determine the strength and direction of relationships between variables, allowing for more accurate decision-making during abnormal events. After data preprocessing, a global information-based elastic time-varying dynamic Bayesian network model is established to capture the causal relationships between multiple variables in the time-varying process and identify potential abnormal operating conditions. Temporal data is projected into a finite-dimensional space, and after learning the structure and parameters of the RTV-DBN model using the probability density function, abnormal time slices are accurately located, identifying the process variables that cause abnormal conditions. Finally, abnormal data is input as evidence into the network model, which reasoning decision-making schemes that can eliminate abnormal conditions and translates them into robust control actions. The effectiveness of the proposed method is validated in the dense medium coal preparation and coal slurry flotation processes, demonstrating the potential application of RTV-DBN models in non-stationary industrial processes.

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