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PAPER

Dynamic Prediction and Optimization of Energy Consumption in Mining Equipment Using Mobile Computing Platforms

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ABSTRACT

With the increasing energy consumption in the mining industry, the effective prediction and optimization of energy consumption in mining equipment have become pressing challenges. Traditional energy consumption prediction methods suffer from data processing delays and the fixed nature of monitoring devices, making them inadequate for meeting the real-time and flexible demands of modern mining operations. The advent of mobile computing platforms has introduced new possibilities for the dynamic prediction and optimization of energy consumption in mining equipment. In recent years, energy consumption prediction techniques based on mobile computing platforms have gained significant attention, enabling real-time data acquisition and analysis for a more precise understanding of energy consumption patterns and the implementation of efficient optimization strategies. However, existing studies predominantly focus on conventional models and methodologies, lacking effective mechanisms to capture spatiotemporal dynamics and optimize energy consumption accordingly. In this study, a spatiotemporal gated graph convolutional prediction model was proposed for the dynamic prediction of energy consumption in mining equipment based on a mobile computing platform. Additionally, an energy consumption optimization strategy was explored using the prediction results. This study provides a novel approach to energy consumption optimization in mining equipment, offering both theoretical significance and practical value.

KEYWORDS

mobile computing platform, mining equipment, energy consumption prediction, spatiotemporal gated graph convolution, energy consumption optimization

1 INTRODUCTION

With the continuous increase in global energy demand, the mining industry, as a high-energy-consuming sector, faces significant pressure related to energy consumption [1, 2]. Against this backdrop, the effective prediction and optimization of

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energy consumption in mining equipment have become focal points of research [3–6]. Mobile computing platforms, known for their flexibility, efficiency, and convenience, have been increasingly applied across various fields [7–10], providing new avenues for the dynamic prediction and optimization of energy consumption in mining equipment.

By leveraging mobile computing platforms for the dynamic prediction and optimization of mining equipment energy consumption, energy utilization efficiency can be improved [11], production costs can be reduced [12], and greenhouse gas emissions can be significantly minimized [13]. Moreover, enhanced economic and social benefits for mining enterprises can be achieved [14]. These advancements hold substantial significance for promoting the green transformation and sustainable development of the mining industry.

Many existing studies primarily rely on traditional fixed devices and data centers for energy consumption prediction and optimization [15, 16]. However, these methods often suffer from issues such as data latency, high costs, and limited flexibility. For instance, Bouguera et al. [17] utilized a fixed sensor network for energy consumption prediction in mining equipment, but delays in data transmission and processing resulted in poor real-time performance. Pablo Mora et al. [18] employed complex mathematical models for energy consumption optimization; however, these models were highly theoretical and challenging to implement in practical production environments.

This study explores three key aspects: (1) dynamic prediction and optimization of mining equipment energy consumption using mobile computing platforms, (2) implementation of a spatiotemporal gated graph convolutional model for energy consumption prediction, and (3) an optimization strategy based on the model's predictions. By addressing these challenges, the study reduces data latency and inflexibility in traditional methods, enabling effective energy consumption prediction and optimization in mining operations. These contributions offer both theoretical and practical value.

2 PROBLEM FORMULATION

Considering the spatial distribution of mining equipment, a graph-based structure was employed to represent the topological relationships among different devices. Specifically, the spatial positions of mining equipment are encoded as a graph, where each node n_u represents a piece of mining equipment and contains its energy consumption data along with other relevant information. The edges r_u between nodes indicate whether two pieces of equipment are directly adjacent, thereby reflecting their spatial relationships. Through this graph-based structure, interactions among mining equipment and the patterns of energy consumption transmission can be effectively captured, facilitating spatiotemporal dynamic modeling for energy consumption prediction and optimization. By leveraging the real-time data acquisition capabilities of a mobile computing platform, continuous collection and updating of energy consumption data for each equipment node can be achieved, therefore providing real-time support for subsequent energy consumption prediction and optimization.

The problem can be formulated as predicting the feature graph H_{s+1} for the next time step based on the given feature graphs (H_1, H_2,..., H_s) of the preceding s time periods. Let H_s represent the topological network graph of mining equipment positions at time step s, which consists of U pieces of mining equipment and their V-dimensional features. The prediction model is denoted as d, and the expression is as follows:

$$H_{s+1} = d(H_1, H_2, \ldots, H_m) \quad (1)$$

To achieve dynamic prediction and optimization, a spatiotemporal gated graph convolutional network (GCN) model was employed in this study. This model integrates graph structures and temporal sequence data to more accurately capture the energy consumption trends in mining equipment. By incorporating spatiotemporal modeling into the graph structure, both the spatial topological relationships among equipment and the temporal dynamics were considered, thereby improving prediction accuracy. Upon obtaining the predicted energy consumption of mining equipment, an optimization strategy based on the prediction model was proposed. By analyzing future energy consumption trends, targeted optimization measures were formulated to reduce equipment energy consumption and improve energy utilization efficiency.

3 MODEL IMPLEMENTATION

The proposed dynamic energy consumption prediction model for mining equipment, based on a mobile computing platform, was designed to enhance the dynamic prediction accuracy and ability of energy consumption by integrating spatial, temporal, and spatiotemporal correlation information. In the model, the spatial correlation module transforms the topological network of mining equipment positions into graph structure data, enabling the extraction of spatial relationship features through a multi-layer graph convolutional neural network. Each node in the graph represents a piece of mining equipment, while the edges reflect spatial connections between equipment units. Through graph convolution operations, the model captures inter-equipment interactions and their collective influence on energy consumption. This module provides fundamental spatial structural information for subsequent dynamic energy consumption prediction, laying a solid foundation for analyzing the equipment energy consumption analysis. The temporal correlation module in the model focuses on the time-series characteristics of mining equipment energy consumption. Historical energy consumption data serve as input to analyze the impact of various temporal factors on the energy consumption of mining equipment. By analyzing temporal fluctuation patterns in energy consumption of mining equipment, the model can reveal the fluctuation law of energy consumption over time, providing an accurate time dimension reference for dynamic prediction. In the spatiotemporal correlation module, a gated GCN was used to extract spatiotemporal features by combining the spatial and temporal factors. Additionally, an attention mechanism was incorporated to dynamically filter significant historical energy consumption data, allowing the model to better capture critical spatiotemporal variation patterns. The output features from these three modules were aggregated into a fully connected layer, ultimately generating precise energy consumption predictions. Figure 1 illustrates the overall framework of the dynamic energy consumption prediction model for mining equipment. A detailed explanation of each module is provided in the sections below.

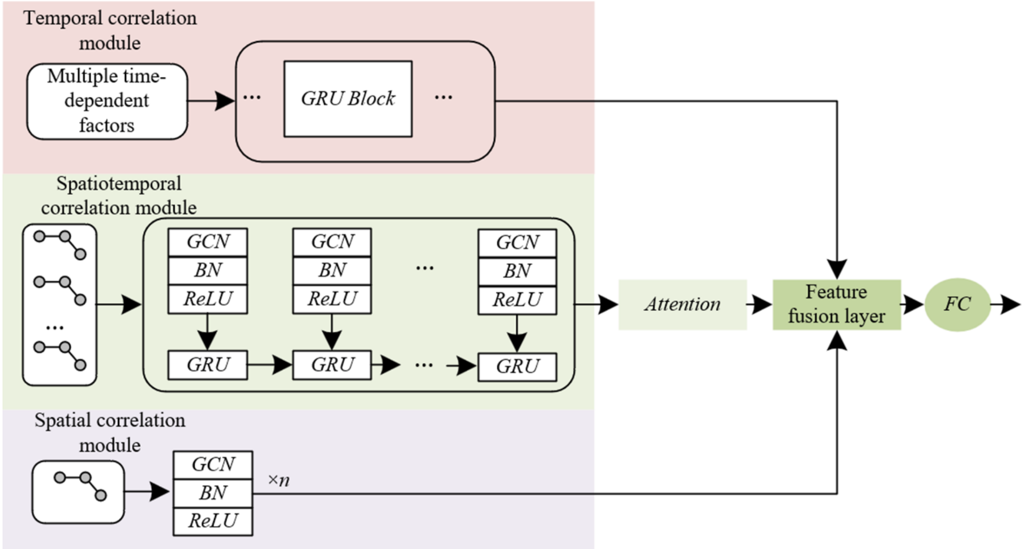


Fig. 1. Framework of the dynamic energy prediction model for mining equipment

3.1 Spatial correlation module

Mining equipment is distributed across different regions, and its relative position, type, and other characteristics determine the spatial relationships and interaction patterns among equipment units. The information is critical for dynamic energy consumption prediction, as energy consumption is not only influenced by the operational status of individual equipment but is also closely related to interactions between equipment units. To extract structural information from the topological network of mining equipment positions, a multi-layer graph convolutional neural network was employed to form the spatial correlation module. This module incorporates various types of data, including node attributes that are unaffected by temporal factors (e.g., absolute position coordinates, equipment type labels, and dynamic properties), connectivity information (e.g., logical association relationships, communication links), dynamic feature information (e.g., movement trajectories, layout modification records, failure propagation paths), and functional zoning information (e.g., production areas, auxiliary areas, hazardous areas).

Various information on mining equipment was firstly used to construct the adjacency matrix of correlation degree, denoted as $X_{u,k}$. Therefore, Jensen-Shannon (JS) divergence was utilized to quantify the similarity between equipment units. JS divergence is a widely used metric for measuring the similarity between two probability distributions, enabling an effective quantification of the correlation degree between mining equipment units within the spatial topology. This approach ensures that the spatial relationships among mining equipment are accurately reflected in the adjacency matrix, thereby providing precise structural input for subsequent graph convolution operations. In the context of mobile computing platforms, this process enables the real-time transformation of equipment attributes into network topology, thereby supporting dynamic prediction and optimization. Let $n_{u,k}$ represent the correlation between mining equipment of any two nodes in the node set n, and $TUL(n_u,n_k)$ represent the similarity between mining equipment n_u and n_k, where a lower value indicates a higher similarity. $X_{u,k}$ is expressed as follows:

$$X_{u,k} = \begin{cases} SIM(n_u, n_k) \in [0,1], n_{u,k} \in N \\ 0, else \end{cases} \quad (2)$$

Let the features of n_u and n_k be represented as $n_u(o)$ and $n_k(o)$, respectively. A V-dimensional vector of node n_u represents the characteristic information of mining equipment. By incorporating it into the JS divergence formula, it leads to:

$$SIM(u,k) = 1 - JS(n_u, n_k) \quad (3)$$

$$JS(n_u, n_k) = \frac{1}{2} KL\left(n_u \parallel \frac{n_u + n_k}{2}\right) + \frac{1}{2} KL\left(n_k \parallel \frac{n_u + n_k}{2}\right) \quad (4)$$

$$KL\left(n_u \parallel n_k\right) = \sum_o n_u(o)\, LN \frac{n_u(o)}{n_k(o)} \quad (5)$$

Based on the similarity results obtained through JS divergence, the top J most similar nodes were selected for each mining equipment unit to form its first-order neighbors. This operation helps to construct the adjacency matrix of correlation degree ($X_{u,k}$) for the topological network graph of mining equipment positions. In the dynamic prediction of energy consumption, the spatial relationships and interaction patterns among mining equipment significantly influence variations in energy consumption. For instance, adjacent equipment units often exhibit similar energy consumption patterns due to shared production tasks or common resource utilization. By selecting the top J most similar nodes, the model effectively captures the mutual influence among equipment units, thereby reflecting the spatial proximity of mining equipment.

Furthermore, GCN facilitates the propagation of information across nodes through multi-layer convolution operations, thereby progressively aggregating the information of neighboring nodes. In the context of dynamic energy consumption prediction, GCN effectively captures interdependencies among mining equipment units, where the energy consumption of one unit is often closely related to the status of adjacent equipment. In the mobile computing platform environment, GCN enables real-time updates of spatial relationship data for mining equipment, ensuring that the model maintains accuracy under evolving mining conditions. Let U denote the identity matrix and F represent a diagonal matrix, where $\tilde{F}_{u,k} = \Sigma \tilde{X}_{u,k}$. Denoting the input of layer m as $G^{(m)}$, the weight parameters of layer m as Q^m, and the output of layer m as $G^{(m+1)}$, then it leads to:

$$G^{(m+1)} = \delta\left(\tilde{F}^{-\frac{1}{2}} \tilde{X} \tilde{F}^{-\frac{1}{2}} G^{(m)} Q^m\right) \quad (6)$$

To enhance model robustness and prevent overfitting, batch normalization was incorporated after the graph convolutional module, followed by the ReLU activation function to extract nonlinear features from the data. Batch normalization effectively reduces variations in data distribution, ensuring that the input data for each layer remains stable during training. This, in turn, improves training efficiency and accelerates model convergence. On this basis, the ReLU activation function introduces nonlinear features, enabling the model to capture more complex data patterns. Let BN denote batch normalization, and let $G^{(m+1)}$ represent the feature output of layer m. The expression is as follows:

$$G^{(m+1)} = RELU\left(BN\left(\tilde{F}^{-\frac{1}{2}} \tilde{X} \tilde{F}^{-\frac{1}{2}} G^{(m)} Q^m\right)\right) \quad (7)$$

Since energy consumption variations in mining equipment are often influenced by multiple factors, simple linear models struggle to effectively capture such complexities. Through these processing steps, the spatial correlation module maintains high efficiency in energy consumption prediction and optimization even in complex environments, providing support for energy consumption management of mining equipment based on mobile computing platforms.

3.2 Temporal correlation module

The energy consumption of mining equipment is influenced not only by its instantaneous operational state but also by multiple time-dependent factors, including diurnal and seasonal variations, production scheduling, environmental dynamics, equipment status changes, and fluctuations in power grid supply and demand. For instance, diurnal cycles and seasonal shifts may lead to variations in energy consumption patterns at different times. Similarly, the operational scheduling of equipment may result in concentrated energy consumption within specific time windows, while fluctuations in electricity pricing and renewable energy integration into the grid directly affect energy utilization efficiency. By integrating and analyzing these temporal factors, energy consumption patterns of mining equipment across different time scales can be accurately identified, providing strong support for energy management and optimization strategies.

A temporal correlation module was incorporated in this study, especially through data analysis across different time scales, enabling the dynamic energy consumption prediction model to achieve energy consumption prediction and optimization from multiple dimensions. In the mobile computing platform environment, this module integrates and processes energy consumption data and production environment parameters from different time scales, allowing real-time tracking of energy consumption trends and the timely identification of potential anomalies. For example, by monitoring equipment status changes and production scheduling plans, the model can predict fluctuations in energy consumption at future time points, facilitating early warnings and optimization strategies. Additionally, by incorporating environmental factors, the model can adjust energy efficiency under varying operational conditions, thereby minimizing energy wastage. In response to unexpected events, the temporal correlation module can rapidly analyze historical data and predict the impact of such events on equipment energy consumption.

Considering that mobile computing platforms typically operate with limited computational resources and require real-time processing capabilities, the gated recurrent unit (GRU) offers computational efficiency advantages over more complex time-series models. By employing a simplified structure, GRU reduces computational overhead while maintaining high performance, thereby enhancing real-time prediction efficiency. This is particularly critical for the dynamic energy consumption prediction system of mining equipment, as it must process large volumes of energy consumption data from multiple devices across different time intervals and perform energy consumption prediction and optimization in real-time or near-real-time conditions. With the incorporation of GRU, the model can rapidly respond to changes in energy consumption, promptly detect potential anomalies or unexpected events, and make necessary adjustments. This enhances energy efficiency while minimizing energy wastage. Let c_s and e_s denote the update gate and reset gate at time step s, respectively. The candidate state at time step s is represented by $\tilde{g}_s$, while the current state is denoted as g_s. The parameters to be trained are represented by Q_c, I_c, Q_e, and I_e, and the time-dependent feature multidimensional vector is given by a_s. The GRU computational equations are formulated as follows:

$$c_s = \delta(Q_c a_s + I_c g_{s-1} + y_c) \tag{8}$$

$$e_s = \delta(Q_e a_s + I_e g_{s-1} + y_e) \tag{9}$$

$$\tilde{g}_s = \tanh(Q_g a_s + I_g (e_s \otimes g_{s-1}) + y_g) \tag{10}$$

$$g_s = (1 - c_s) \otimes g_{s-1} + c_s \otimes \tilde{g}_s \tag{11}$$

3.3 Spatiotemporal correlation module

The dynamic energy consumption prediction dataset is both large and complex. Directly utilizing raw data presents challenges in computational efficiency and processing power. Therefore, effective data processing techniques are required. In this study, the spatial region was divided into \ (*a* *times a*\) subregions, and the shared average dynamic energy consumption prediction value was computed for each subregion. This approach reduces data dimensionality and enhances computational efficiency. For equipment located at the region's boundary, an average latitude and longitude of the start and end positions was computed to assign the equipment to the appropriate subregion accurately. This ensures spatial data completeness and accuracy, thereby providing more reasonable input data for the spatiotemporal correlation module. Figure 2 presents the spatiotemporal information map of mining equipment energy consumption.

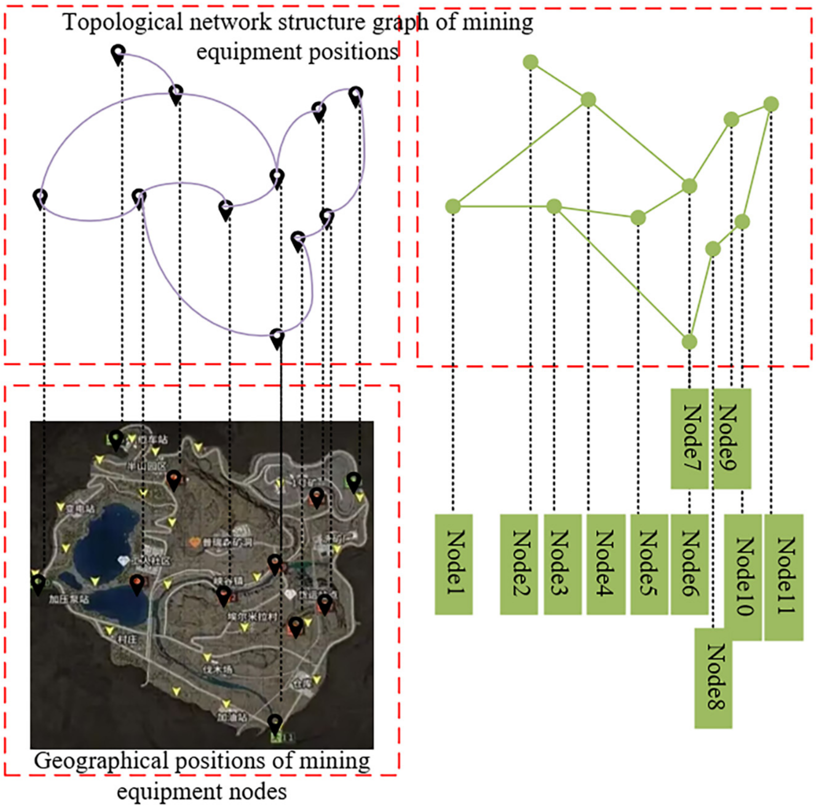


Fig. 2. Spatiotemporal information map of mining equipment energy consumption

Specifically, the latitude of the starting and ending positions of mining equipment is denoted by $LATS_u$ and $LATE_u$, respectively, while the longitude of these positions is represented by $LNGS_u$ and $LNGE_u$. The processed coordinate of mining equipment u is represented by RO_u. The latitude and longitude of mining equipment are denoted as LAT_u and LNG_u, respectively. The coordinates of mining equipment in boundary regions are formulated as follows:

$$RO_u = (LAT_u, LNG_u) \tag{12}$$

$$LAT_u = \frac{|LATS_u - LATE_u|}{2} \tag{13}$$

$$LNG_u = \frac{|LNGS_u - LNGE_u|}{2} \tag{14}$$

The spatiotemporal correlation module integrates GCN and GRU to extract deep spatiotemporal features of mining equipment energy consumption. First, GCN was utilized to capture spatial features, effectively capturing the spatial relationships between mining equipment and the distribution patterns of energy consumption. Next, GRU was used to process the GCN output matrix to extract temporal sequence features, thereby capturing variation patterns in energy consumption across different time periods. Since features extracted from different time intervals exert varying influences on energy consumption fluctuations and potential anomalies, an attention mechanism was introduced in this study to assign different weights to each feature, emphasizing the impact of historical information on energy consumption prediction outcomes. Let r_s denote the score value corresponding to the current state g_s extracted by the GRU at time step s. The corresponding weight coefficient at time step s is denoted as x_s. The final output o denotes the weighted representation of spatiotemporal features extracted at time step s. The computation is expressed as follows:

$$r_s = n_r^S \tanh(Q_r g_s + y_r) \tag{15}$$

$$\beta_s = \frac{\exp(r_s)}{\sum_{u=1}^{S} \exp(r_u)} \tag{16}$$

$$o = \sum_{u=1}^{S} \beta_u g_u \tag{17}$$

3.4 Feature fusion layer

The spatial correlation module, temporal correlation module, and spatiotemporal correlation module each extract spatial and temporal features of mining equipment using methods such as GCN and GRU. These extracted features exhibit distinct patterns and dependencies across different dimensions. To effectively integrate these complex features, a feature fusion layer was used to convert the extracted features from multiple modules into a one-dimensional tensor for further processing. Through feature fusion, spatial, temporal, and spatiotemporal features were analyzed at the same hierarchical level, ensuring that the model comprehensively considers the spatial relationships, temporal variations, and their interactions of equipment during the final prediction process.

The feature fusion layer further processes the integrated features through a fully connected layer, ultimately generating the final energy consumption prediction. To enhance the accuracy of experimental results, particularly in scenarios involving major incidents in mining equipment, a weighted L2 loss function was introduced in this study. By assigning higher weights to severe incidents, this approach addressed the zero-inflation problem. In the dynamic energy consumption prediction of mining equipment, major incidents often cause drastic fluctuations in energy consumption. However, such anomalies occur infrequently in datasets, leading to poor predictive accuracy for these critical events. The weighted L2 loss function increases the weight of these data points of serious accidents, ensuring that the model pays greater attention to crucial time periods during prediction.

Let B represent the true values, $\tilde{B}$ denote the predicted values, V indicate the number of samples, and j_u be the weight coefficient. To assign different weights to different features, the weighted L2 loss function introduced is formulated as follows:

$$LOSS(B,\tilde{B}) = \frac{1}{V}\sum_{v}^{V} j_u (B_v - \tilde{B}_v) \tag{18}$$

4 OPTIMIZATION STRATEGY

The dynamic prediction system enables real-time collection and analysis of mining equipment energy consumption data, facilitating the identification of anomalies and high-energy consumption periods. Through in-depth analysis of the data, key factors affecting energy consumption—such as equipment usage frequency, environmental conditions, and production scheduling—can be determined. Based on these factors, targeted optimization strategies can be formulated. For instance, production scheduling and equipment operation times can be adjusted to prevent concentrated use of high-energy-consuming equipment during peak periods, thereby balancing energy loads and minimizing unnecessary energy waste. Additionally, by utilizing the prediction model, potential energy fluctuations and anomalies can be anticipated, allowing preemptive adjustments and optimizations to maximize energy efficiency.

Beyond real-time monitoring of energy consumption, the dynamic prediction system also provides insights into equipment operational status and health conditions. Energy consumption data analysis facilitates the early detection of aging, wear, and potential faults, enabling timely maintenance and repairs to prevent energy surges caused by equipment failures. Furthermore, advanced energy-saving technologies and equipment upgrades—such as high-efficiency motors and variable frequency drives—can be introduced to enhance overall equipment energy efficiency. By integrating environmental dynamics, operational parameters can be optimized to ensure that mining equipment maintains optimal performance under varying environmental conditions. These measures significantly reduce energy consumption, improve energy utilization efficiency, and promote green production and sustainable development. The specific implementation steps may include:

a) **Data collection and analysis:** The real-time prediction capabilities of the mobile computing platform were leveraged to continuously collect energy consumption data from mining equipment. These data were then integrated with production scheduling and environmental dynamics for comprehensive analysis.

b) **Anomaly detection and prediction:** The spatiotemporal correlation module and time-series models were utilized to detect energy consumption anomalies in real time and predict future energy consumption trends, providing data-driven support for optimization decisions.
c) **Optimized scheduling and operations:** Based on the results of energy consumption data analysis, production schedules and equipment operation times were adjusted to prevent concentrated usage of high-energy-consuming equipment during peak periods, thereby balancing energy loads.
d) **Equipment maintenance and upgrades:** The aging, wear, and potential faults of equipment were identified to enable timely maintenance and upgrades. The adoption of high-efficiency, energy-saving equipment further enhanced operational efficiency.
e) **Parameter optimization and technological improvements:** By incorporating environmental dynamics, operational parameters were optimized to ensure that mining equipment maintains peak performance under varying environmental conditions. Advanced energy-saving technologies and equipment upgrades were also implemented.
f) **Continuous monitoring and feedback:** A continuous monitoring and feedback mechanism was established to enable the dynamic adjustment of the optimization strategy, ensuring the long-term stability and effectiveness of energy consumption optimization.

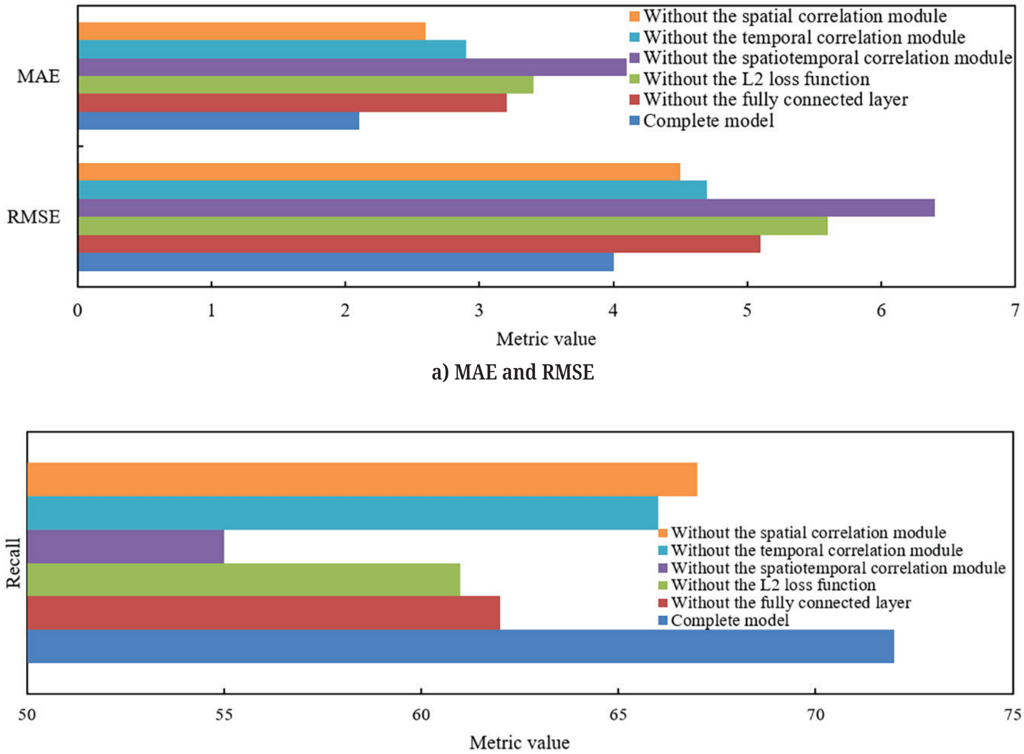
By implementing these steps, mining equipment energy consumption can be effectively reduced, energy utilization efficiency can be improved, and green production and sustainable development can be achieved.

5 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Comparison of dynamic energy consumption monitoring performance of different models for mining equipment

Models	Training Set			Testing Set		
	RMSE	*MAE*	*Recall* (%)	*RMSE*	*MAE*	*Recall* (%)
SGC	7.56	4.32	58.6	9.12	5.24	55.6
MobileGCN	8.12	4.68	53.2	9.36	5.36	51.2
DwGCN	8.32	4.23	54.5	9.62	5.58	51.8
GLSTM	6.32	3.58	63.2	8.12	4.26	61.2
T-GCN	5.69	3.24	64.8	7.36	4.12	61.4
MixHop Graph Convolution	5.74	3.29	65.6	7.56	4.26	61.8
Edge-GCN	5.21	2.87	66.9	6.42	3.58	64.5
SparseGCN	4.56	2.69	68.5	6.12	3.26	65.9
Proposed model	4.12	2.25	72.3	5.69	3.15	67.8

Based on the experimental results presented in Table 1, the proposed model demonstrates superior performance in dynamic energy consumption monitoring for mining equipment compared to the baseline models. Specifically, for the training set, the root mean square error (RMSE), mean absolute error (MAE), and recall achieved by the proposed model are 4.12, 2.25, and 72.3%, respectively. For the testing set, the corresponding values are 5.69, 3.15, and 67.8%. In contrast, other models exhibit higher RMSE values on the testing set. For instance, the simplified graph convolution (SGC) model produces an RMSE of 9.12, while MobileGCN yields 9.36. Although Edge-GCN (6.42) and SparseGCN (6.12) perform relatively better, their RMSE values still remain higher than that of the proposed model. Additionally, in terms of MAE and recall, the proposed model consistently outperforms the alternatives. It achieves an MAE of 3.15 and a recall of 67.8%, which are significantly better than the 5.24 MAE and 55.6% recall of SGC, as well as the 5.58 MAE and 51.8% recall of DwGCN.



a) MAE and RMSE

b) Recall

Fig. 3. Results of the ablation experiment for the proposed model

Based on the ablation experiment results presented in Figure 3, performance degradation was observed when individual modules were removed from the proposed model. In terms of MAE and RMSE, the complete model achieved an RMSE of 4.0 and an MAE of 2.1. However, when different modules were removed, performance declined to varying degrees. For instance, after removing the fully connected layer, RMSE increased to 5.1 and MAE rose to 3.2. When the L2 loss function was removed, RMSE reached 5.6 and MAE increased to 3.4. Eliminating the spatiotemporal correlation module resulted in a more substantial decline in performance, with RMSE increasing to 6.4 and MAE rising to 4.1. Removing the spatial correlation module and temporal correlation module led to a moderate decline in performance compared to the complete model, but their impact was relatively smaller than other components. The RMSE values for these cases were 4.5 and 4.7, while the MAE values were 2.62 and 2.9, respectively. For recall, the complete model achieved 72%, while the removal of different modules resulted in a general decline. After removing the fully connected layer, recall dropped to 62%, while removing the L2 loss function reduced it further to 61%. The most significant drop was observed after removing the spatiotemporal correlation module, which resulted in recall decreasing to 55%. Removing the temporal correlation module caused recall to decrease to 66%, while removing the spatial correlation module reduced it to 67%. These results demonstrate the critical role of the spatiotemporal correlation module and the fully connected layer in model performance. Removing the spatiotemporal correlation module led to a significant increase in RMSE and MAE, highlighting the essential role of spatiotemporal feature integration in achieving precise energy consumption predictions. The removal of the fully connected layer also resulted in a noticeable decline in performance, indicating its importance in extracting high-order features. Although removing the L2 loss function had a considerable impact, it was still less pronounced compared to the effects of removing the spatiotemporal correlation module and the fully connected layer. Furthermore, while the removal of the spatial and temporal correlation modules had a relatively smaller impact on recall, performance degradation was still observed. Notably, removing the temporal correlation module caused recall to drop by 6%.

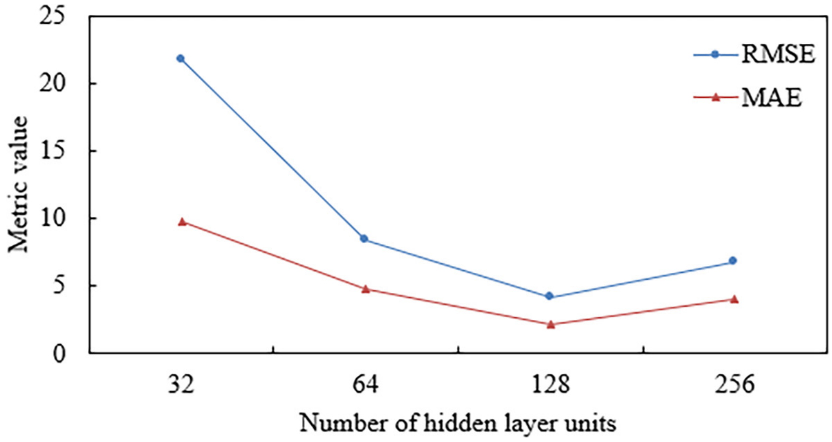


Fig. 4. Performance of the model in dynamic energy consumption prediction for mining equipment under different numbers of hidden layer units

Based on the experimental results presented in Figure 4, the performance of the model in the dynamic energy consumption prediction task varies with the number of hidden layer units. For RMSE, when the number of hidden layer units is 32, the RMSE is 21.8, indicating poor performance. As the number of units increases to 64, the RMSE decreases to 8.4. Further increasing the number of hidden layer units to 128 leads to an RMSE reduction to 4.2, achieving the best performance. However, when the hidden layer units are increased to 256, the RMSE rises again to 6.8, indicating performance fluctuations. Regarding MAE, a similar trend is observed. As the number of hidden layer units increases, the MAE gradually decreases from 9.8 to 4.8 and then to 2.1. However, at 256 units, the MAE slightly increases to 4.0. These results suggest that the lowest prediction error is achieved at 128 hidden layer units. Based on these findings, it can be concluded that increasing the number of hidden layer units effectively improves prediction performance, particularly at 128 units, where the model achieves the best RMSE and MAE performance. This indicates that, under this configuration, the model is capable of better capturing the underlying patterns and features in the data. However, when the number of hidden layer units increases to 256, the rebound in model performance indicates that excessive hidden layer units may lead to overfitting or a decrease in computational efficiency. Therefore, 128 hidden layer units appear to be the optimal choice for this task, ensuring low error while preventing unnecessary computational resource consumption.

Figure 5 presents the scatter plots of energy consumption predictions for key mining equipment, including both single-day predictions (Figure 5a) and single-week predictions (Figure 5b). Upon analyzing these plots, it is evident that most prediction points are closely clustered around the regression line, indicating that the predicted values are highly consistent with the actual values, thereby demonstrating high prediction accuracy. Notably, in the single-week prediction plot, a greater number of points align with the regression line, suggesting that the model effectively captures variations in mining equipment energy consumption over extended time periods. These results further validate the effectiveness and accuracy of the spatiotemporal gated graph convolutional model in handling the dynamic energy consumption prediction task for mining equipment.

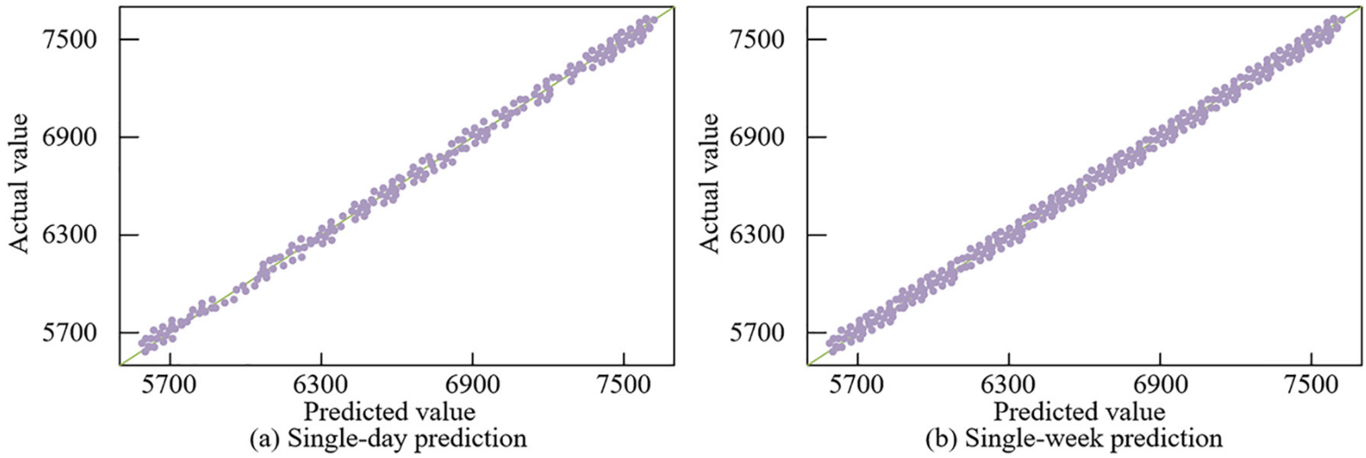


Fig. 5. Example of scatter plots for energy consumption prediction of key mining equipment

6 CONCLUSION

This study focused on the dynamic prediction and optimization of energy consumption in mining equipment and proposed an innovative solution based on a spatiotemporal gated graph convolutional model. First, a method for utilizing mobile computing platforms to achieve real-time dynamic energy consumption prediction and optimization for mining equipment was presented. This approach provides intelligent support for energy efficiency management in mining equipment. Second, a spatiotemporal gated graph convolutional prediction model was designed and implemented. This model effectively captures spatiotemporal correlations in mining equipment energy consumption, thereby enhancing prediction accuracy and reliability. Finally, an optimization strategy based on the output of the prediction model was explored, offering new approaches and methodologies for equipment scheduling and energy efficiency improvement. The experimental results demonstrate that the proposed model outperforms baseline models in the task of mining equipment energy consumption prediction. In comparative experiments, the model achieves superior performance in RMSE, MAE, and recall metrics. Additionally, ablation studies confirm that the inclusion of the spatiotemporal correlation module and the fully connected layer is critical to improving prediction accuracy. Furthermore, the scatter plot experiments further validate the model's effectiveness in practical applications, as most predicted points align closely with the regression line, reflecting high prediction accuracy. These findings confirm the practicality and accuracy of the proposed model in dynamic energy consumption prediction for mining equipment.

Despite improvements in prediction accuracy and optimization, this study has some limitations. While the model performs well on training and testing sets, its generalization in complex environments remains unverified. Additionally, it focuses on energy consumption prediction but lacks extensive exploration of real-time data integration for dynamic optimization, especially in large-scale mining. Future research should enhance the model's generalization, explore its integration with real-time scheduling for better energy management, and optimize computational efficiency to ensure practicality and scalability in industrial applications.

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