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Safety control scheme of non-stationary complex industrial processes based on resiliently time-varying dynamic Bayesian network

Jianwen WANG[1], Fei CHU[1,2*], Chen PENG[3], Guo-Qiang ZENG[4] & Fuli WANG[5]

[1]*School of Information and Control Engineering, China University of Mining and Technology, Xuzhou 221116, China*
[2]*State Key Laboratory of Intelligent Optimized Manufacturing in Mining & Metallurgy Process and Beijing Key Laboratory of Process Automation in Mining & Metallurgy, Beijing 100160, China*
[3]*Department of Automation, School of Mechatronic Engineering and Automation, Shanghai University, Shanghai 200444, China*
[4]*National-Local Joint Engineering Laboratory of Digitalized Electrical Design Technology, Wenzhou University, Wenzhou 325035, China*
[5]*College of Information Science and Engineering, Northeastern University, Shenyang 110819, China*

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Complex industrial processes are influenced by various factors during operation, such as variations in operational conditions and process drift, which lead to variations in process characteristics and behaviors over time. For example, processes like coal preparation and metallurgical exhibit high dynamics and non-stationary characteristics [1–3]. Non-stationary industrial processes often exhibit the characteristic of time-varying parameters and structures, which leads to continuous changes in process states and parameters [4]. This makes it difficult for a single fixed model to accurately describe and evaluate system behavior, thus affecting the accuracy of control performance and decision-making. Moreover, the complexity and multivariable interrelationship of industrial processes further increase the difficulty of process control and safety management. Achieving safe control of non-stationary industrial processes in dynamic environments has become an urgent problem in the field of industrial process control.

Existing safety control methods for non-stationary complex industrial processes can be categorized into model-based methods, knowledge-driven methods, and data-driven methods. In this section, a brief summary of the motivation for this work is presented. Appendix B provides a more comprehensive literature review.

To address the safety control problem of non-stationary processes, this study 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, an 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.

Key theory. Complex industrial processes are dynamic and non-stationary. Therefore, this study proposes an RTV-DBN. This network is an extended dynamic Bayesian network (DBN) model specifically designed to handle non-stationary complex processes with dynamically changing time series data and structures [5]. This model combines the advantages of 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

$$\mathrm{Pa}(X_i[t]) = \{\mathrm{Pa}_d(X_i[t]), \Theta_i[t]\}, \tag{1}$$

where $\mathrm{Pa}_d(X_i[t])$ 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 study introduces two transition models: one for parameter transitions and one for structural transitions.

* Corresponding author (email: chufei@cumt.edu.cn)

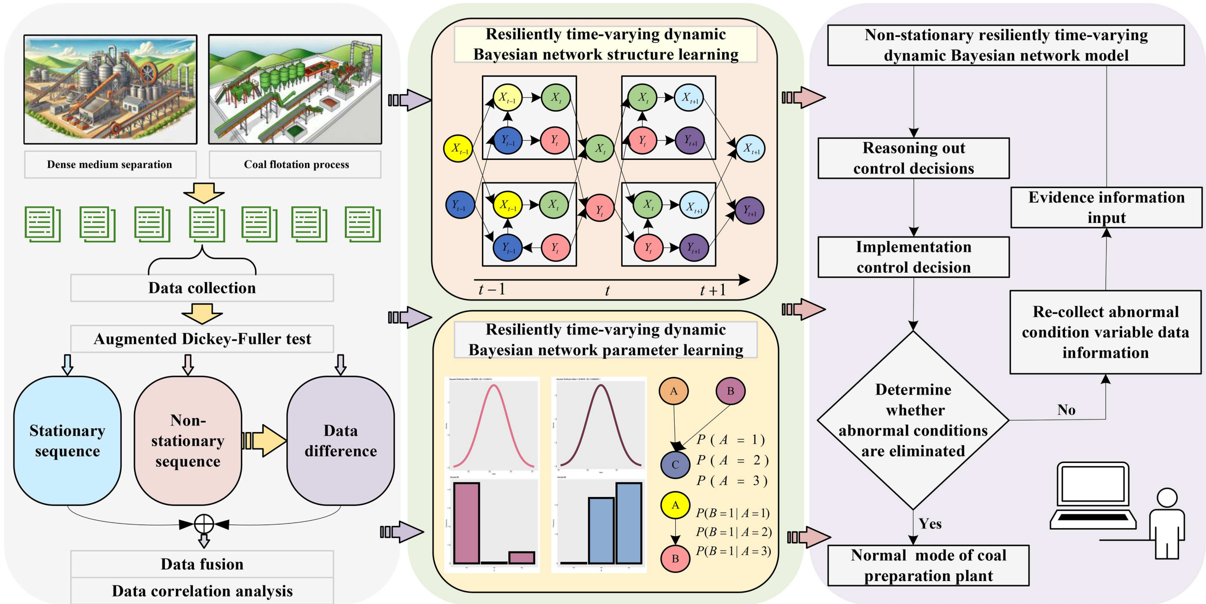

Figure 1 (Color online) Safety control model for non-stationary complex industrial processes based on RTV-DBN.

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

$$\Theta_i[t+1] \sim GP(\mu_i, K_i), \tag{2}$$

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

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

$$P(G[t+1]|G[t]) = \prod_{i,j} P(e_{ij}[t+1]|e_{ij}[t]), \tag{3}$$

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

$$\begin{aligned} &P(\Theta[t+1], G[t+1]|\Theta[t], G[t]) \\ &= P(\Theta[t+1]|\Theta[t])P(G[t+1]|G[t]), \end{aligned} \tag{4}$$

where $P(\Theta[t+1]|\Theta[t])$ represents the parameter transition process, and $P(G[t+1]|G[t])$ represents the structure transition process. Appendix C provides a more comprehensive theory.

The RTV-DBN decision model combines data-driven and industry 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. As shown in Figure 1, 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. Appendix D provides a more comprehensive complex industrial process non-stationary analysis and modeling.

Simulation. The method proposed in Appendix D will be experimentally validated on a laboratory simulation platform through a case study of the coal preparation process. The detailed results of this simulation example can be observed in Appendix E.

Conclusion. This study 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 method 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. 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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Supporting information Appendixes A–F. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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