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Recent advanced technologies in dynamic modeling of multi-modal data-driven coal mine equipment complex system: Review and prospects

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Declaration of interests

☒The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Highlights

- Comprehensive review of multi-modal data fusion and alignment techniques for CMECS.
- Systematic analysis of dynamic modeling methods for multi-modal data driven CMECS.
- In-depth discussion on robustness evaluation and optimization methods for CMECS.
- Identify challenges and future research to enhance intelligent, precise, and safe in CMECS.

Recent advanced technologies in dynamic modeling of multi-modal data-driven coal mine equipment complex system: Review and prospects

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Abstract: With the continuous development of coal mine intelligence, coal mine equipment complex system (CMECS) has gradually evolved from a traditional simple association system into a multi-level, multi-modal, and highly complex giant system. However, multi-modal data-driven CMECS confront persistent issues of pronounced data heterogeneity, intricate multi-scale behavioral relationship propagation, and insufficient capability in handling abrupt situations. To overcome these issues, this paper reviews the latest research progress on dynamic modeling methods for multi-modal data-driven CMECS, aiming to promote ongoing innovation and application in the coal mining industry. Focusing on three aspects: multi-modal data processing and analysis, dynamic modeling of CMECS, and robustness evaluation and optimization of CMECS. First, recent advances in multi-modal data fusion and alignment methods are summarized. Second, the development and frontiers of modeling methods based on temporal neural networks, differential equations, and graph neural networks are discussed. Third, the current research on robustness evaluation metrics, evaluation methods, and optimization strategies are thorough analyzed. The characteristics, limitations, applicable scenarios, and challenges of various methods are systematic generalizations. Finally, future research directions for dynamic modeling of multi-modal data-driven CMECS are proposed to facilitate its development and application, offering methodological and theoretical support for intelligent decision-making, precise control, and safety assurance.

Keywords: Coal mine equipment; Complex system; Multi-modal data; Dynamic modeling; System robustness

1. Introduction

In recent years, with the continuous construction and development of large-scale coal mines with annual production capacities exceeding ten million tons, the levels of intelligence and automation in coal mine equipment have been steadily advancing, while the complexity and uncertainty of their operating environments have increased significantly [1]. The structure of coal mine equipment systems has evolved from traditional linear configurations into highly complex giant systems, covering various aspects such as production monitoring, equipment operation, and safety early warning [2], as illustrated in Fig. 1. The Chinese government has successively issued a series of policy documents and development strategies, which explicitly emphasize the importance of the complexity, operational reliability, and safety of coal mine equipment complex systems (CMECS), and highlight the crucial role of intelligent technologies in promoting high-quality development of the coal industry [3]. Academician Guofa Wang also pointed out that coal mine intelligence is a systematic engineering task that must realize intelligent operation throughout the entire process, including mining, excavation (stripping), transportation, ventilation, coal preparation, safety assurance, and management, with none of these links being dispensable [4]. Currently, the ten major intelligent systems in coal mines are composed of numerous interrelated intelligent subsystems. Hundreds of these subsystems operate collaboratively, exhibiting characteristics such as high dimensionality, strong coupling, and nonlinearity, which still pose significant technical and application challenges for intelligent decision-making, precise control, and safe production within CMECS [5].

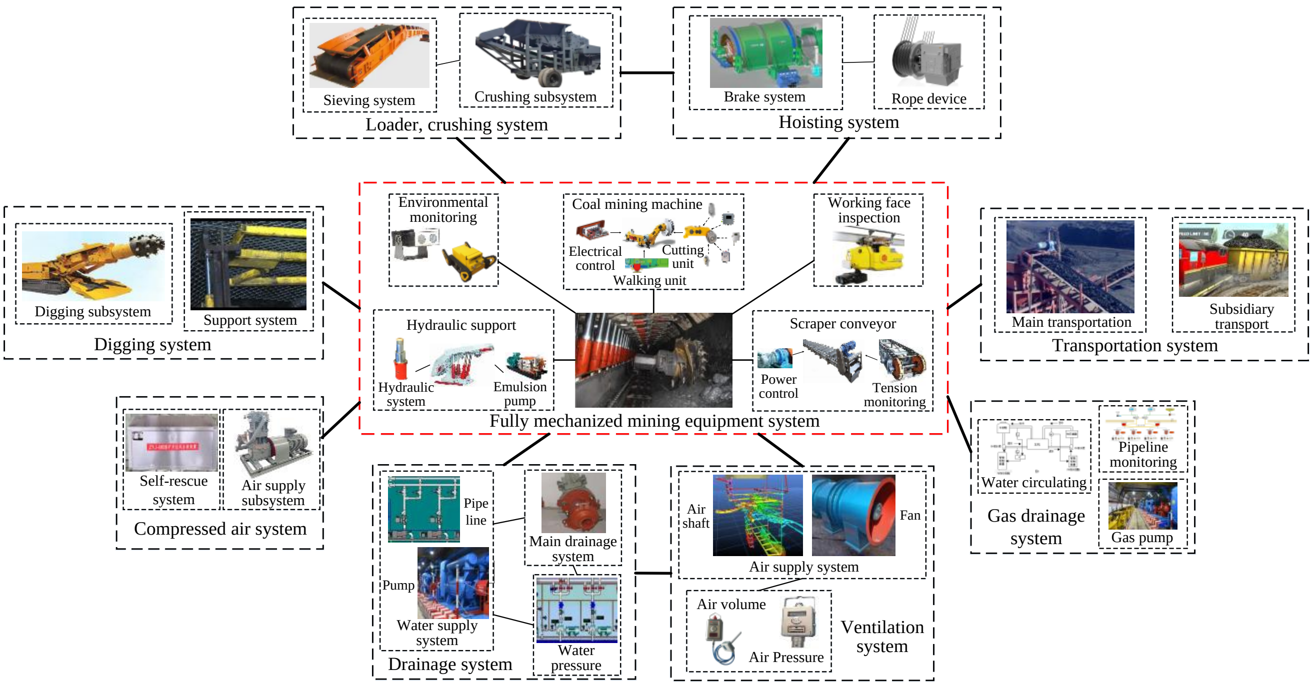


Fig. 1. The CMECS structure.

In modern intelligent coal mines, the widespread application of technologies such as sensors, inspection robots, and mining robots enables comprehensive real-time monitoring of CMECS [6]. Meanwhile, distributed control systems, manufacturing execution systems, and production safety monitoring systems continuously generate massive amounts of heterogeneous data daily, covering various forms including digital signals, text, video, and audio [7]. These monitoring data contain rich operational mechanisms and behavioral patterns ranging from microscopic to macroscopic scales. As the volume of data continues to grow dynamically, a multi-modal big data landscape is gradually taking shape, posing significant challenges for the modeling and control of CMECS [8]. Scholars have made notable research progress in areas such as data processing and system modeling. However, dynamic modeling of data-driven CMECS still faces numerous challenges, including the lack of unified planning, incompatibility among multiple systems, and the persistence of information silos, which hinder efficient sharing of data and collaborative operation of system [9]. These challenges are primarily reflected in the following aspects [10]: (1) The diversity in the formats and content of CMECS data, characterized by multi-modality, multi-layer structures, and multi-source heterogeneity, makes the modeling of dynamic multi-modal macro- and microscopic objects highly complex. Issues such as multi-modal data association, matching, cleaning, cross-system conversion, and fusion have yet to be effectively addressed; (2) CMECS consists of hundreds of independently operated and managed distributed subsystems, which are characterized by multi-level, multi-operating condition patterns, and high interdependencies. The nonlinear dynamics of the interaction, the heterogeneity of interaction modes and the diversity of time scales among subsystems further increase the difficulty of modeling and evolution analysis of complex systems; (3) CMECS is highly susceptible to cascading failures under external attacks and internal failures, potentially causing severe economic losses and even major production safety accidents, making it difficult to ensure continuous and stable system operation.

To address these issues, emerging approaches based on multi-modal data-driven methods, complex system modeling, and robustness analysis offer promising pathways to break through existing bottlenecks. By integrating multi-modal data, the dynamic characteristics and evolutionary patterns of CMECS can be more accurately captured, providing both theoretical foundations and core technical support for advancing coal mine intelligence [11,12].

At present, the modeling research of CMECS is still in its infancy, and there is still a lack of in-depth understanding of the role and potential of multi-modal data in the modeling of complex systems in a coal mine field. The existing research is still difficult to comprehensively sort out the core methods, research progress, key difficulties, and future development direction of dynamic modeling of multi-modal data-driven CMECS.

Therefore, this paper focuses on the dynamic modeling of multi-modal data-driven CMECS, and systematically reviews the research status of the following three aspects: (1) Multi-modal data processing and analysis methods for coal mine equipment; (2) Dynamic modeling methods of CMECS; (3) Robustness evaluation and optimization methods of CMECS. On this basis, the key bottleneck problems of CMECS are summarized, such as pronounced data heterogeneity, intricate multi-scale behavioral relationship propagation, and insufficient capability in handling abrupt situations, along with a discussion of related research applications and existing challenges. Finally, the future research directions of dynamic modeling of multi-modal data-driven CMECS are prospected.

2. Multi-modal data processing and analysis methods for coal mine equipment

Coal mine equipment encompasses multiple hierarchical levels, including the system-level, equipment-level, and component-level. A wide range of large and small subsystems collectively form a highly complex system [13]. The operating environment of CMECS is complex, and the working conditions are harsh. The data has the characteristics of multi-mode, multi-level, and strong coupling, involving vibration, audio, temperature, voltage, current, text, image, and video data modes [14]. These multi-modal data sources contain rich and valuable information for accurately perceiving equipment status and environmental conditions. However, they also present significant challenges in terms of data processing and analysis [15]. To address these challenges, multi-modal data processing and analysis methods have emerged as a response to the evolving demands of intelligent coal mine systems. These methods aim to integrate heterogeneous data sources deeply, thereby maximizing the utility and insight derived from the available data. By effectively fusing and aligning multi-modal data, the limitations inherent in single-modality analysis can be overcome, ultimately improving the accuracy, robustness, and reliability of CMECS monitoring and decision-making processes, as shown in Fig. 2. This section will focus on a comprehensive analysis and summary of multi-modal data fusion and multi-modal data alignment techniques. Furthermore, it will explore strategies for achieving deep integration and efficient collaboration among diverse data modalities within CMECS. The goal is to provide a solid foundation for equipment condition monitoring and intelligent decision-making, enabling safer and more efficient operations in modern coal mine environments [16].

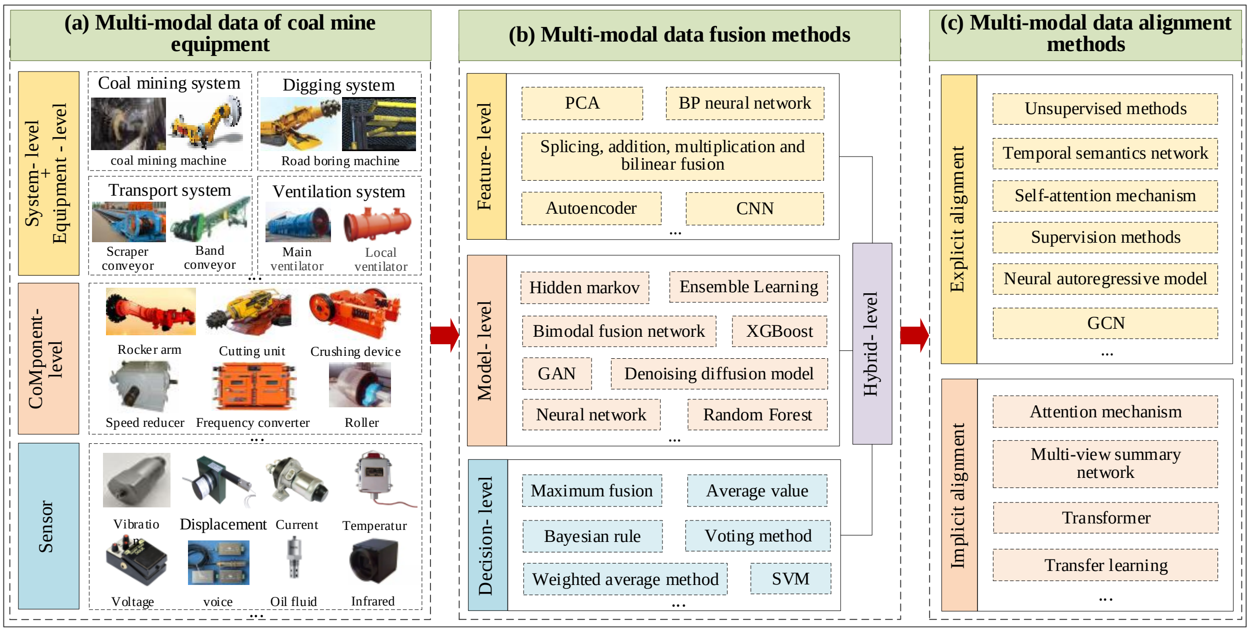


Fig. 2. Multi-modal data processing and analysis methods for coal mine equipment.

2.1. Multi-modal data fusion methods

Multi-modal data fusion is a vital research direction in the fields of artificial intelligence and data science. Its core objective is to integrate information from diverse data modalities (such as images, text, audio, video, and various sensor signals) to fully leverage the complementary strengths of each modality, thereby enhancing model performance and decision-making accuracy [17, 18]. In multi-modal tasks, each modality is first processed by a dedicated feature extractor to obtain modality-specific representations, forming single-modal features. These representations are then projected into a shared semantic subspace, where joint fusion and interactive modeling of multi-modal features are performed. At present, multi-modal data fusion approaches can be broadly categorized into four types: feature-level fusion, model-level fusion, decision-level fusion, and hybrid-level fusion.

2.1.1. Feature-level fusion

Feature-level fusion aims to integrate raw data or extracted feature representations from different modalities at the input stage of the model, thereby providing a unified data representation as input. Since the original data may lack sufficiently salient features, both the direct fusion of raw data and the fusion of extracted features are generally classified as feature-level fusion methods. In this fusion process, the original multi-modal data along with the modality-specific features extracted using dedicated feature extractors are employed as inputs, aiming to ensure the informativeness and effectiveness of the data fed into the model. For example, image features can be extracted using convolutional neural network (CNN), text features via word embeddings or text CNN, and audio features through spectrogram analysis or autoencoders. Subsequently, the feature representations from different modalities are further fused. Common fusion strategies include feature splicing, addition, multiplication and bilinear fusion methods, etc. For instance, Wang et al. [19] proposed a multi-modal fault diagnosis method for hydraulic pumps based on the fusion of vibration and pressure signals, which improved fault diagnosis accuracy by analyzing the complementary characteristics of multi-modal information. In another study, Liu et al. [20] developed a multi-modal feature fusion method based on an L2-regularized stacked autoencoder, which effectively reduced the loss of deep features during the fusion process and significantly enhanced recognition performance.

2.1.2. Model-level fusion

Model-level fusion aims to enable information interaction and integration of multi-modal features within the model architecture by designing effective fusion mechanisms. Unlike simple feature concatenation, this approach leverages the structural advantages of deep learning models to facilitate cross-modal interaction and joint representation learning at a deeper semantic level. For example, Saadi et al. [21] proposed an efficient hierarchical model for multi-modal fusion, which employed a hidden Markov model in conjunction with an iterative proportional fitting hierarchical algorithm to optimize both the marginal and multivariate joint distributions, thereby achieving more accurate modality fusion. In the field of underwater image enhancement, Chen et al. [22] utilized a generative adversarial network (GAN) based on multi-feature fusion, significantly improving image quality through the integration of diverse feature information. Zhao et al. [23] introduced a multi-modal image fusion method based on a denoising diffusion model (DDFM), as shown in Fig. 3. The approach incorporates an unconditional generation module and a conditional likelihood correction module to achieve efficient fusion of infrared and visible medical images without the need for fine-tuning. In another study. Chen et al. [24] applied ensemble learning techniques (such as random forests and XGBoosting) to fuse vibration and acoustic data at the model-level, effectively enhancing the accuracy of fault diagnosis in coal mine equipment. Furthermore, Han et al. [25] developed an end-to-end dual-modal fusion network that models both the dynamic independence and correlation between modalities, enabling the extraction and integration of key multi-modal information and achieving optimal performance in complex scenarios.

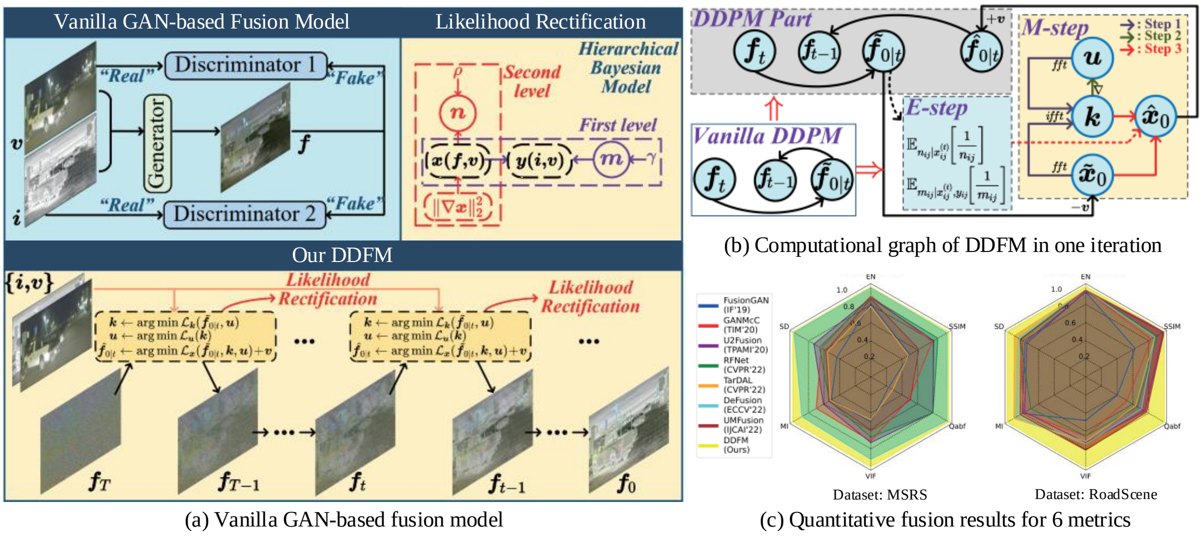


Fig. 3. Framework and resulting figure of the DDFM model [23].

2.1.3. Decision-level fusion

Decision-level fusion focuses on integrating the independent decision outputs of each modality to generate a final decision, typically through mathematical models or weight assignment schemes. This approach is particularly effective in addressing the challenges posed by asynchrony and heterogeneity in multi-modal data, while also offering high flexibility and robustness. Common fusion strategies include maximum selection, average fusion, Bayesian rule-based fusion, majority voting, and weighted averaging. For instance, Huang et al. [26] employed a support vector machine (SVM) to extract posterior probabilities from three types of features, which were then fused using a particle swarm optimization algorithm to enhance decision-making accuracy and robustness. Ning et al. [27] proposed a decision-level fusion strategy based on model reliability, which was used to optimize a target detection algorithm for visible and infrared images. In addition, the majority voting method determines the final output based on the category that appears most frequently among the decisions of individual modalities. Compared with early fusion approaches, decision-level fusion allows modality-specific feature extraction strategies and is more adaptable to asynchronous inputs, making it highly suitable for complex real-world scenarios. Furthermore, Yang et al. [28] introduced a two-stage multitask sentiment analysis framework, combining a two-stage training strategy with multitask learning to fully leverage pre-trained models and enhance the classification performance across different modality representations.

2.1.4. Hybrid-level fusion

Hybrid-level fusion aims to integrate the strengths of feature-level, model-level, and decision-level fusion methods, enabling the flexible selection and combination of different fusion strategies based on specific application requirements. This approach seeks to fully leverage the potential of multi-modal data, enhance the comprehensiveness and robustness of the fusion process, and ensure high model performance across diverse scenarios. For instance, Guo et al. [29] constructed a hybrid fusion framework that combined rule-based decision-making with the outputs of machine learning models to perform fault detection for coal mine equipment. Liu et al. [30] implemented a fusion strategy that integrated feature-level and model-level fusion, utilizing both CNN and long short-term memory (LSTM) networks to process multi-modal inputs, thereby achieving significant improvements in fault diagnosis accuracy. In another study, Liu et al. [31] proposed a hybrid fusion strategy (BAHFS) that incorporated a bidirectional gated recurrent unit and an attention mechanism, as shown in Fig. 4. Initially, a dual-modal attention fusion module was applied to merge single-modal features into dual-modal representations. These, along with the original single-modal features, were then fed into both a tri-modal attention fusion module and a tri-modal concatenation fusion module to generate two sets of tri-modal features. Finally, decision-level fusion was employed to comprehensively analyze the multiple fusion outputs, thereby improving the overall performance and interpretability of the model.

Based on the comparative analysis of the multi-modal data fusion methods presented above, the detailed summary is shown in Table 1. In practical applications, it is crucial to select appropriate fusion strategies according to the specific task scenarios and to reasonably adjust the model architecture and experimental parameters to achieve optimal multi-modal fusion performance. Such approaches facilitate the efficient capture of collaborative relationships and coupling characteristics among different modalities, thereby providing strong support for the accurate modeling of complex tasks.

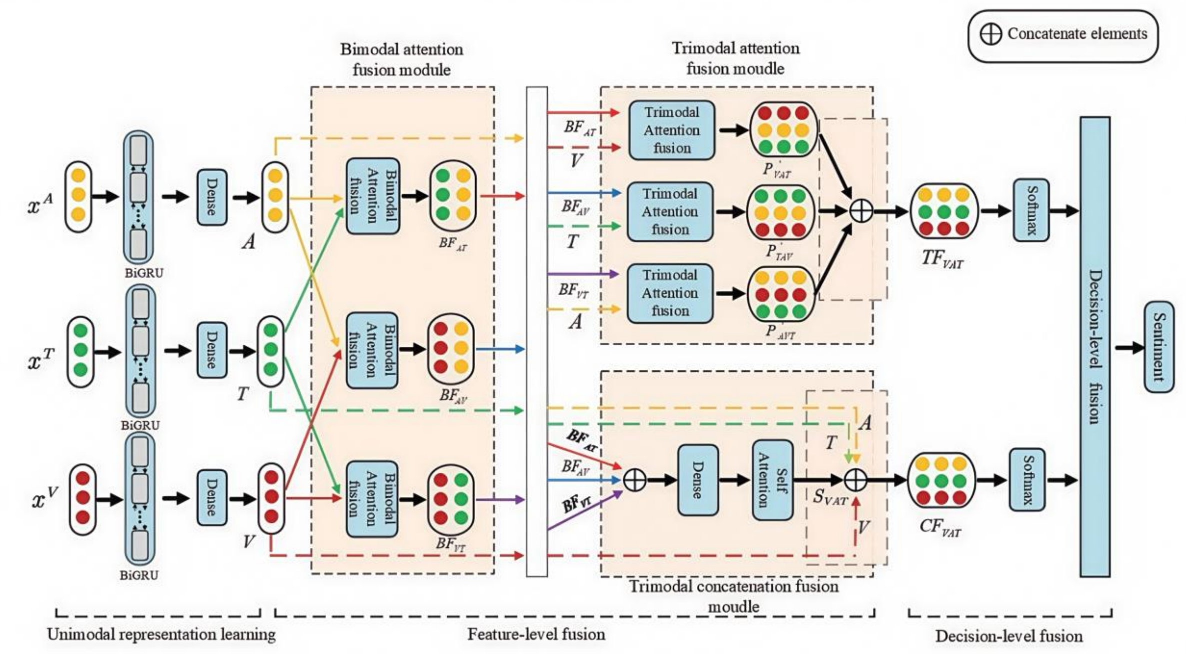


Fig. 4. Architecture of the BAHFS model [31].

Table 1 Comparison of multi-modal data fusion methods

Methods	References	Information loss	Fusion difficulty	Fault tolerance	Fusing stage
Feature-level fusion	[19-20]	Medium	Easy	Poor	Before the inference model
Model-level fusion	[21-25]	Small	Moderate	Good	Simultaneity
Decision-level fusion	[26-28]	Large	Moderate	Moderate	After the inference model
Hybrid level-fusion	[29-31]	Small	Difficult	Good	Simultaneity

2.2. Multi-modal data alignment methods

To comprehensively capture the multi-modal data information of CMECS, it is necessary to perform an effective alignment of data representations from different modalities, ensuring that the information can be coherently expressed within a unified feature space [32]. The core of multi-modal alignment lies in establishing mapping relationships between sub-branch elements corresponding to the same instance across different modalities, and enforcing consistency within a shared semantic space through similarity constraints, thereby enabling more accurate modality alignment and feature representation [33]. According to the alignment strategy, multi-modal alignment methods can be classified into two types: explicit alignment and implicit alignment.

2.2.1. Explicit alignment

Explicit alignment mainly solves the problem of aligning sub-components between modalities and directly relates and aligns the information of different modalities through explicit algorithms or labels. This method aims to provide the alignment relationship between modalities without additional design models to achieve information alignment, so as to improve the efficiency and accuracy of information integration. Explicit alignment can be further divided into two types: unsupervised alignment methods and supervised alignment methods.

Unsupervised methods do not rely on manually annotated labels in the subcomponent alignment task and have a significant cost advantage. Tapaswi et al. [34, 35] proposed an unsupervised alignment method based on dynamic time warping to solve the problem of non-sequential alignment of multi-view time series and text and video. Chen et al. [36] proposed an unsupervised learning temporal semantic interaction network, which has a fine-grained temporal alignment mechanism to simulate the temporal dependence between frames and words. Li et al. [37] proposed a decoupled feature alignment and fusion framework, which was divided into the stage of aligning multi-modal features through unsupervised representation learning and modal adaptive module, and the stage of combining medical image features and clinical data through self-attention fusion module, which was successfully applied to medical disease prediction. Sun et al. [38] proposed a completely unsupervised Network alignment framework, which constructed high-order topological consistency based on the multi-track perception training mechanism, and fused it into the information aggregation process of graph convolutional network (GCN), which had good robustness in structural noise. Liu et al. [39] proposed an unsupervised domain adaptation method to promote the representation learning of instance-level feature adaptation by designing a feature similarity maximization mechanism. At the same time, the domain adaptation mask was used to fuse the semantic level and instance-level features to realize the panoramic level cross-domain feature alignment.

Supervised methods use labeled data to train models that can effectively align and integrate data from different modalities. With the help of manually labeled information, this method explicitly guides the model to capture the association between modalities, which is suitable for tasks with high alignment accuracy. Compared with unsupervised alignment methods, supervised alignment methods can not only directly improve the model performance, but also introduce supervised information based on unsupervised alignment to further optimize the alignment effect. Zhang et al. [40] proposed a supervised neural autoregressive model, which effectively solved the core problem of marketing strategic intention analysis by enhancing the recognition ability of hidden features, fusing multi-modal data, and using GCN to extract features. In addition, an appropriate amount of supervision information can help guide the model to learn more accurate modal alignments, thereby improving the accuracy and effectiveness of explicit alignment.

2.2.2. Implicit alignment

Implicit alignment realizes the correspondence between different modal data through autonomous learning of the model and does not need to explicitly specify alignment rules, thus significantly reducing the cost of manual labeling in modal fusion tasks, especially suitable for alignment requirements of large-scale data sets. Representative methods such as neural networks, attention mechanisms, and transfer learning can automatically establish semantic mappings between languages during training, thereby effectively reducing the dependence on manual labeling and improving the efficiency and generalization ability of alignment. Qu et al. [41] proposed a context-aware multi-view summarize network to cope with the semantic gap between visual and textual modalities. This method uses an adaptive gated self-attention module to extract the representation of visual regions and text words, adaptively captures context information by controlling the information flow, and uses a multi-view matching module to accurately align image features and text features. Messina et al. [42] proposed a Transformer encoder inference and alignment network, which uses a self-attention module to project visual and textual information into the same dimensional space, calculates the global similarity matrix between the image and the text, and finally realizes fine-grained word region alignment through the Max pooling mechanism.

In summary, a comparison of existing multi-modal data alignment methods is presented in Table 2. Considering the characteristics of CMECS multi-modal data, it is necessary to reasonably select or design appropriate alignment strategies based on specific application scenarios, to ensure effective alignment and collaborative representation of multi-modal data within a unified semantic space in the coal mine domain.

Table 2 Comparison of multi-modal data alignment methods

Methods	References	Characteristics	Limitations	Application Scenarios
Explicit Alignment	[34-40]	● Aligning modalities using predefined algorithms or labels; ● Providing clear and interpretable results.	● Requiring extensive labeled data; ● Incurring high labor cost and long deployment time.	Suitable for tasks requiring precise alignment, such as fault analysis of coal mine equipment.
Implicit Alignment	[41-42]	● Learning alignment automatically; ● Reducing labeling effort and offers high adaptability.	● Involving high computational cost; ● Requiring large datasets and long training time.	Ideal for large-scale multi-modal modeling of coal mine equipment.

The multi-modal data processing and analysis methods of CMECS face many challenges in practical applications. The sources of multi-modal data on coal mine equipment are diverse and have strong heterogeneity. The data from different sensors, monitoring equipment, and external environments often have defects such as noise interference, semantic conflict, redundancy, and missing, resulting in poor comprehensiveness and effectiveness of information. At the same time, the coding methods and information quality of different modal data differ significantly, and low-quality multi-modal data often suffer from problems such as noise contamination, incomplete data, and data imbalance. In addition, there is information asymmetry or weak correlation in cross-modal data, which makes the task of cross-modal joint feature learning and modal relationship alignment more complex. The CMECS is in a dynamic working environment, and the difference in time resolution or acquisition delay of different modal data causes the difficulty of data direct fusion and collaborative learning. Therefore, it is necessary to process and analyze the multi-modal time series data in real-time to ensure the efficient response and accurate judgment of the system.

3. Dynamic modeling methods of CMECS

The dynamic modeling of CMECS is of critical importance, with its core objective centered on deeply mining the interaction patterns embedded within multi-modal data and scientifically predicting the future evolution of system states through advanced modeling approaches. CMECS can be abstracted as a dynamic network composed of multiple functional units, where each unit interacts according to specific dynamic rules and continuously evolves as mining operations progress. At present, the control of various subsystems within coal mine equipment primarily relies on the classical "sensor-controller" logic framework [43, 44]. However, due to the concurrent operation of numerous subsystems with varying scales and functions, the complex latent interaction relationships within the system remain difficult to effectively uncover. The lack of a unified correlation architecture and reliable dynamic models poses significant challenges for achieving coordinated optimization and intelligent control of CMECS under complex and variable working conditions [45]. Traditional physics-based modeling approaches are constrained by the system's opaque internal interaction mechanisms, highly dynamic and complex operating environments, and the difficulty in acquiring accurate model parameters, making it challenging to precisely characterize the dynamic evolution processes and predict the future state transitions of CMECS [46]. Meanwhile, the multi-modal data collected from coal mine equipment contains rich, in-depth information ranging from microscopic to macroscopic operational mechanisms, behavior patterns, and regulation strategies, offering essential data support and a foundational basis for addressing the above challenges [47, 48]. Therefore, it is urgently necessary to explore data-driven dynamic modeling methods tailored to the characteristics of CMECS multi-modal data, enabling in-depth mining of interaction patterns and scientific prediction of future system states [49]. To this end, this section focuses on three representative dynamic modeling approaches for complex systems: Temporal Neural Networks (TNNs), differential equation-based models, and Graph Neural Networks (GNNs). These methods provide theoretical foundations for the dynamic modeling and intelligent development of CMECS, and the specific content is shown in Fig. 5.

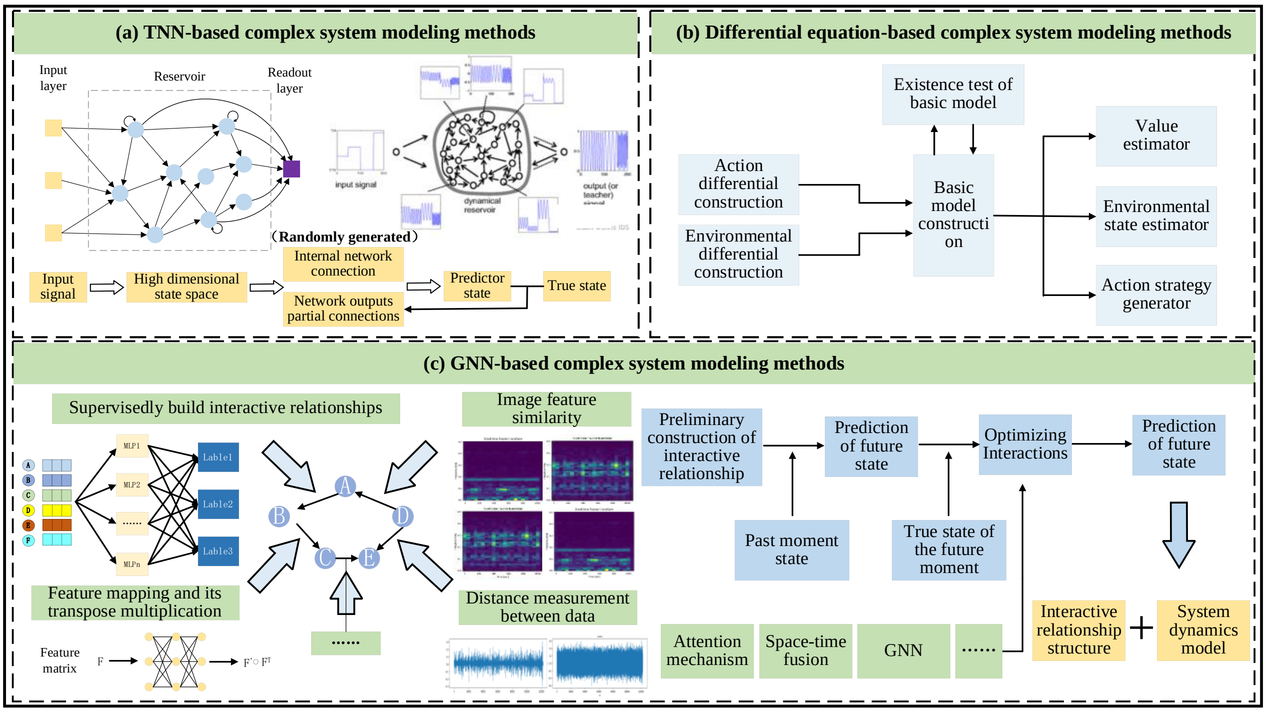


Fig. 5 Dynamic modeling methods of CMECS.

3.1. TNN-based complex system modeling methods

TNNs use the historical state information to learn the optimal parameters of the objective function and realize forward mapping, to predict the future state [50, 51] effectively. With the powerful nonlinear mapping ability, TNNs can automatically extract and learn the potential dynamic features such as nonlinearity, time-varying, and strong coupling in complex systems, and has shown excellent performance in temporal dependency mining and complex system modeling. However, TNNs still face the problems of high training difficulty, high computational cost, complex high-dimensional data processing, non-Markovian characteristics, and insufficient interpretability. By combining emerging deep learning technologies and optimization methods, the accuracy, robustness, and interpretability of complex system modeling can be further improved.

Bo et al. [52] proposed an asynchronous deep reservoir computing (RC) time-series data modeling method based on feature recombination, which has rich dynamics and flexible short-term memory, and effectively solves the modeling problem of time-dependent tasks. Gallicchio et al. [53] and Yuzgec et al. [54] based on deep echo state network, integrated domain prior knowledge into the data-driven model to realize nonlinear time series modeling. Zhang et al. [55] proposed a robust recurrent neural network (RNN) based on local stochastic sensitivity, aiming to alleviate the noise uncertainty of real-time series data and improve the generalization ability of the model. In addition, Qin et al. [56]proposed a hierarchical gated recurrent unit (GRU) network, which uses a forgetting gate with a learnable lower bound and increases monotonically when moving up layers, so that the upper layer is suitable for long-term dependency modeling. In contrast, the lower layer focuses on the learning of local short-term dependency features. Lin et al. [57] proposed an RNN model based on piecewise iteration and parallel multi-step prediction strategy (SegRNN), which reduced the number of loop iterations required for long-term time series modeling and improved the prediction accuracy and inference speed, as shown in Fig. 6. Langeroudi et al. [58] designed a deep fuzzy LSTM architecture to deal with high-order uncertainties in time series in a more transparent way and improve the interpretability and accuracy of complex system modeling. Hu et al. [59] proposed a prediction and compensation strategy based on a GRU neural network to accurately extract time series dependencies with the help of deep learning models, which can effectively capture the dynamic characteristics of complex systems.

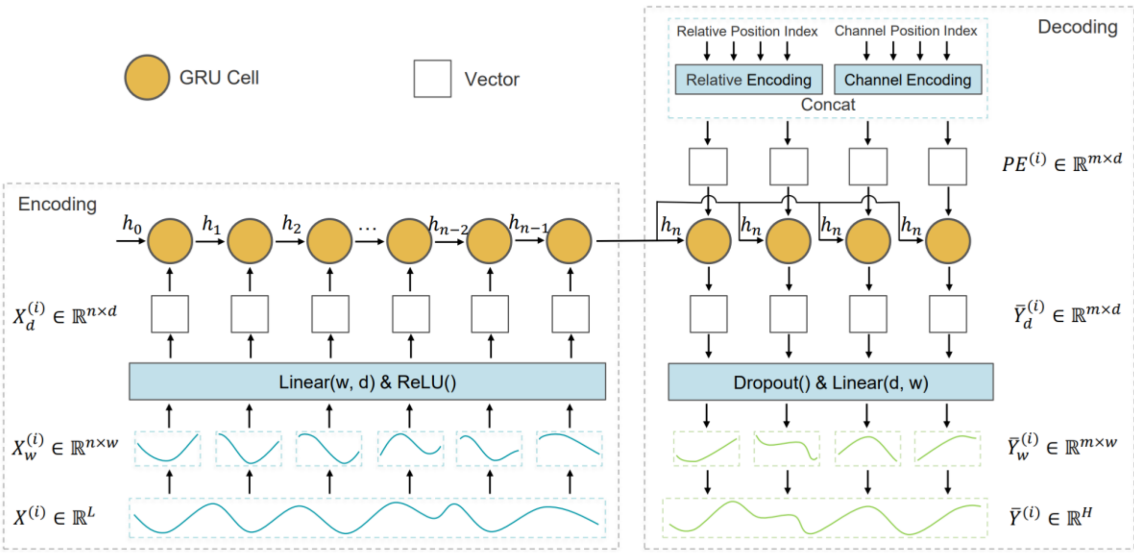


Fig. 6 The architecture of SegRNN model [57].

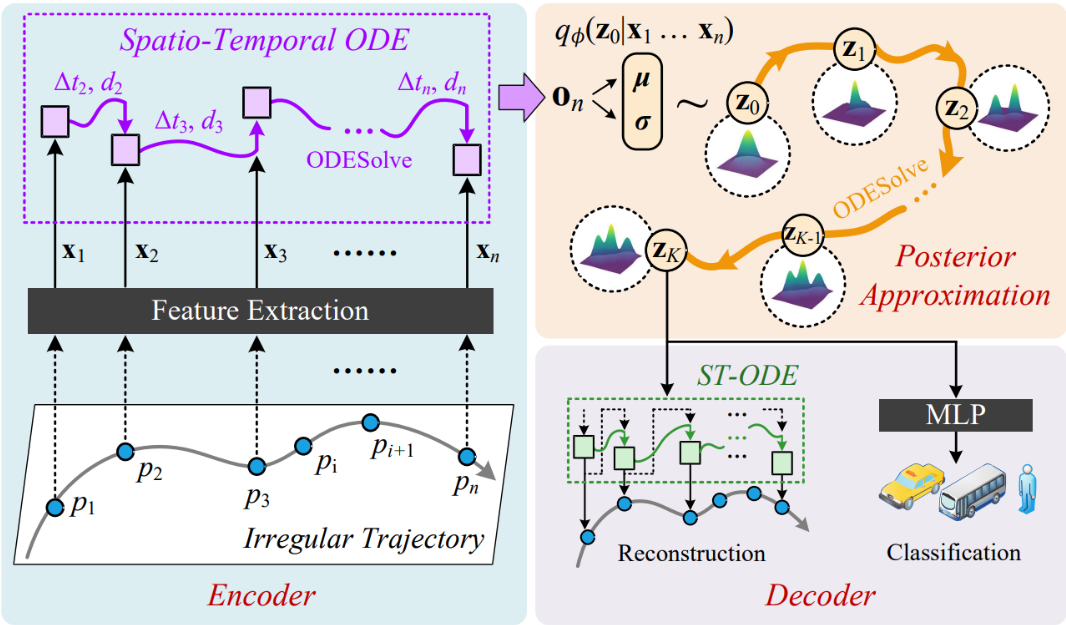
3.2. Differential equation-based complex system modeling methods

The dynamics of complex systems often exhibit special properties such as nonlinearity, emergence, spontaneous order, adaptability, and feedback loops, which cannot be represented by a deterministic function.

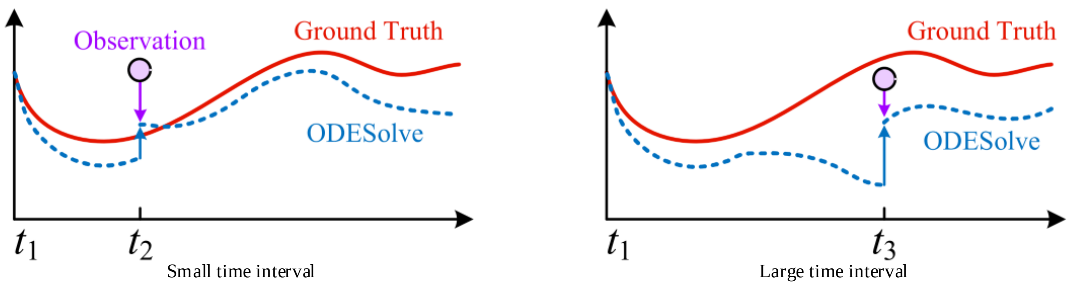
However, for continuous dynamical systems, the evolution of the system over time can be described by differential equations in many cases [60]. Although differential equation-solving methods improve the interpretability of deep learning models to a certain extent and alleviate the "black box problem", in practical applications, especially in complex systems such as coal mine equipment, they still face challenges such as high computational cost, low solution efficiency, and difficulty in parameter optimization. By combining efficient numerical methods, data-driven modeling, and intelligent optimization techniques, the computational efficiency and practicability of dynamic modeling can be further improved.

Yu et al. [61] proposed a step-by-step data-driven framework to effectively model complex systems with long-range interactions by mining fractional differential equations directly from data. In this method, a deep neural network is used as an alternative model to denoise and reconstruct the sparse and noisy observation data to improve the reliability and availability of the data. Liang et al. [62] designed a neural ordinary differential equation (ODENet) of trajectories, which combined the continuous-time characteristics of ODENet and the robustness of stochastic latent space. Implement complex system modeling with continuous-time dynamics and noise effects, as shown in Fig. 7. Sun et al. [63] proposed a neural network-based method to construct a model from dynamic data using ordinary differential equation (ODE) and partial differential equation (PDE). The unknown control model is parameterized using multilayer perceptrons and nonlinear differential terms to incorporate correlations between spatiotemporal samples in complex systems. Linnet et al. [64] proposed a data-driven ODENet architecture that accurately captures the shock and chaotic dynamics by training a sparse linear CNN to learn linear terms and a dense fully connected nonlinear neural network to learn nonlinear terms.

PDE is often used to model the dynamics of large-scale complex systems. Ruthotto et al. [65] proposed a data-driven deep CNN partial differential equation modeling method to interpret multi-modal data as a discretization of multivariate functions. Thomas et al. [66] proposed a tensor field neural network based on the theory of partial differential equations and introduced spherical harmonics into the filter to optimize the key mapping function. In addition, some researchers have tried to incorporate physical laws into the model as additional constraints. For example, Karpatne et al. [67] added a prior knowledge penalty term to the loss function, while Rassi et al. [68] proposed a physical information neural network by enforcing the structure of the governing equation to improve the accuracy and physical consistency of complex system modeling.



(a) Framework of TrajODE model



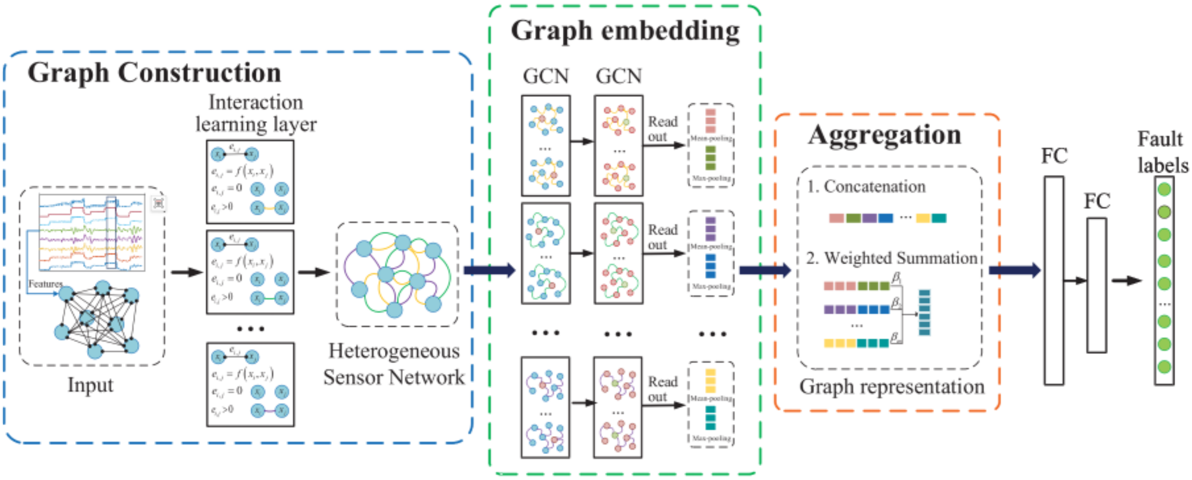
(b) Ground truth vs. ODE curves of hidden states in different sizes of time interval

Fig. 7 Framework of TratODE model and hidden states in different sizes of time interval [62].

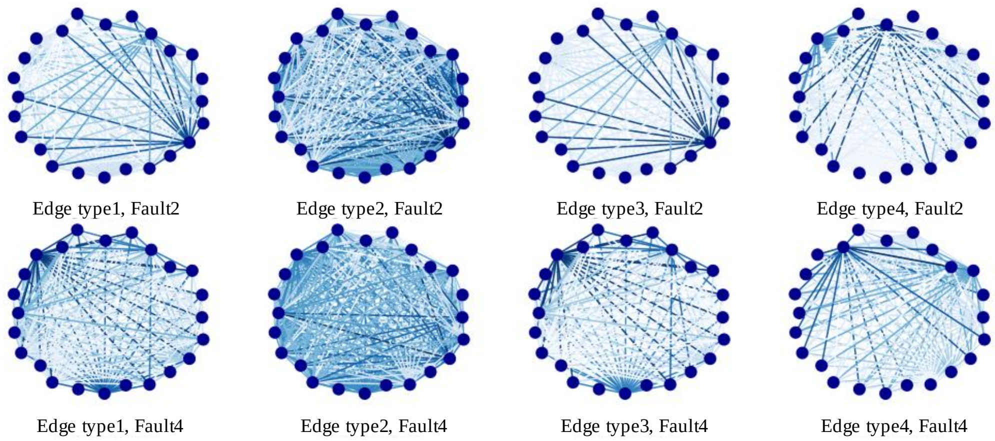
3.3. GNN-based complex system modeling methods

GNNs primarily include five major categories [69]: GCN, graph attention networks (GAT), graph autoencoders (GAE), and graph spatio-temporal networks (GSTN). The core idea behind GNNs is to integrate relational priors into neural networks through a fixed graph structure, thereby learning the mapping relationships between nodes and edges [70]. In complex systems, edges often represent causal relationships. Analyzing time series data from a dynamic perspective enhances the interpretability of interaction patterns within the system and improves the effectiveness of system modeling. The modeling paradigm of GNNs aligns well with the structural characteristics of complex systems. Compared to traditional time series modeling approaches, GNNs are better equipped to handle high-dimensional, nonlinear, and strongly coupled dynamic interactions [71]. In this framework, the smallest functional units of a complex system are represented as nodes, while the internal interactions among them are represented as edges. This transformation enables the construction of a graph network that captures both local and global characteristics, enhancing the model's ability to learn long-term dependencies. By leveraging the expressive power of graph structures, this approach can accurately describe the internal topological relationships and dynamic evolution mechanisms of complex systems. Consequently, it significantly improves the information representation capability, predictive accuracy, and interpretability of system modeling.

For small-scale complex systems, some researchers analyze the internal interaction patterns of the system from the perspective of data similarity, including causality, emergence, and correlation, and build interaction graphs based on this, and then use GNN for dynamic modeling. Chen et al. [72] proposed an interactive perception graph neural network (AGNN), which uses multiple independent interactive perception layers to supervise the learning of node correlation of different fault types, and fuses the features of each subgraph by weighted summation to generate the final graph embedding, as shown in Fig. 8. Zhang et al. [73] proposed a GNN method based on the granger causality test, which used granger causality tests to quantify the influence of fault and noise on signal changes, calculate weights construct an adjacency matrix and feature matrix, and obtain the structure of the interaction graph. Wang et al. [74] divided the relationship between nodes into shortcut feature relationship and causal feature relationship and proposed a causal learning and attention GNN strategy to mine causal features and filter shortcut features by estimating soft masks and causal interventions. Yang et al. [75] used a short-time Fourier transform to convert one-dimensional features into two-dimensional image signals, extracted image features with the help of CNN and constructed a correlation based on the similarity between image signals. Xu et al. [76] proposed a collaborative CNN based on graph guidance, which combined the graph reasoning fusion module to explore the intrinsic correlation between multi-source signals. Gu et al. [77] proposed an edge prediction method based on node attributes and GAT. The graph structure was learned through the feedforward neural network, and part of the network was reconstructed to infer the missing network structure, construct the complete interaction graph structure, and realize the dynamic modeling of complex systems.



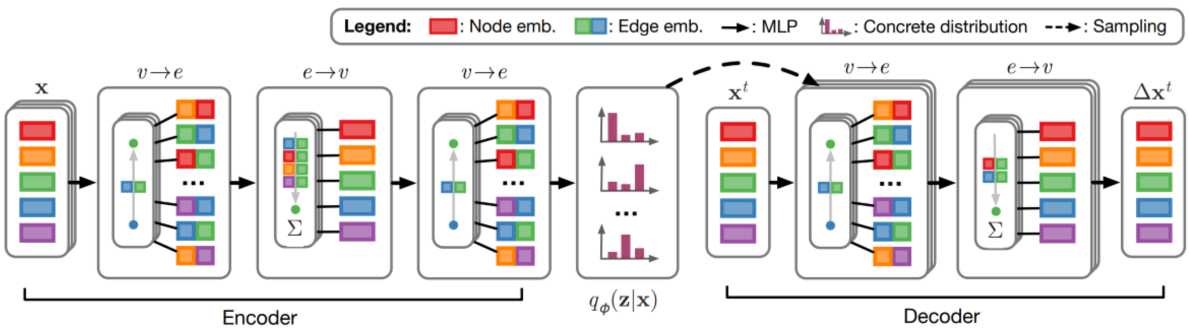
(a) Framework of the proposed IAGNN



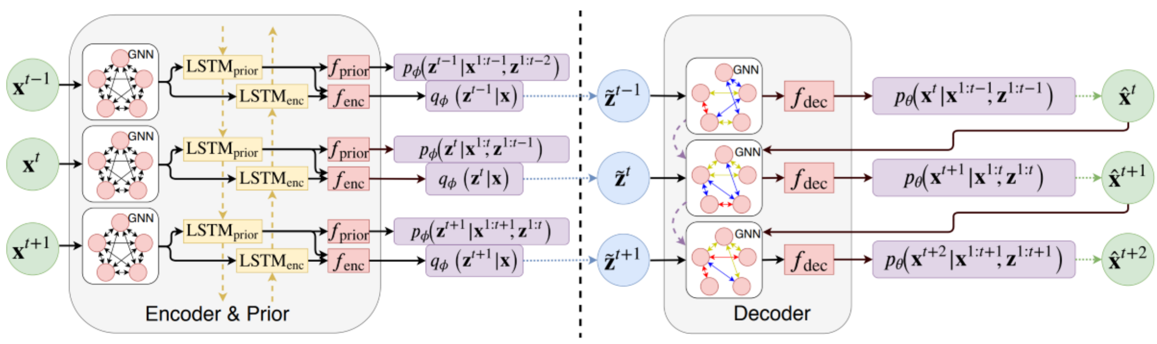
(b) Graph structure illustration

Fig. 8 Framework of AGNN model and graph structure illustration [72].

For large-scale or highly complex systems, observation data is often limited, and the internal behaviors tend to be nonlinear, time-varying, and multi-modal. These characteristics hinder the effectiveness of methods based on distance or similarity measurements, making it difficult to accurately capture intricate interaction patterns. To address this, Wu et al. [78] proposed a Transformer-based modeling approach for complex systems, utilizing the self-attention mechanism to learn dynamic patterns from time series data. Similarly, Zheng et al. [79] introduced a graph multi-head attention network incorporating a spatio-temporal attention mechanism to establish direct dependencies between historical and future time steps. However, the interaction graphs generated via attention mechanisms are structurally variable, which limits their suitability for in-depth analysis. To overcome this, Kipf et al. [80] proposed neural relational inference (NRI), a pioneering method that integrates GNNs with a probabilistic latent variable model based on edge types. By employing an encoder-decoder framework, NRI reconstructs the causal graph structure, enabling accurate modeling and prediction of system dynamics, as shown in Fig. 9(a). Building upon this, Zhang et al. [81] developed a data-driven Gumbel Graph Network architecture, which enhances model adaptability through a network generator and a dynamic learner, thereby optimizing and dynamically reconstructing network connections. In real-world scenarios, especially in complex systems, the relationships between network nodes evolve over time. To address this, Graber et al. [82] proposed the dynamic neural relational inference (DNRI) mechanism, which explicitly reasons about the dynamic evolution of interactions between agents, improving both interpretability and model performance, as shown in Fig. 9(b). Further advancing this line of work, Li et al. [83] introduced a dynamic relationship reasoning approach that constructs adaptive interaction graphs to model the evolving relationships among multiple heterogeneous nodes. In the context of CMECS, Cao et al. [48] proposed an interaction relationship inference method for CMECS, which predicts the dynamic evolution process of the system based on coal mine equipment monitoring data and inferred interaction relationships, as shown in Fig. 10.

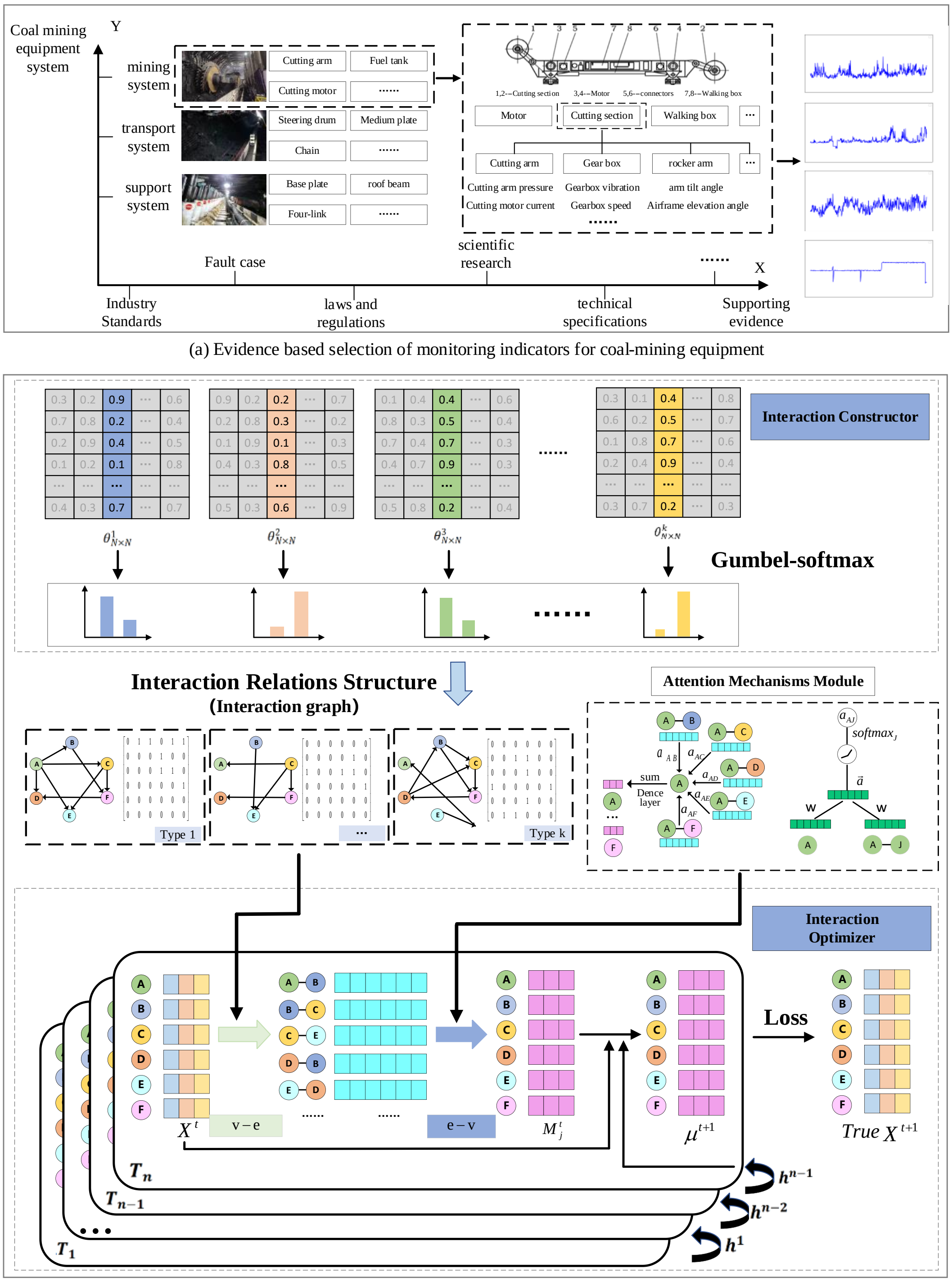


(a) NRI model [80]



(b) DNRI model [82]

Fig. 9 Framework of neural relational inference models [80, 82].



(a) Evidence based selection of monitoring indicators for coal-mining equipment

(b) Interaction-relation inference model

Fig. 10 An interaction relational inference method for CMECS [48].

In summary, the comparative analysis of the characteristics, limitations, and applicable scenarios of dynamic modeling methods for CMECS is presented in Table 3. At present, most dynamic models of CMECS primarily focus on individual subsystems, facing challenges related to multi-level and multi-scale modeling complexity. System nodes exhibit intricate interaction relationships across different hierarchical levels and scales, while the network structure continuously evolves in response to changing environments and operating conditions. These factors make it difficult to comprehensively characterize the internal interaction patterns and dynamic evolution laws of the system, which may result in deviations or even failures in subsystem control and decision-making. On the other hand, as a typical semi-discrete system, CMECS is subject to harsh underground working conditions and human factors, leading to issues such as severe data noise, high missing rates, and low data availability. These challenges hinder the accurate prediction of equipment-environment-personnel interaction relationships in complex environments and degrade the precision of dynamic models. Moreover, deep uncertainties and multi-source disturbances significantly impact system modeling, while the processing of large-scale 3D data, real-time perception in complex environments, and decision-making under uncertain conditions remain critical technical problems to be addressed. Meanwhile, existing complex system models suffer from limited interpretability, weak adaptability, and low transparency of dynamic equations, further constraining the practical engineering applications of dynamic modeling approaches for CMECS.

Table 3 Comparison of dynamic modeling methods of CMECS

	Methods	References	Characteristics	Limitations	Application Scenarios
TNNs	RC	[52]	● Significantly reducing computational complexity; ● Supporting short-term memory and complex state evolution; ● Enabling low-cost computation.	● Relying on empirical design; ● Poorly adapting to complex tasks; ● Being sensitive to input and reservoir initialization.	Suitable for processing time series data, particularly for tasks with temporal dependencies, such as time series forecasting, fault detection, and health monitoring.
	DESN	[53, 54]	● Extracting hierarchical temporal features via multi-layer reservoirs; ● Improving representation while maintaining training efficiency.	● Requiring complex hyperparameter tuning; ● Increasing computational cost with deeper states; ● Having high requirements for stability and initialization.	
	RNN	[55, 57]	● Processing sequence data through recurrent structure; ● Capturing temporal dependencies via internal states.	● Being susceptible to gradient vanishing/explosion; ● Being limited in modeling long-range dependencies; ● Exhibiting low computational efficiency.	
	GRU	[56, 59]	● Using gated information flow to simplify structure, improve efficiency, and mitigate vanishing gradients while enhancing long-range modeling.	● Failing to completely eliminate gradient decay in long sequences; ● Still suffering from low parallelism in sequential computation.	
	LSTM	[58]	● Regulating information flow via forget, input, and	● Having large parameter size and high computation	

			output gates; ● Enhancing long-term dependency learning; ● Mitigating gradient vanishing.	cost; ● Being prone to overfitting due to complex gating; ● Being difficult to parallelize.	
Differential equations	ODE	-	● Modeling system evolution via continuous-time equations; ● Being suitable for natural phenomena; ● Being supported by analytical and numerical methods.	● Struggling to solve high-dimensional nonlinear cases; ● Having numerical precision limited by step size and algorithm; ● Being sensitive to initial conditions.	Applicable to systems governed by clear physical laws, especially in scenarios requiring precise modeling of dynamic processes, such as the dynamic response of hydraulic supports and pneumatic equipment in coal mines.
	PDE	-	● Modeling spatiotemporal evolution via multivariate differential equations; ● Being backed by solid mathematical theory and numerical solutions.	● Rarely providing analytical solutions in nonlinear high-dimensional settings; ● Involving high numerical cost; ● Being sensitive to boundary and initial conditions.	
	FDE	[61]	● Modeling memory effects and long-range dependencies using fractional derivatives; ● Accurately capturing historical and dynamic behaviors.	● Requiring complex numerical solutions and making theoretical analysis difficult; ● Facing challenges in parameter identification and experimental validation·	
	ODENet	[62-64]	● Modeling data evolution using continuous-time dynamics; ● Supporting adaptive step sizes and parameter	● Being sensitive to initial conditions and struggling with discrete data; ● Involving expensive gradient computation;	

			efficiency.	● Being hard to impose physical constraints.	
	TFN	[66]	● Being efficient for multi-dimensional data; ● Preserving spatial correlation, suited to physical simulation and high-dimensional features.	● Having high computational and storage cost; ● Being complex in model structure, strongly relying on preprocessing, and lacking interpretability.	
	PINN	[68]	● Integrating physical equations with data-driven learning to enhance generalization in data-scarce settings.	● Causing distortion due to model errors or simplifications; ● Involving complex multi-objective optimization; ● Having high computational cost in high dimensions.	
GNNs	GCN	-	● Aggregating neighbor node features for graph modeling; ● Supporting semi-supervised learning for node classification and graph representation.	● Being prone to over-smoothing in deep networks; ● Exhibiting poor adaptability to heterogeneous or dynamic graphs; ● Being dependent on the adjacency matrix; ● Being sensitive to noise.	Suitable for modeling CMECS with intricate topological structures and inter-device interactions, such as sensor networks and fault propagation analysis.
	GAT	-	● Allocating attention weights to nodes; ● Enhancing relationship modeling; ● Improving robustness through multi-head attention.	● Having high computational cost, over-smoothing issues, and being noise-sensitive; ● Struggling with long-range dependencies and heterogeneous graphs.	
	GAE	-	● Reconstructing the adjacency matrix through unsupervised learning and uncovering latent node	● Involving high cost on large graphs; ● Being prone to overfitting in sparse or noisy settings;	

		relationships; ● Being suitable for link prediction and graph generation.	● Being hard to model complex high-order patterns.
GSTN	-	● Capturing spatial dependencies and temporal dynamics of dynamic graphs; ● Being suitable for spatiotemporal tasks like traffic prediction.	● Having complex spatiotemporal coupling; ● Exhibiting high resource consumption and being limited in adaptability to long-term or abrupt patterns.
NRI	[80]	● Capturing and reasoning about complex inter-node relationships; ● Being well-suited for heterogeneous and structured data.	● Being high in computational complexity; ● Having large data requirements and being noise-sensitive; ● Having limited capacity for high-order relationships.
DNRI	[82]	● Modeling time-varying graph structures and evolving node relations; ● Adapting to dynamic networks.	● Involving high computational demands; ● Struggling with modeling long dependencies; ● Being sensitive to noise; ● Facing challenging training and having low robustness.

4. Robustness evaluation and optimization methods of CMECS

In the previous section, the dynamic modeling methods for CMECS is systematically conducted, aiming to achieve scientific prediction of future system states through multi-modal data-driven approaches. However, due to the unique production environment of coal mines, CMECS has gradually evolved into a large-scale complex network structure characterized by strong coupling and numerous interconnected nodes [84]. Under harsh operating conditions, the system frequently encounters various unexpected abnormal events, such as gas leakage, equipment failures, and operational errors. These uncertainties make the system highly susceptible to external disturbances and internal faults, severely threatening the behavioral control and response capabilities of CMECS [85]. Therefore, robustness evaluation and optimization have become essential components for ensuring the safe and stable operation of CMECS. On one hand, robustness evaluation helps identify potential vulnerabilities within the system and quantify its ability to withstand initial failures and external disturbances based on its inherent structure and mechanisms. On the other hand, robustness optimization can provide scientific support for decision-making in areas such as equipment maintenance, scheduling management, and resource allocation, thereby enhancing the overall stability of the system and its rapid recovery capability under abnormal conditions [86]. This plays a crucial role in preventing system malfunctions and control failures induced by environmental disturbances, mitigating the risk of major accidents, and guaranteeing the continuous, safe, and stable operation of CMECS [87]. Accordingly, this section conducts an in-depth investigation into the robustness evaluation and optimization methods of complex networks, providing a theoretical foundation and methodological support for the robustness analysis of CMECS. The details are shown in Fig. 11.

4.1. Robustness evaluation methods for complex systems

The robustness evaluation research of CMECS mainly focuses on the robustness evaluation metrics and the robustness evaluation methods, which aims to quantify the stability and recovery ability of the system under faults and disturbances. These studies provide a fundamental theoretical basis for the advancement of robustness optimization techniques in complex systems such as coal mine equipment.

4.1.1. Robustness evaluation metrics

The selection of robustness evaluation metrics should follow the following principles: 1) Measurability; 2) Completeness; 3) Non-uniqueness of metric combination; 4) Objectivity; 5) Sensitivity; 6) Consistency

[88]. Robustness evaluation indicators not only include some basic network performance indicators, such as average path length, clustering coefficient, network connectivity, network efficiency, and maximum connected subgraph relative scale, etc., which are helpful to analyze the stability and resilience of the system in case of attack or failure [89]. At the same time, complex evaluation indicators such as tolerance, failure recovery time, attack durability, reliability, and availability are also included to evaluate the performance of the system under different challenges [90]. For example, tolerance measures a ability of system to withstand failures or attacks, failure recovery time measures how quickly a system recovers from failures, attack durability reflects ability of system to resist continuous attacks, and reliability and availability directly reflect the stability and use value of a system.

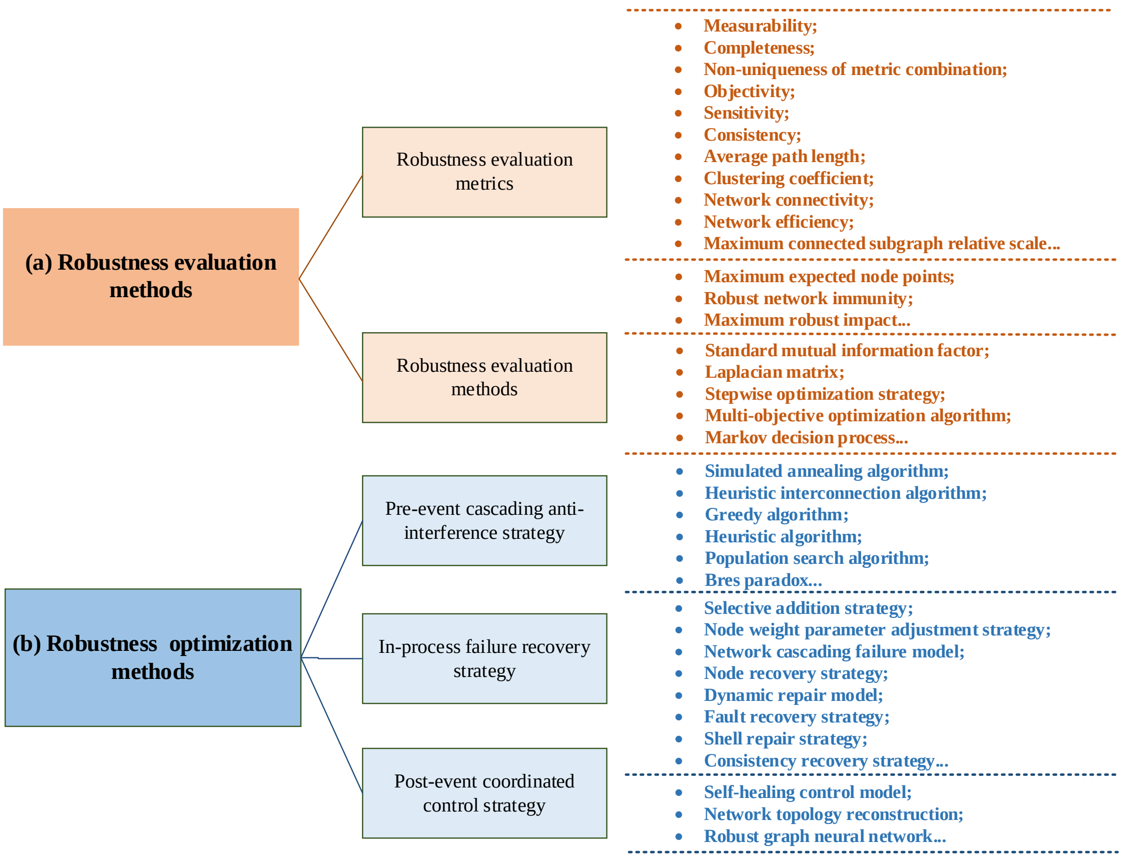


Fig. 11. Robustness evaluation and optimization methods for complex systems

In addition, for specific network models, experts and scholars have proposed a personalized robustness evaluation metric. Logins et al. [91] introduced three robustness evaluation metrics, namely maximum expected node points, robust network immunity, and maximum robust impact, to evaluate the viability of the network under all possible node attack degrees, aiming at the two uncertain factors of attack strategy and probabilistic diffusion results of diffusion networks vulnerable to node attacks. Lu et al. [92] proposed a communication robustness metric, which not only confirmed the global influence of the largest connected branches on network communicability but also captured the local communicability of all locally connected branches. These evaluation metrics comprehensively evaluate the robustness of complex networks from different dimensions and perspectives, which can not only provide a more comprehensive understanding of the robustness and reliability of complex systems but also provide a basis for system robustness evaluation methods and improve the evaluation ability of systems in complex environments.

4.1.2. Robustness evaluation methods

The robustness evaluation methods aim to measure the resilience and stability of the system after damage by quantifying the performance of the network after external attack or internal failure interference. In the robustness evaluation methods, the change in the evaluation metrics reflect the change in system function and performance after network nodes and edges are disturbed [93, 94]. The types of external attacks include random attacks and deliberate attacks, as defined in Table 4.

Table 4 Types and definitions of external attacks

Types	Definition
Random attack	Non-subjective factors randomly damage network nodes and edges, whose cumulative effects over time may eventually trigger unexpected failures under specific conditions.
Deliberate attack	Typically, key nodes with high importance are targeted first to maximize network damage at minimal attack cost [95] (see Fig. 12). The more important the node, the weaker the ability of network information transmission after an attack.

In recent years, Experts and Scholars have proposed a variety of robustness evaluation methods, ranging from node and edge attacks to the structure and function of complex networks, covering a variety of network types, such as un-weighted networks, weighting networks, random walks, directed networks, and multilayered network. These methods not only focus on traditional topological characteristics but also introduce innovative methods such as spectral analysis, reinforcement learning, modular analysis, optimization algorithms, etc., to more accurately and efficiently evaluate the robustness of the network under different attack scenarios. Wang [96] comprehensively considered the attack modes against nodes and edges, used standard mutual information factors to evaluate the similarity between the community segmentation results in the damaged network and the original community distribution in the network, and then quantified values to evaluate the robustness of the community structure. Zheng [97] proposed new robustness measurement methods for powerless networks and weighted networks based on the spectrum analysis method of network normalization Laplacian matrix. Based on network random walk, a new method for measuring the robustness of directed networks is proposed. It not only overcomes the shortcomings of the current network robustness measurement, such as high computing cost, inapplicability to unconnected networks, and difficulty in measuring dynamic networks, but also improves its applicability to complex network systems such as large-scale social networks, communication networks, transportation networks, and protein networks. Wang [98] built a network robustness evaluation system based on the topological characteristics of a multi-layer freight network and its single-layer network and evaluated the network robustness from two dimensions of multi-layer attack and layered attack. Lin et al. [99] introduced a stepwise optimization strategy to study the robustness of the dependent network under different coupling strategies by dynamically adjusting the coupling coefficient during the cascade failure process to maintain the network scale. Lou et al. [100] adopted a multi-objective optimization algorithm to optimize multiple robustness indicators at the same time, solving the problem that a single indicator sometimes cannot fully reflect the robustness of the network. Dey et al. [101] proposed a network elasticity and reliability analysis method based on modular bodies, and incorporated local higher-order structures into the elasticity and reliability analysis of complex networks, revealing the local dynamics and vulnerability of networks. Tian et al. [102] proposed a reinforcement learning method for partially observable Markov decision processes to realize dynamic robustness analysis of complex networks with incomplete information. Li et al. [103] established a double-layer high-speed railway network combining network functional characteristics and network topological characteristics and proposed a comprehensive robustness evaluation method for high-speed railway networks based on travel time and passenger flow. Xiang et al. [104] used the cascade failure model to simulate the dynamic response process of ecological networks under different attack strategies, and found that attacking low-degree nodes and high-degree nodes would lead to different degrees of network damage, and evaluated the robustness of complex networks based on this.

The above methods overcome the problems of high computation cost and poor applicability of traditional robustness evaluation and can provide a more accurate and comprehensive evaluation scheme for the robustness evaluation of CMECS. A comprehensive understanding of the robustness of CMECS and identification of potential vulnerable links can provide a scientific basis for system optimization, and maintenance and has a wide application prospect.

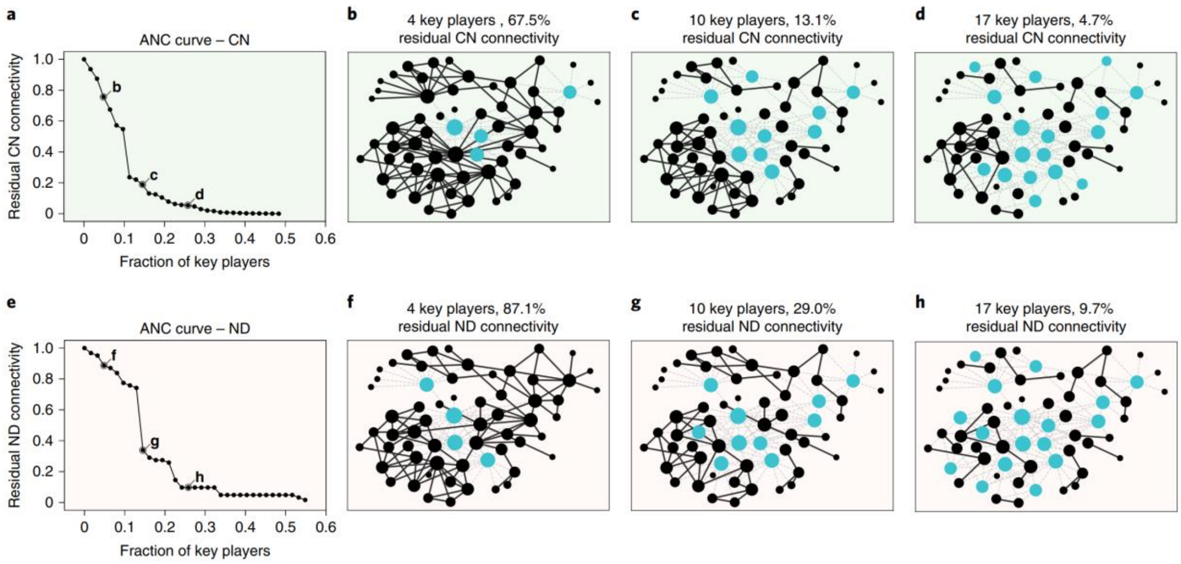


Fig. 12 The process of finding key players in a network [95].

4.2. Robustness optimization methods for complex systems

The robustness optimization method of the CMECS aims to study the ability of the system to stabilize in the process of development, remain unchanged in the disturbance, and recover quickly after damage [105, 106]. When the network has internal faults, random failures, or is subjected to deliberate attacks, a cascade effect can be triggered, and a small initial attack or failure can trigger a global crash [107], as shown in Fig. 13. Therefore, robustness optimization emphasizes the ability of the network to resist risks and recover from failures, so that the system can maintain stable operation under a certain degree of damage or attack, without completely crashing or failing. Complex system robustness optimization methods can be divided into three aspects [108]: pre-event cascading anti-interference strategy, in-process failure recovery strategy, and post-event coordinated control strategy, as shown in Fig. 14. Ex ante defense strategies focus on reducing risk exposure by designing redundancy and strengthening network structures; The in-process recovery strategy aims to quickly restore critical functions in the event of a failure; The post-coordination control strategy ensures that normal operation can still be restored after damage by optimizing resource allocation and system adjustment. See Table 5 for a detailed description, method characteristics, and limitations. These optimization strategies can significantly improve the performance of complex systems under extreme conditions and keep the whole system in a normal state [109].

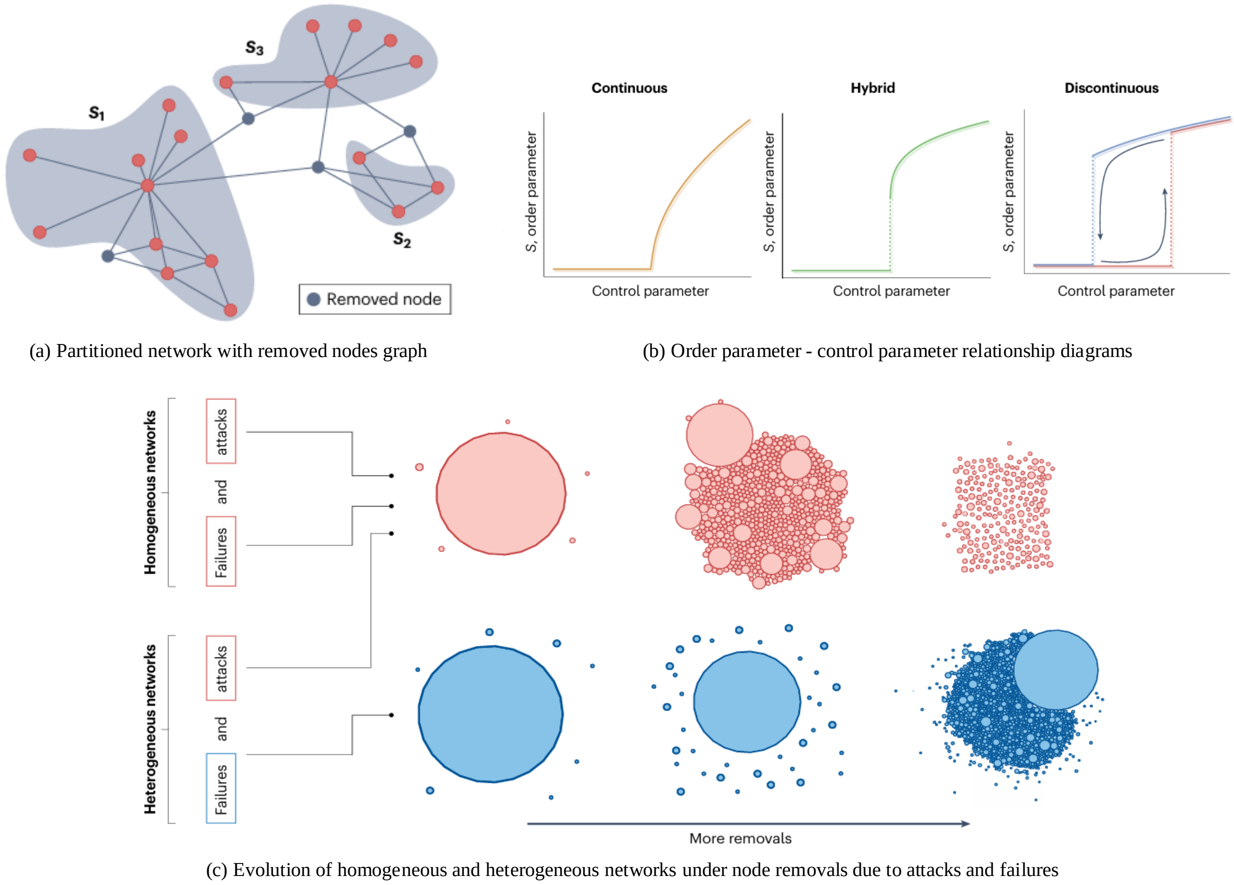


Fig. 13 Impact of attacks or perturbations on the robustness of the network [107].

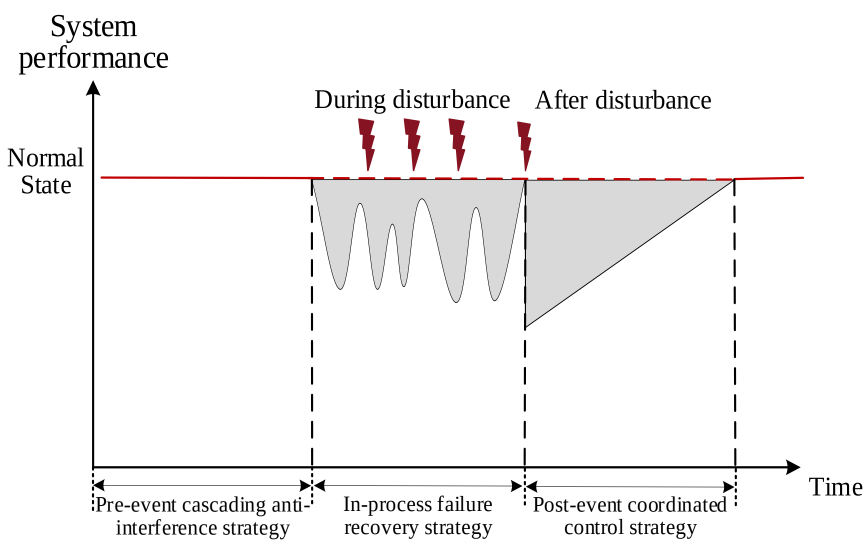


Fig. 14 Schematic diagram of the robustness optimization of a complex system.

4.2.1. Pre-event cascading anti-interference strategy

Before the system is disturbed, the cascade defense strategy aims to establish a system composed of interconnected defensive lines by designing multi-level and multi-stage high-performance defense measures to minimize the probability or impact of potential risks and threats, prevent system crashes, and improve the robustness of the system. This strategy takes a topological look at existing defense approaches and focuses on proactively enhancing network security by building robust defenses against potential failures. By anticipating, preventing, and intervening in advance, defenders can strengthen the network's anti-disturbance capabilities in advance and fully deploy before problems occur.

Lu et al. [92] proposed a simulated annealing algorithm, heuristic interconnection algorithm, and greedy algorithm to improve the robustness of network communication, which quickly improved the robustness of the network. Wang. [96] used heuristics, population search, and other algorithms to complete the corresponding community structure robustness optimization task, and obtained a network structure with more reliable performance. Cai et al. [110] proposed a method inspired by Brace's paradox, introduced a non-dominated sorting genetic algorithm, and developed a two-objective optimization model that maximizes network robustness and minimizes the number of edges to be deleted, thus improving the robustness of the system. Xiao et al. [111] proposed a controllable dynamic optimization method that modifies any given network through strict structural perturbation to effectively enhance its robustness to malicious attacks. Tu et al. [112] established a grid cascade fault model combining network topology and electrical characteristics and used a simulated annealing method to find the optimal network topology to achieve the best network robustness. Kaviani et al. [113] proposed a defense mechanism based on a scale-free structure. By strengthening the stability of key links in the network and reducing the potential risks of non-important links, the robustness of the neural network against backdoor attacks before the network is attacked can be improved, thus effectively enhancing the security and anti-interference ability of the system.

4.2.2. In-process failure recovery strategy

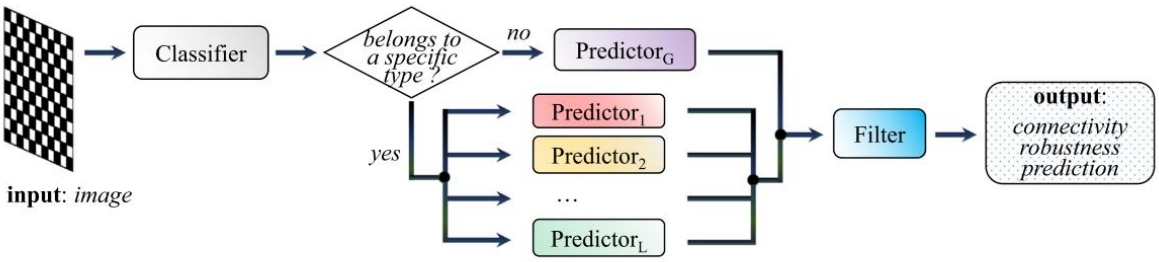
Failure recovery strategy in the network is designed to reduce the performance loss caused by the failure of nodes or edges in complex networks by an effective mechanism when nodes are attacked or fail. After the node function fails or the node and the corresponding edge fail together, the cascade failure and recovery mechanism of the fault will be adjusted according to the network characteristics, fault behavior, and consequences to repair and remedy the damaged network. This strategy restores the complex network to the normal state as soon as possible by quickly restoring node and edge functions, thus reducing the impact of faults on the overall performance of the network. This strategy can not only improve the resilience and risk resistance of the network but also ensure that the system has strong stability and sustainability in the face of inevitable failures.

Lei [114] studied the robustness enhancement strategies of complex networks with adjustable weights for edge failure, node failure, and dynamic load changes, respectively, and proposed a selective edge-adding robustness enhancement strategy based on the minimum neighbor edge capacity threshold and a node weight parameter adjustment robustness enhancement strategy based on the minimum node critical capacity threshold. The cascaded fault model of a complex network is established. Di et al. [115] studied the competitive model between cascading failures and repair strategies of interdependent network systems and proposed a node recovery strategy to improve system robustness by repairing failed nodes within functional network boundaries and reconnecting them. Fu et al. [116] built a dynamic repair model for complex and variable situations, systematically described the impact of network structure and energy transfer behavior on network repair, and proposed an algorithm that could screen out the targets (nodes or links) that had the greatest impact on the strongly coupled structure, so that the failed network could be repaired later at the lowest cost. Hong et al. [117] proposed a fault recovery strategy, which restores the boundary of the faulty node when a probabilistic cascade failure occurs, reduces the critical seepage threshold of the network, and improves the robustness of the system. Hong et al. [118] studied the process recovery strategy after the initial failure. The recovery effect largely depends on the trigger time, recovery probability, and priority of the recovery action and additional disturbance, and robust optimization can be achieved through reasonable construction and management of the system. Based on the Shell repair strategy, Fu et al. [119] minimized the risk of secondary node failure caused by the cascade effect. By identifying a group of important nodes that have a significant impact on network repair and defense, the number of switching nodes facing secondary failure risk during dynamic repair was reduced, and the resilience of the network was enhanced. Li et al. [120] proposed a consistency recovery method to study the consistency problem of generally directed nonlinear multi-agent networks in the case of node failure and reduce the adverse effects caused by the failed nodes through compensation strategies.

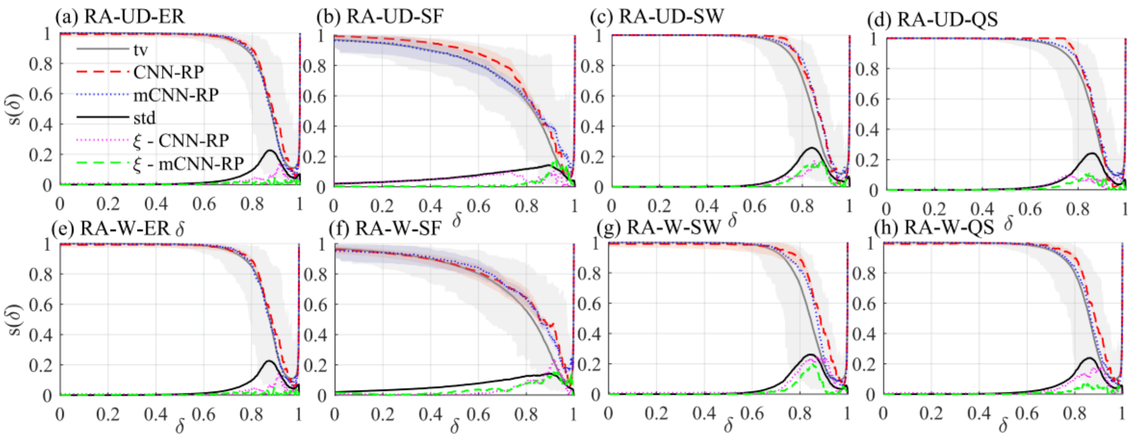
4.2.3. Post-event coordinated control strategy

The coordinated control strategy of the network after the attack is designed to adjust the system quickly after interference or attack without or with little human intervention, to minimize the impact on the combat capability of the system. The structural integrity and functional persistence of a network after an attack are analyzed by complex network theory. This strategy reveals the anti-attack capability, evolution process, and collapse condition of complex network systems, and focuses on the coordination and control of control systems in complex network topology. Special attention is paid to how the switching of different topological candidate systems affects the controllability of the network and the relationship between the switching and the coordination behavior of the network control system. In the complex system of coal mine equipment, improving the resilience and recovery ability of the system against attack is a key issue in the control and management of the complex system. However, previous studies mainly focus on random failure and deliberate attack of nodes, and few studies on the consistency of the system recovery. The current research is gradually changing from the traditional "prevention" strategy to the intelligent and more adaptable "post-regulation response" strategy to improve the resilience and operation continuity of the system in complex environments.

Chen [121] designed a self-healing control model from two aspects: network repair model and dynamic task adjustment. After some equipment entities are attacked or interfered with, self-healing control is used to reduce the impact of function failure on the combat capability of the formation. Shang [122] proposed a network consistency recovery strategy to reconstruct the network topology after network attacks and restore the connectivity and consistency of continuous directed nonlinear multi-agent systems after they are deliberately attacked by cutting points and cutting edges, thus enhancing the adaptive resilience of complex systems in the face of malicious attacks. Wei et al. [123] proposed an efficient robust GNN model based on topology reconstruction, which carried out targeted optimization of addition or deletion operations in the attack model, and selected the most favorable edge to reduce the impact of the attack edge on information transmission, and solved the problem of poor robustness of GNN with edge perturbations. Lou et al. [124] proposed an efficient robustness predictor based on multiple convolutional neural networks (mCNN-RP) for predicting network connectivity robustness, a natural extension of the single CNN-based predictor, as shown in Fig. 15. This method measures the connectivity of the remaining network after a series of node or edge removal attacks.



(a) Framework of mCNN-RP model



(b) Comparison of robustness of undirected and weighted networks under random attacks

Fig. 15 Framework and robustness results for the mCNN-RP model [124].

To sum up, the robustness evaluation and optimization of complex networks is a hot research direction at present, but there are still many practical challenges in the field of CMECS. First of all, the CMECS has the characteristics of mutual coupling and cooperative operation, and system disturbance often leads to strong nonlinear responses and abrupt behavior. Traditional methods make it difficult to effectively extract key features from complex data, resulting in insufficient robustness evaluation accuracy and stability. Secondly, when some key nodes suffer from equipment failure or external attack failure, it is easy to induce the cascading propagation effect inside the system, and there is a lack of effective defense strategies to contain or alleviate the fault diffusion, resulting in a large-scale paralysis of system functions. In addition, under the background of multiple types of failure modes, the existing recovery mechanisms and system control strategies are generally independent of each other, and there is a lack of a unified evaluation and response framework, which makes it difficult to ensure rapid robust reconstruction and efficient recovery of the system. Finally, due to factors such as sensor deployment density, communication bandwidth, and environmental interference, the data collected during actual operation is often sparse, incomplete, and delayed. Traditional steady-state regulation methods are difficult to adapt, resulting in robust regulation effects that cannot meet system requirements.

Table 5 Comparison of robust optimization methods for complex systems

Methods	References	Method interpretation	Characteristics	Limitations
Pre-event cascading anti-interference strategy	[92,96,110-113]	This approach establishes multi-layered, interrelated defense mechanisms before disturbances occur, aiming to minimize risks and prevent system failures.	● Improving system robustness; ● Reducing potential risks; ● Preventing and identifying vulnerabilities in advance.	● Facing difficulty in predicting all possible failure propagation paths; ● Being limited in handling unknown or emergent failures.
In-process failure recovery strategy	[114-120]	When nodes are attacked or fail, this strategy mitigates performance degradation in complex networks through efficient recovery mechanisms.	● Enabling rapid response and minimal loss; ● Being suitable for real-time or near-real-time fault recovery.	● Demanding high recovery speed and system responsiveness; ● Experiencing transitional instability during recovery.
Post-event coordinated control strategy	[121-124]	After disturbances or attacks, this strategy enables swift system adjustment with minimal human intervention to reduce operational impact.	● Enhancing fault tolerance and system optimization, especially in large-scale systems.	● Slower response; ● Having limited effectiveness in the short term and under extreme conditions.

5. Research prospect of dynamic modeling of multi-modal data-driven CMECS

With the continuous development of artificial intelligence, deep learning, and large models (such as ChatGPT and Deepseek), the modeling technology of CMECS is moving towards the direction of intelligence and adaptability. Future research will focus on core domains including multi-modal data processing, dynamic modeling, robustness evaluation and optimization, to improve the accurate modeling and intelligent decision-making ability of the system. The research prospects for dynamic modeling of multi-modal data-driven CMECS are illustrated in Fig. 16.

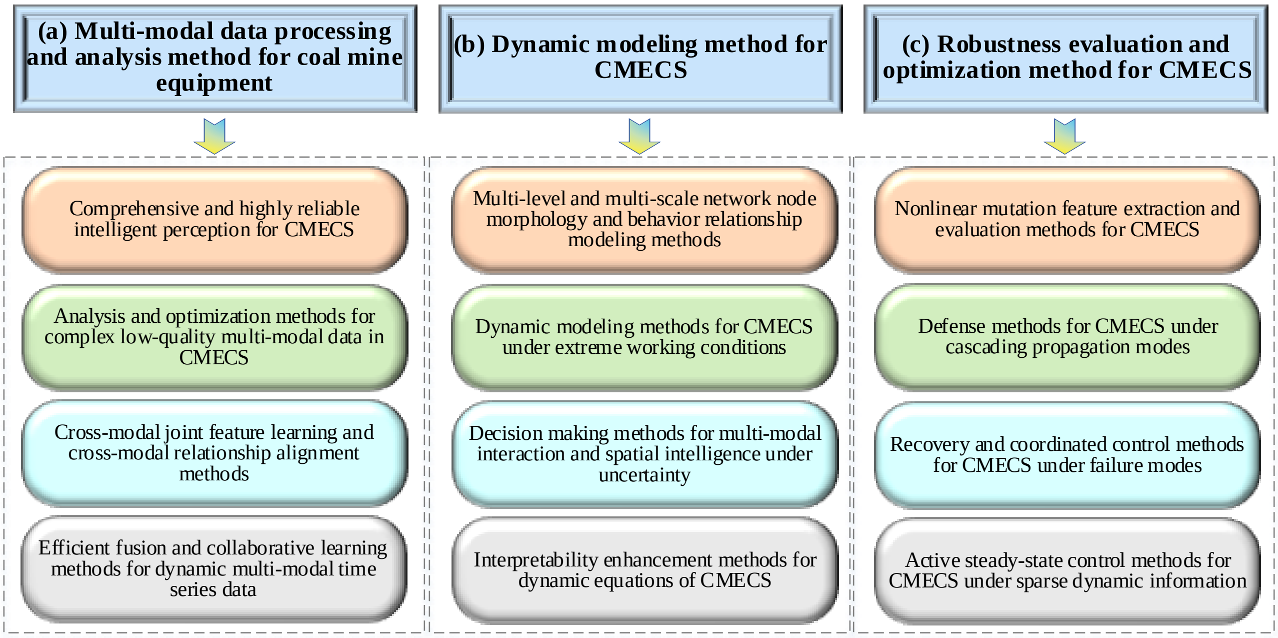


Fig. 16 Research prospect of dynamic modeling of multi-modal data-driven CMECS.

(1) High-quality processing of multi-modal data is the primary task for the dynamic modeling of CMECS. Relying on the three-level collaboration method of hardware, software, and algorithm, the development of novel high-reliability sensors tailored for CMECS will be pursued, alongside the construction of intelligent IoT sensor networks. This will comprehensively enhance the accuracy and flexibility of data acquisition and perception systems, providing robust data support for subsequent analysis and decision-making. The analysis and optimization of complex, low-quality multi-modal data of CMECS will be researched, addressing challenges such as noise contamination, partial data loss, and data imbalance under harsh mining conditions, thereby effectively improving the quality of multi-modal data samples. Based on multi-task learning and cross-modal embedding techniques, methods for joint cross-modal feature learning and relationship alignment will be investigated to explore deep associations among different modalities, achieving effective

alignment and fusion of multi-modal data in temporal, spatial, and semantic dimensions. Furthermore, through the deep time series model, fusion and collaborative learning methods for dynamic multi-modal data will be studied to tackle the challenges of long-term temporal data fusion in CMECS, thereby enhancing the effectiveness and reliability of models in dynamic and complex environments.

(2) The development of high-precision and strong adaptability models constitutes the central task in the dynamic modeling of CMECS. Research will focus on evolution method of multi-level and multi-scale network node morphology and behavior relationship, aiming to elucidate the dynamic characteristics across various levels and scales within CMECS. Dynamic modeling methods for CMECS under extreme working conditions will be investigated to mitigate disturbances from harsh environments and human factors during coal mining operations, thereby addressing the challenges posed by nonlinear behaviors and and mutation responses of equipment in complex environments. Decision making methods for multi-modal interaction and spatial intelligence under uncertainty will be explored. By integrating 3D scene reconstruction, multi-modal spatial graph construction, and language-interactive control, the environmental perception, semantic understanding, and autonomous decision-making capabilities of CMECS will be enhanced. Efforts will be devoted to improving the interpretability of CMECS dynamic equations. By combining physical models and data-driven models, the internal interaction types and strengths within the system will be explicitly expressed, thereby increasing model transparency and interpretability.

(3) The accurate evaluation and optimization of robustness of CMECS is the key link to ensure its safe and stable operation. It is necessary to investigate nonlinear mutation feature extraction and evaluation methods for CMECS, addressing challenges such as noise in raw data, data incompleteness, dynamic variability, and sudden failures, and to clarify the causal factors that induce instability, periodic oscillations, and mutations during system operation. Research should focus on defense methods for CMECS under cascading propagation modes, constructing defensive frameworks for risk cascade propagation, and resolving issues related to system fault propagation triggered by network mutations and internal dependencies. The recovery and coordinated control strategies for CMECS under failure modes should be explored to effectively prevent incidents such as malfunctions or control failures caused by environmental interference, thereby ensuring the safe and stable operation of CMECS. Based on dynamic group perception effects, it is also essential to develop active steady-state control methods for CMECS under sparse dynamic information, build complex system modeling frameworks for multi-stable subsystem coupling, and optimize

the interactive adjacency matrix of subnetworks, ultimately achieving steady-state regulation of CMECS in complex environments.

6. Conclusion

This paper comprehensively reviews the progress of research and key methods of dynamic modeling for multi-modal data-driven CMECS, which provides a solid theoretical basis for the intelligent development of coal mine equipment. The main content covers three aspects: the multi-modal data processing and analysis methods of coal mine equipment, the dynamic modeling methods of CMECS, and the robustness evaluation and optimization methods of CMECS. The paper systematically summarizes the technical characteristics, limitations, and application scenarios of existing methods, thoroughly analyzes their performance in practical engineering applications, and further highlights the core challenges and industry-related issues currently faced in the dynamic modeling of multi-modal data-driven CMECS.

On this basis, considering the development needs of dynamic modeling for multi-modal data-driven CMECS, the paper discusses future development trends and key research directions from the multi-modal data processing and analysis methods of coal mine equipment, the dynamic modeling methods of CMECS, and the robustness evaluation and optimization methods of CMECS. The development blueprint for dynamic modeling methods for multi-modal data-driven CMECS is proposed, aiming to comprehensively enhance the modeling, optimization, and control capabilities of CMECS. This will foster both theoretical innovation and practical engineering applications in the field, providing robust support for the intelligent upgrading and high-quality development of the coal mine equipment industry.

In the future, it is necessary to continue to accelerate the key technology research and achievement transformation, and promote the coal mine equipment industry to a new stage of more efficient, safer, and smarter development under the guidance of the state, industry promotion, and enterprise implementation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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