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Innovation of Graph Neural Network in Power Material Transportation Path Optimization

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Abstract. Traditional Dijkstra and A* algorithms cannot quickly adapt to the dynamic changes in the transportation of power materials. In the face of traffic jams, bad weather, and equipment failures, they lead to low computational efficiency and difficulty in meeting real-time requirements. This paper applies a path optimization method based on Graph Neural Network (GNN) to improve the accuracy of path prediction and real-time adjustment capabilities by learning dynamic information. First, the transportation problem is modeled as a directed graph, and each edge is attached with dynamic features including traffic time, cost, and road conditions. Through GNN, these dynamic features are used as input, and the graph convolutional network (GCN) model is used to dynamically update the graph structure through the information propagation mechanism to learn the features of nodes and edges. To deal with multi-objective optimization problems, the model sets multiple objective functions and uses a multi-task learning framework to automatically adjust the weights between the objectives. At the same time, based on real-time traffic flow, weather conditions, and other data, the model has the ability to adjust the path in real-time. Whenever the environment changes, the network automatically adjusts the path planning to ensure transportation efficiency and timeliness. Experiments show that the standard deviation of path consistency in emergencies is within 7.8-12.6 meters, and the computational time is lower than that of Dijkstra and A* algorithms, which is sufficient for efficient power material transportation.

Key words. Power Material Transportation, Graph Neural Networks, Path Optimization, Multi-objective Optimization, Real-time Path Adjustment

1. Introduction

As an important part of the operation of the power system, the transportation of power materials is directly related to the stability of power production and supply. The power material transportation network usually covers a large area, including multiple warehouses, terminal stations, power stations, etc. With the growth of demand in the power industry, the scale of the power material transportation network has gradually expanded, and the transportation task has become more complicated. However, the existing traditional path optimization methods usually assume that the cost, time, distance, and other factors of the transportation network are static and unchanged. This simplified assumption does not hold true in reality [1-3]. The transportation of power materials is often affected by a variety of dynamic factors during the execution process, such as traffic flow fluctuations, weather changes, equipment failures, etc. These factors may cause changes in the cost, time, and efficiency of the path [4,5]. GNN, as an emerging deep learning method, has demonstrated powerful capabilities in processing graph structured data and learning dynamic features [6-8]. Although traditional path optimization algorithms (Dijkstra, A*, etc.) give the optimal path in a static environment, they are usually unable to adapt quickly when faced with dynamic environments and emergencies, and the efficiency and accuracy of path optimization are also affected. In addition, since traditional methods cannot effectively handle large-scale complex networks and real-time data, their computational efficiency and timeliness are greatly limited in the practical application of power material transportation [9,10]. Therefore, how to quickly adjust the path in a dynamically changing transportation network to achieve efficient power material transportation has become an important issue that needs to be solved urgently.

There have been many studies in academia and industry on the problem of optimizing the path of power material transportation. Early studies mainly focused on using graph theory and heuristic algorithms to optimize path selection. Researchers used classic graph algorithms such as the Dijkstra algorithm and the A* algorithm to find the shortest path or the optimal path. In recent years, with the increasing complexity of optimization problems, more and more researchers have tried to use more advanced algorithms to solve multi-objective optimization problems in power material transportation. Some scholars used cutting-edge algorithms to deal with multi-objective path optimization problems, taking into account multiple factors such as time, cost, and path stability, and achieved certain results in power material transportation [11-13]. Ojstersek R et al. [14] focused on reviewing multi-objective optimization production scheduling methods, and then introduced the classification of power transportation algorithms for production scheduling and optimization of power transportation paths. Cappart Q [15] studied the combinatorial optimization and reasoning problems of graph neural networks, and used graph neural networks as the key building blocks of combined tasks to optimize paths. In general, although existing studies provide effective solutions for path optimization, they are weak in coping with dynamic environments, especially in terms of the real-time performance of path selection and adjustment. Therefore, the limitations of traditional path optimization methods have given rise to the need for more adaptive optimization algorithms.

In recent years, scholars in related fields have applied GCN-based methods for traffic flow prediction. By capturing the complex dependencies in traffic flow, dynamic prediction and optimization of traffic networks have been achieved [16-18]. Graph Attention Network (GAT) optimizes path selection in logistics transportation and solves the balance problem between multiple objectives in a dynamic environment. The application of GNN in transportation, logistics, and other fields shows that graph-based neural network models effectively handle path optimization problems in dynamic networks and have strong real-time response capabilities and adaptability [19-21]. However, existing research is mostly focused on the fields of transportation or logistics, and there are few studies on the specific scenario of power material transportation. In particular, in power material transportation, combining dynamic features such as real-time traffic, weather, and equipment failures, using graph neural networks for path optimization is still a research gap that is rarely touched [22,23]. Recent work [24,25] improve the performance of heterogeneous graphs by automatically selecting meta-paths. This method further integrates dynamic features based on this. This paper applies graph neural networks to power material transportation path optimization, fully utilizing its advantages in dynamic network optimization, and applies a new method for real-time optimization of power material transportation paths, making up for the lack of application of existing methods in the power industry.

The research of this paper aims to improve the real-time, accuracy, and adaptability of power material transportation path optimization through GNN. To this end, the power material transportation problem is first modeled as a graph structure, with nodes representing transportation stations and edges representing transportation paths, and real-time data (traffic flow, weather conditions, equipment status, etc.) are applied as dynamic attributes of edges . Then, this paper uses GCN and GAT in graph neural networks to dynamically learn and optimize the path to solve multi-objective path optimization problems (time, cost, path stability, etc.) [26,27]. Through the input of real-time data and online learning mechanism, the method applied in this paper automatically adjusts the path according to environmental changes during the transportation of power materials and optimizes the path selection. The research results of this paper have been verified by simulation experiments. The results show that the path optimization performance of this method in a dynamic environment is better than that of traditional path optimization algorithms, effectively improving the efficiency and accuracy of power material transportation. Through these innovative methods, this paper not only provides a new solution for the optimization of power material transportation paths, but also provides a useful reference for the research of other dynamic logistics optimization problems.

2. Application of Graph Neural Network in Power Material Transportation Path

A. Construction of Graph Model of Power Material Transportation Network

To construct the graph model of power material transportation network, the node set V and edge set E are first defined. Among them, the node V represents each site in the transportation network, including warehouses, distribution points, power stations, etc. Each node has some specific characteristics, such as demand, transportation capacity, etc. The edge E represents the transportation path between sites, indicating the transportation path from one node to another. Each edge has multiple attributes, such as transportation time, transportation cost, traffic flow, etc. These attributes are the key factors to be considered in the optimization of power material transportation. Specifically, the power material transportation network is usually a directed graph, and the direction of the edge represents the flow direction of the material. There are different transportation directions such as from warehouse to distribution point and from power station to warehouse. To solve the path optimization problem in large-scale transportation networks, the scale of the graph may be very large [28,29]. The method proposed in this paper is a dynamic perception model, updating the edge feature matrix A through real-time data (such as traffic flow and weather) to achieve dynamic optimization of the path.

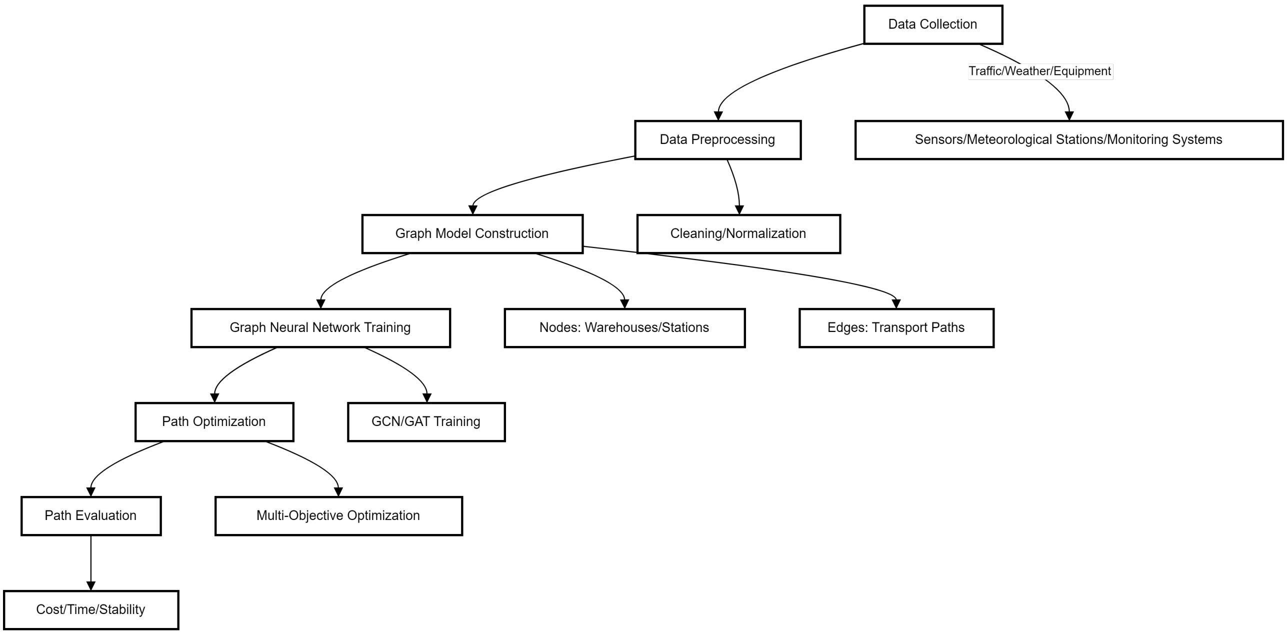

Figure 1. Optimization process of power material transportation routes

Figure 1 shows the process of optimizing power material transportation routes. First, traffic, weather, and equipment data are collected through sensors, weather stations, and monitoring systems. Then, data cleaning and normalization are performed to build a graph model containing warehouses, site nodes, and transportation path edges. Next, the graph convolutional network (GCN) and graph attention network (GAT) are used to train the model and optimize the transportation path. Finally, multi-objective optimization is performed to evaluate the cost, time, and stability of the path.

In the graph model, the characteristics of the edge are crucial for path optimization. In addition to the basic transportation distance and time, the attributes of each edge also include factors such as traffic flow, road congestion, and weather conditions. These attributes change dynamically with time and environment. Therefore, it is very important to establish the edge feature matrix A to dynamically reflect these features.

First, for each edge, multiple dynamic features are defined. The travel time is calculated by traffic flow and road conditions; the transportation cost is dynamically adjusted by economic factors such as oil prices and fuel consumption; the road congestion level is evaluated by real-time traffic data. The value of each edge feature is updated in real-time during the actual transportation process to ensure that the optimization model reflects the changes in the current environment. During the calculation process, these feature matrices are updated by data fusion technology using real-time data sources such assensors and traffic monitoring systems. The dimension of the edge feature matrix A is $|E| \times k$, where $|E|$ is the number of edges, and k is the number of features of each edge. Each row represents multiple attributes of an edge, such as travel time, transportation cost, road conditions, etc., forming a multidimensional feature vector. This matrix is used for information transmission and dissemination during the training process of the graph neural network.

In addition to the characteristics of the edges, the characteristics of the nodes are also crucial to path optimization. In the power material transportation network, each site has unique needs and capacity. The storage capacity of the warehouse, the demand of the distribution point, the load capacity of the power station, etc., may affect the transportation decision. Therefore, the node feature matrix X needs to be defined according to the specific situation of each node. The dimension of the node feature matrix X is $|V| \times m$, where $|V|$ is the number of nodes, and m is the number of features of each node. Node features include location type (warehouse, distribution point, etc.), demand, capacity, priority, etc. In actual operation, node features are adjusted according to different transportation needs to ensure that path planning meets the specific needs of each node [30,31]. The construction of the node feature matrix forms a complete node feature representation by integrating existing transportation data, real-time information, and historical transportation data. During the training process of the graph neural network, these features are used as input to help the network understand the needs of different sites and optimize path selection and transportation strategies.

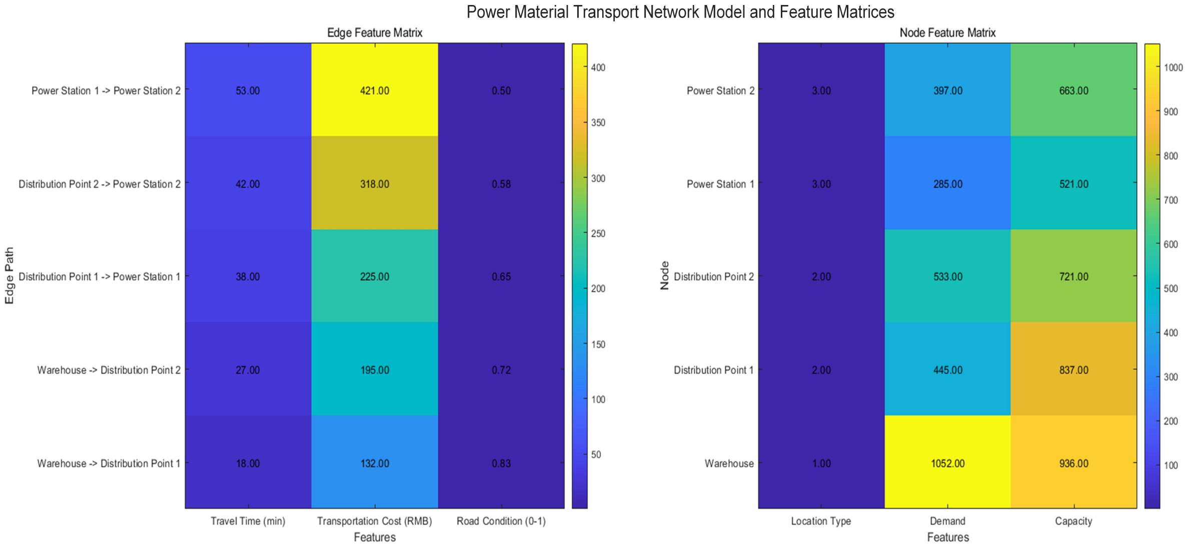

Figure 2. Edge feature and node feature matrix of the power material transportation network

Figure 2 shows the edge feature and node feature matrix of the power material transportation network. The edge feature matrix shows the transportation time, cost, and road conditions. The transportation time from the warehouse to the distribution point 1 is 18 minutes; the cost is 132 yuan; the road condition is 0.83, indicating that the path efficiency is relatively high. The transportation cost from distribution point 2 to power station 2 is high (318 yuan), and the road condition is poor (0.58). The node feature matrix shows the demand and capacity of each node. The demand of the warehouse is 1052 units, and the capacity is 936 units, indicating its large storage demand; the demand of distribution point 1 is 445 units, and the capacity is 837 units, with relatively small demand. Through these feature data, an effective reference can be provided for path optimization.

Through the above steps, the graph model of the power material transportation network is constructed, and the feature matrix of the edges and nodes reflects the changes in the network status in real-time, providing a sufficient information basis for subsequent path optimization. Based on this graph structure, the graph neural network is trained to learn the relationship and dynamic changes between nodes, thereby providing a more precise solution for path optimization.

B. Fusion and Learning of Dynamic Features

1) Collection of Real-time Data and Construction of Dynamic Features

To achieve dynamic path optimization, it is necessary to first collect various dynamic features that affect the transportation path in real-time. The path of power material transportation is affected by many external factors, mainly including traffic flow, weather conditions, equipment failures, etc. Traffic flow data reflects the real-time traffic capacity of the road section; weather data affects road conditions and traffic speed; equipment status (availability of transportation vehicles, failure rate of transportation equipment, etc.) is directly related to the feasibility and timeliness of transportation.

In the data collection process, traffic flow information is first obtained through sensors, GPS (Global Positioning System) equipment, intelligent transportation systems, and other channels to monitor road traffic conditions in real-time. Weather data is collected through meteorological stations and meteorological forecasting systems, covering factors such as rainfall, wind speed, and temperature that affect the transportation process [32-34]. In addition, equipment status data is collected in real-time through the monitoring system in the power material transportation system to monitor the equipment operation status and failure conditions.

These dynamic feature data need to be cleaned and preprocessed to ensure their quality and availability. The preprocessing process includes operations such as removing outliers, filling missing data, and data normalization. The processed data is used as the edge feature input of the graph model to provide timely environment update information for the graph neural network.

2) Input of Dynamic Features and Construction of Graph Neural Network Model

In the implementation of graph neural network, dynamic features are input into the input layer of the network as the attributes of the edge. By taking the real-time collected features such as traffic flow, weather conditions, equipment failures, etc., as the features of the edge, a dynamic feature matrix is constructed and embedded into the structure of the graph. Each edge contains not only static transportation path information, but also dynamic data that changes over time. These dynamic features affect the evaluation and selection of the path, prompting the graph neural network to adjust the path according to real-time data.

In the process of model construction, GCN and GAT are used as the basic architecture. GCN propagates information to nodes in the graph through the adjacency matrix and uses graph convolution operations to propagate the feature information of the edge to adjacent nodes, thereby adjusting the weight of the path [35,36]. GAT uses the self-attention mechanism to dynamically assign different weights according to the importance of adjacent nodes, thereby more precisely capturing the complex correlation in the graph.

Graph neural network effectively learns the relationship between edge features and node features through the propagation mechanism, so that the optimization of the path not only depends on static data, but also can reflect the changes in the dynamic environment in real-time. When traffic volume suddenly increases, the graph neural network updates the cost of the path in time and dynamically adjusts the transportation path to avoid delays caused by congestion. Similarly, changes in weather conditions also affect the choice of path by dynamically updating the features of the edges.

The input layer of GCN receives the node feature matrix X (including site demand, capacity, etc.) and the edge feature matrix A (dynamic attributes such as traffic volume, weather), aggregates neighborhood information through multi-layer convolution, and finally outputs the updated node features $\mathbf{h}_v^{(L)}$ for calculating the path weight w_e.

3) *Information Propagation and Feature Update*

Graph neural networks use information propagation mechanisms to achieve dynamic updates and feature learning of graph structures. Under the framework of GCN and GAT, the feature information of the edge is propagated through multiple layers of graph convolution or graph attention, gradually affecting the node features and edge features of the entire graph structure. Each layer of information propagation contains features transmitted from adjacent nodes, which are used to update the states of nodes and edges after nonlinear transformation.

During the propagation process, GCN updates the features of nodes by calculating the average of the weighted neighbor node features of each node. This weighted method incorporates the dynamic features of the edge (traffic volume and weather conditions) into the decision of the node, affecting the choice of path. GAT dynamically evaluates the importance of each adjacent node through the self-attention mechanism and assigns different weights according to the features of the adjacent nodes, making information propagation more refined and accurate in responding to changes in dynamic environments.

Specifically, the dynamic features of the edge are continuously updated and affect the evaluation of the path during the propagation process of each layer of the graph neural network. If the traffic flow of a section of a transportation path increases, the graph neural network adjusts the evaluation value of the path according to the change of dynamic features to avoid selecting this path for material transportation. In this way, the graph neural network optimizes the transportation path in real-time so that the path selection always meets the changing needs of the current environment.

The key advantage of this information propagation mechanism lies in its end-to-end learning ability, which adaptively adjusts the path according to real-time data, thereby maintaining efficient path optimization in a dynamic environment. Compared with traditional static path optimization methods, graph neural networks have stronger adaptability and real-time performance and provide more precise path planning solutions in complex dynamic environments. The process is shown in Figure 3.

The model is trained by minimizing the total path cost and the time-weighted loss function $L = \lambda_1 L_{\text{cost}} + \lambda_2 L_{\text{time}}$, and the GCN/GAT weights are updated using the Adam optimizer. The output layer generates the path selection probability through Softmax to ensure path coherence.

The improved GCN layer formula is Formula 1:

$$\mathbf{h}_v^{(l+1)} = \sigma\left(\sum_{u \in N(v)} \frac{1}{c_{vu}} \mathbf{W}^{(l)} \mathbf{h}_u^{(l)} \right) \quad (1)$$

In the formula, c_{vu} is the dynamic weight of edge (v,u), which is calculated based on traffic volume, weather, and other characteristics.

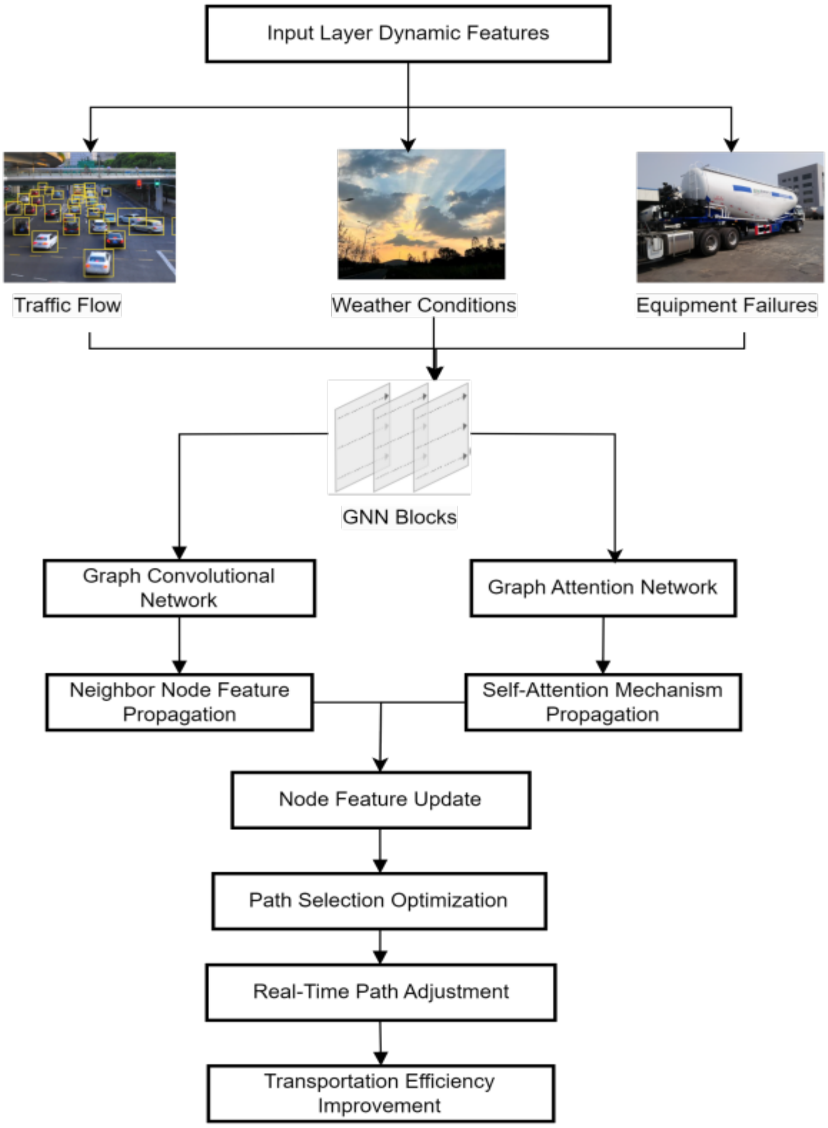

Figure 3. Information propagation and feature update process

Through the propagation mechanism of real-time data input, graph convolution, and graph attention, the path optimization model of this paper continuously learns and adjusts the path selection to cope with dynamic changes in the transportation of power materials. This process not only improves the efficiency of path optimization, but also enhances the model's ability to cope with sudden changes, providing strong support for real-time path adjustment of power material transportation.

C. Multi-objective Optimization and Constraint Processing

1) Setting and Optimization of Multi-objective Functions

In the optimization of power material transportation routes, there are multiple objectives that need to be optimized, such as the shortest path, minimum cost, and time window limit. In different situations, the priority of these objectives may be different. For example, in an emergency, the priority is to minimize the transportation time, while in cost-sensitive situations, the priority is to reduce the cost. To adapt to these changing needs, this paper sets multiple objective functions in the graph neural network and assigns weight coefficients to each objective for comprehensive optimization. Specifically, the objectives such as path cost, transportation time, and path length are expressed in mathematical form, and the weighted optimization is performed. Assuming that the transportation cost of each edge e is $cost(e)$, the objective function of minimizing the transportation cost is expressed as Formula 2:

$$\text{minimize } C = \sum_{e \in E} cost(e) \cdot x_e \quad (2)$$

Among them, x_e is a binary variable, indicating whether edge e is selected, and E is the set of all edges in the graph. Assuming that the transportation time of each edge e is $time(e)$, the objective function of minimizing the transportation time is Formula 3:

$$\text{minimize } T = \sum\nolimits_{e \in E} time(e) \cdot x_e \quad (3)$$

Similarly, x_e is a binary variable, indicating whether edge e is selected. Assuming that the transportation time of each edge e is $time(e)$, which needs to meet the time window limit $time_{\text{window}}$, then the constraint condition is Formula 4:

$$time(e) \le time_{\text{window}}, \quad \forall e \in E \quad (4)$$

In summary, the comprehensive objective function and constraint conditions can constitute the following optimization problem, expressed by Formula 5:

$$\text{minimize } Z = w_{\text{cost}} \sum cost(e) \cdot x_e + w_{\text{time}} \sum time(e) \cdot x_e \quad e \in E \quad (5)$$

Among them, the weight coefficients w_{cost} and w_{time} are dynamically adjusted according to actual needs. The network is optimized according to the priority of different objectives. To ensure that each objective is effectively considered at the same time, the weight parameters in the objective function are dynamically learned during the training process and adjusted according to real-time needs.

The pseudo code of the multi-task learning framework is as follows:

```
for epoch in epochs:

    for batch in data_loader:

        h = GCN(features)

        loss_cost = MSE(pred_cost, true_cost)

        loss_time = MAE(pred_time, true_time)

        total_loss = α * loss_cost + β * loss_time

        optimizer.zero_grad()

        total_loss.backward()

        optimizer.step()

        α, β = update_weights(α, β)
```

2) Weight Adaptive Learning and Constraint Processing

The advantage of graph neural networks is that they automatically adjust the weights between different objectives, which is achieved through feature learning of nodes and edges in the network. Traditional path optimization methods usually require users to manually adjust weights, while graph neural networks automatically learn weights based on historical data and real-time data, making the balance between objectives more flexible and precise. By learning the relative importance of each objective function, graph neural networks dynamically adjust the priorities between objectives to achieve comprehensive optimization of multiple objectives.

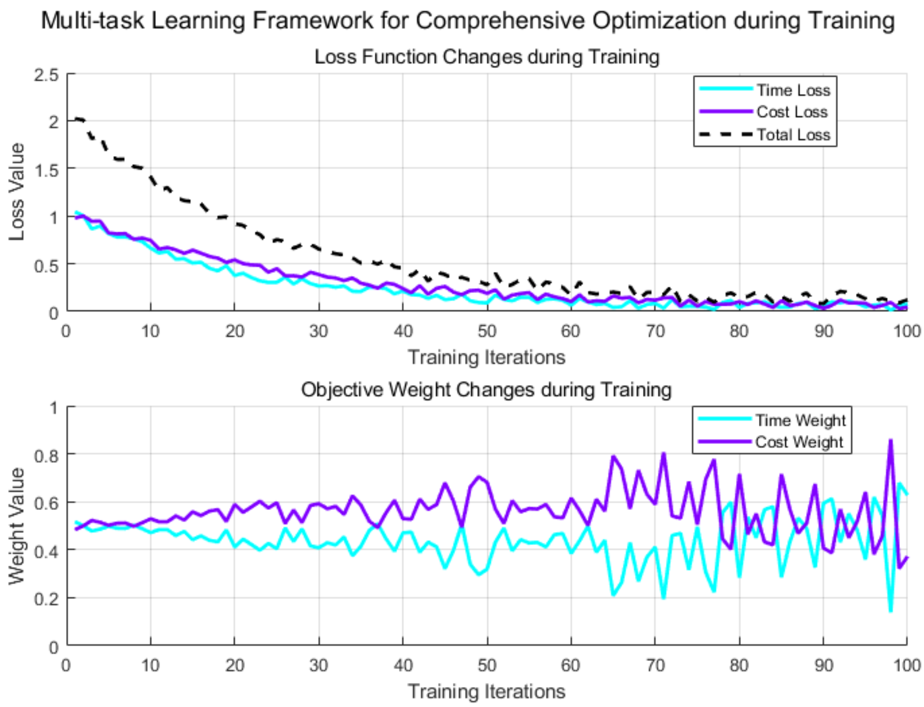

Figure 4. Training process of power material transportation path optimization. Figure 4(a) Loss function change; Figure 4(b) Dynamic adjustment of weights.

Figure 4 shows the training process of power material transportation path optimization under the multi-task learning framework. The upper figure of Figure 4 shows that as the number of iterations increases, the time loss and cost loss gradually decrease, and the time loss decreases faster, indicating that the model prioritizes the optimization of the time target. The lower figure shows that the time weight and cost weight are dynamically adjusted from 0 to 1, and the cost weight is slightly higher than the time weight under adjustment, meeting the needs of power material transportation.

In the optimization process, constraints (time window, capacity limit, maximum load, etc.) need to be fully considered. To this end, in addition to optimizing the objective function during training, the graph neural network also needs to deal with a series of constraints. For each transportation path, it is necessary to ensure that the transportation time does not exceed the specified time window, and it is necessary to ensure that the transportation volume of each path does not exceed the load limit of the transportation tool. To achieve the processing of these constraints, the graph neural network applies hard constraint and soft constraint mechanisms.

Hard constraints refer to those conditions that must be strictly met, load limits, and time windows. During the training process of the network, hard constraints are forced into the optimization process through the design of constraints. If the transportation time of a certain path exceeds the predetermined time window, the graph neural network automatically adjusts the path selection through the information propagation mechanism to avoid the path being selected [37,38]. Soft constraints are soft restrictions on the target, such as minimizing the transportation cost, but tolerating a certain cost excess within a certain range. The processing of soft constraints is achieved through the penalty term in the loss function, and the constraints of different targets are balanced by optimizing the loss function during the training process. Hard constraints (such as time windows) are enforced to exclude timed-out paths through an encoding mechanism; soft constraints (such as cost) are implemented through the penalty term $\gamma \cdot \max(0, C - C\_max)$ in the loss function.

D. Real-time Path Adjustment and Prediction

1) Construction of Real-time Path Prediction Framework Based on Graph Neural Network

To achieve real-time path adjustment, this paper first constructs a real-time path prediction framework based on graph neural network. The core of this framework is to continuously update the path based on graph neural network using real-time dynamic data. Different from the traditional batch computing method, this framework automatically adjusts the network structure and path planning every time the environment changes through an online learning mechanism.

In this framework, all transportation paths are regarded as edges of the graph, and the nodes represent transportation stations. The edges in the graph contain multiple real-time data features, such as traffic flow, road conditions, weather conditions, etc. These data are input into the graph neural network for update. Every time new dynamic data enters, the model adjusts the edge features in real-time, thus affecting the node and path weights in the graph [39,40]. Unlike static models, graph neural networks dynamically update path selection schemes based on changing input data.

The graph neural network in the framework continuously integrates new real-time data through a hierarchical propagation mechanism to ensure that the evaluation of each path reflects the current transportation conditions. In the event of a traffic accident, traffic flow and road conditions affect the evaluation value of the path. The model recalculates the cost of all paths in real-time and selects the optimal alternative path for material transportation.

2) Application of Graph Convolutional Network and Graph Attention Network in Dynamic Information Propagation

In this study, the transportation paths of electric power materials are optimized using graph convolutional networks (GCNs) and graph attention networks (GATs). First, the electric power material transportation network is modeled as a directed graph, where nodes represent transportation stations, and edges represent transportation paths, containing dynamic attributes such as traffic time, cost, and road conditions. GCN updates node features by propagating feature information of adjacent nodes through graph convolution operations, thereby dynamically adjusting the cost and time of the path. GAT introduces a self-attention mechanism to dynamically assign different weights according to the current environment, giving priority to safer and more efficient paths. Although this model significantly improves the accuracy and real-time performance of path selection, it should be noted that no algorithm can guarantee 100% selection of the optimal path in all cases. Experimental results show that compared with traditional Dijkstra and A* algorithms, methods based on GCN and GAT have higher adaptability and flexibility in dealing with dynamic environmental changes.

GCN propagates the feature information of nodes and edges in the graph through graph convolution operations, while GAT assigns different weights to each adjacent node through the self-attention mechanism, which has a more precise impact on the optimization of the path.

In real-time path adjustment, GCN calculates the weighted average of each node by using the features of adjacent nodes and updates the features of the node. In the path optimization problem, the features of the node not only include the information of the station, but also the traffic conditions, costs, and other data of its connecting paths. Through multiple graph convolution operations, GCN gradually adjusts the evaluation value of the path according to the adjacency relationship of each node. If the traffic flow of a certain path increases, GCN automatically adjusts the weight of the path through the feature update mechanism of the adjacent nodes, so that its transportation cost and time are reflected in real-time. GAT enhances GCN by incorporating a self-attention mechanism, which automatically assigns different weights to adjacent nodes based on their importance. This allows the model to adapt more flexibly to changing environments. For instance, when traffic on a path increases, GAT assigns higher weight to alternative paths, avoiding congestion. This mechanism is crucial for dynamic path optimization in power material transportation, as path selection depends not only on node features but also on the interactions between nodes and edges in the graph. The relationship between nodes is captured more precisely using this weighted approach, as shown in Formula 6.

$$\mathbf{h}_v^{(k+1)} = \sigma\left(\sum\nolimits_{u \in N(v)} \alpha_{vu} \mathbf{W} \mathbf{h}_u^{(k)}\right) \quad (6)$$

Among them: $\mathbf{h}_v^{(k+1)}$ is the updated feature of node v at the $k+1$ -th layer. α_{vu} is the attention coefficient between node v and adjacent node u, indicating the importance of node u's influence on node v.

3) Path Recalculation and Automatic Update under Environmental Changes

The real-time path adjustment capability of graph neural networks depends on their powerful information propagation mechanism and dynamic feature update. Whenever an environmental change occurs, the model automatically recalculates the path based on the new input data. The path update process caused by environmental changes is automated and does not require human intervention. In the model's training phase, dynamic data is used as the feature input of the edge, and the graph neural network quickly recognizes and responds to these changes in the actual environment through multiple iterations of learning.

When a traffic accident occurs, traffic flow data changes immediately. The graph neural network updates the evaluation function of the traffic path in real-time through the feature propagation mechanism of nodes and edges, and reselects the optimal path based on the latest traffic information. Similarly, in the case of equipment failure, the status information of the equipment is also updated to the node features of the graph, affecting the choice of path. In this way, the graph neural network flexibly adapts to various emergencies and avoids the negative impact of path selection on environmental changes.

In addition, this paper also designs an incremental update mechanism to improve the model's real-time responsiveness. When new dynamic data is input, the graph neural network not only adjusts the path, but also ensures the efficiency of the model in the calculation process through the incremental learning mechanism. After each environmental change, the network only updates the affected part of the nodes and edges, avoiding the high cost of recalculating the entire graph. This enables the graph neural network to perform path optimization efficiently and in real-time in large-scale power material transportation networks.

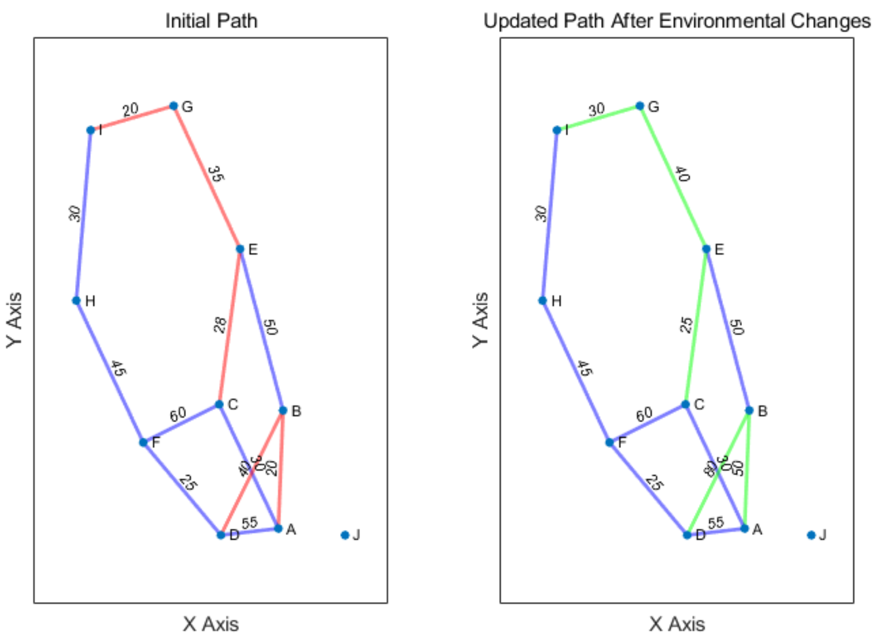

Figure 5. Weight adjustment process of graph neural network in power material transportation. Figure 5 (a) Initial path; Figure 5 (b) Path adjustment after environmental changes.

Figure 5 shows the path adjustment process of graph neural network in power material transportation. The left figure is the initial path, and the number on the path represents the weight of this path. The right figure shows the path adjustment after the environment changes. For example, the time cost of path I-G increases due to a traffic accident, and the weight increases from 20 to 30. The weight of path A-B increases from 20 to 50 due to equipment failure, and the transportation chooses a new path. Through these adjustments, the total path cost and transportation efficiency are optimized, demonstrating the adaptive adjustment ability of graph neural network in a dynamic environment.

3. Evaluation of Path Optimization Effect

The experimental data in this paper comes from the Guangxi Electric Power Transportation Monitoring System (January-June 2023) and the public urban traffic dataset.

A. Path Cost Evaluation

Total path cost is a key evaluation metric in optimizing power material transportation. It considers factors like time, economic cost, and transportation load. The goal is to minimize these costs by evaluating different path combinations. This paper's path optimization algorithm uses GNN to assess and select the optimal path. To evaluate the total cost, its components are first considered: time cost, which includes both vehicle driving time and dynamic factors such as traffic and weather. Economic cost refers to the direct costs incurred during the transportation process, including fuel costs, driver wages, etc. In addition, the load of the path needs to be considered. Excessive load may increase additional costs. Therefore, the total cost of the path includes not only time and economic costs, but may also be affected by other dynamic factors on the path (road conditions, equipment failures, etc.).

During the evaluation process, the total cost of each candidate path is first calculated and compared with the optimal path. By comparing the total cost of the paths of different algorithms, the performance of the optimization algorithm under different conditions can be understood. Minimizing the total cost of the path often means lower transportation costs and shorter transportation time, which is crucial for the transportation of power materials.

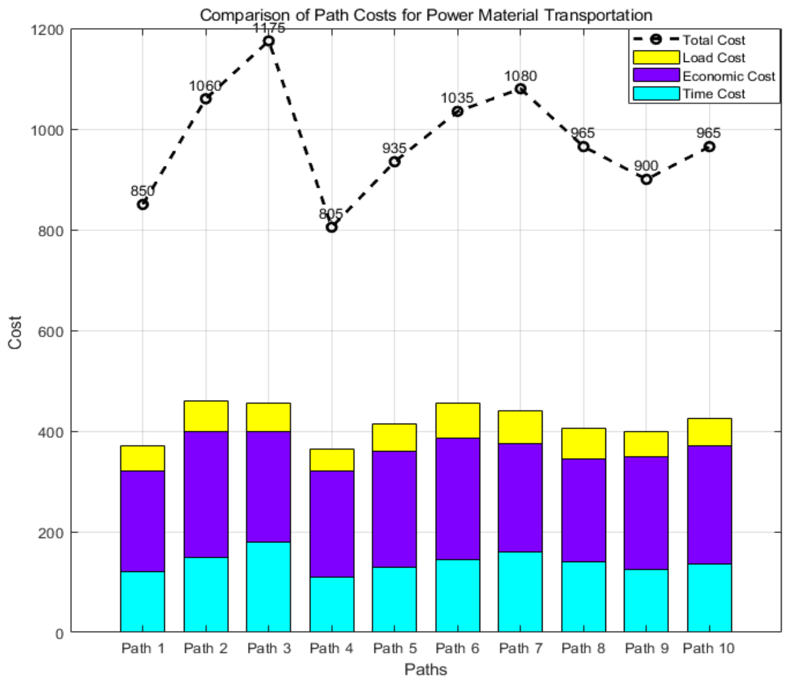

Figure 6. Cost of 10 power material transportation paths

The bar chart in Figure 6 shows the time cost, economic cost, and load cost of 10 power material transportation paths, as well as the total cost of each path. The total cost is calculated based on the weights of the three different costs. Among them, the total cost of path 4 is the lowest (805 yuan), while the total cost of path 3 is the highest (1175 yuan), with load cost and economic cost accounting for a large proportion. These data show that path selection is not only affected by time cost, but economic and load costs are also critical, and path optimization needs to consider multiple factors comprehensively.

B. Path Computational Time Evaluation

Path computational time is an important indicator to measure the real-time performance of path optimization algorithms. In practical applications, the transportation of power materials faces dynamic environmental changes, so it is necessary to be able to quickly calculate new optimal paths. In this process, the shorter the path computational time, the faster the algorithm responds to environmental changes and can better meet the real-time requirements.

When evaluating the path computational time, this paper mainly measures the time required for the algorithm to receive input data and output the optimized path. The real-time performance of the algorithm depends not only on the computational complexity, but also on the frequency and size of data input, the design of the network architecture, and other factors. To evaluate the computational efficiency of different algorithms, this paper compares the computational time difference between the traditional path optimization method based on Dijkstra and A* algorithms and the GNN-based method.

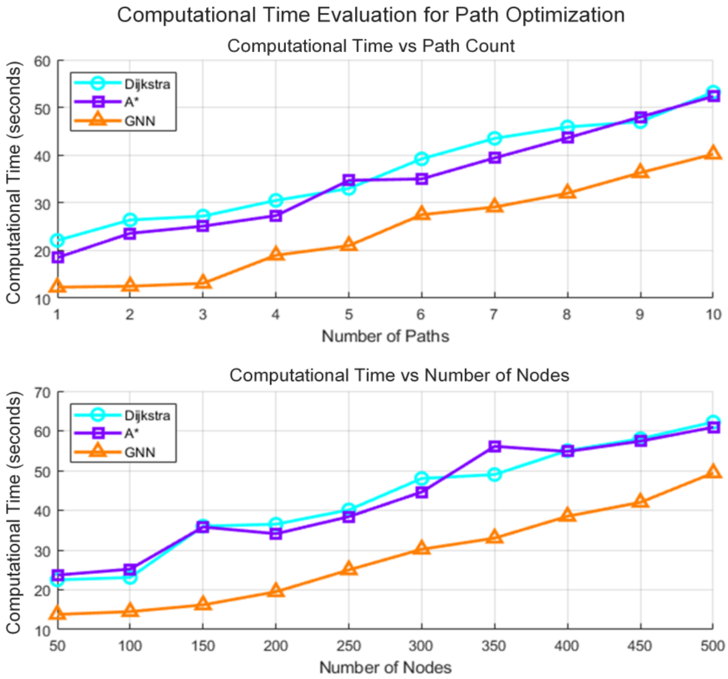

Figure 7. The impact of the number of paths and nodes on the computational time. Figure 7 (a) The impact of the path on the calculation time; Figure 7 (b) The impact of the number of nodes on the calculation time.

Figure 7 shows the impact of the number of paths and nodes on the computational time. As the number of paths increases, the computational time of the Dijkstra algorithm gradually increases to 53.2 seconds; the A* algorithm finally reaches 52.3 seconds; the GNN algorithm maintains a low computational time of only 40.2 seconds, showing higher efficiency. For the number of nodes, the computational time of the Dijkstra algorithm increases from 22.5 seconds to 62.2 seconds; the A* algorithm increases from 23.7 seconds to 60.9 seconds; the GNN algorithm increases more slowly and has a shorter computational time of 49.4 seconds. This shows that GNN is significantly more efficient than traditional algorithms when dealing with large-scale problems.

C. Path Stability Evaluation

Path stability refers to the consistency of the optimization algorithm in multiple experiments, especially the adaptability of the algorithm in the face of environmental changes. The main purpose of stability evaluation is to test whether the path optimization algorithm can maintain a good optimization effect under different input conditions and changing scenarios. Especially in the actual transportation of power materials, environmental changes such as traffic, weather, equipment status, and other factors are inevitable.

To evaluate the path stability, this paper conducts multiple experiments to simulate sudden traffic accidents, weather changes, equipment failures, etc., and uses the same starting point and end point for path calculation in each experiment. By statistically analyzing the consistency of path selection in each experiment, a quantitative evaluation index of path stability is obtained. The standard deviation of path selection or the range of variation of total path cost can be used as an indicator of stability evaluation.

The importance of path stability evaluation lies in that it can reflect the adaptability of the optimization algorithm. Traditional path optimization algorithms usually perform poorly in the face of emergencies and often require manual adjustment of weights or recalculation of paths. The path optimization algorithm based on GNN, by learning historical data and real-time data, can quickly adapt to changing environments and dynamically adjust path selection, thereby maintaining a high path stability. By comparing the stability of different algorithms under the same experimental conditions, the effect of graph neural network methods in dynamic environments is further verified. This study aims to evaluate the performance of different algorithms (Dijkstra, A*, and

GNN) in path optimization under sudden environmental changes. By simulating scenarios such as no change, traffic accidents, bad weather, and equipment failure, the path consistency standard deviation and total cost variation range of each algorithm are evaluated. These evaluation indicators help understand the ability of each algorithm to cope with unexpected events in a dynamic environment.

Table 1 shows the path stability evaluation results of Dijkstra, A*, and GNN algorithms under different sudden environmental changes. Key data shows that the path consistency standard deviation of GNN in the face of traffic accidents is 9.1 meters, which is significantly better than Dijkstra's 18.6 meters and A*'s 15.4 meters, showing its higher stability. In addition, in the case of equipment failure, the path cost variation range of GNN is 243 yuan, which is lower than Dijkstra's 288 yuan and A*'s 267 yuan, indicating that GNN can better adapt to dynamic changes and maintain the stability of the optimized path. These results verify the advantages of graph neural networks in dynamic environments. To verify the effectiveness of the GNN algorithm in practical applications, this paper conducts multiple simulation experiments. In one simulated traffic accident scenario, the GNN algorithm is able to quickly adjust the route after the accident to ensure that the materials arrive at the destination on time. The experimental results show that the GNN algorithm not only has advantages in theory, but can also effectively respond to emergencies in actual operations.

Table 1. Path stability evaluation results of Dijkstra, A*, and GNN algorithms under different sudden environmental changes

Environmental Change Type	Algorithm	Path Consistency Standard Deviation (Units: meters)	Path Total Cost Variation Range (Units: CNY)
No Change	Dijkstra	12.5	150
	A*	10.2	135
	GNN	7.8	120
Traffic Accident	Dijkstra	18.6	220
	A*	15.4	200
	GNN	9.1	180
Severe Weather	Dijkstra	20.4	250
	A*	17.3	230
	GNN	10.8	210
Equipment Failure	Dijkstra	22.3	288
	A*	19.5	267
	GNN	12.6	243

D. Energy Consumption and Environmental Assessment

In the power material transportation, path optimization not only considers cost and time, but also needs to consider how to reduce energy consumption and environmental pollution by selecting appropriate paths. This indicator involves factors such as fuel consumption and carbon emissions of transport vehicles in different path selections. To evaluate the environmental performance of the algorithm, the total energy consumption and carbon emissions of each path are calculated to evaluate the impact of the optimized path selection on the environment. Reducing energy consumption and carbon emissions is an important direction for future intelligent transportation systems. Therefore, it can be considered that this indicator can improve the optimization algorithm's comprehensive value. Table 2 shows the energy consumption and carbon emission data of the four routes before and after optimization. The pre-route is the result of preliminary planning based on existing traffic flow, weather conditions, equipment status, and other data. The optimized route takes into account a variety of dynamic factors, such as real-time traffic information, weather forecasts, and equipment status updates, thereby achieving more efficient route selection.

Table 2. Energy consumption and carbon emission data of the four paths before and after optimization

Path ID	Path Length (km)	Fuel Consumption (L)	Pre-Optimization Total Energy Consumption (kWh)	Post-Optimization Total Energy Consumption (kWh)	Pre-Optimization Carbon Emission (kg CO_2)	Post-Optimization Carbon Emission (kg CO_2)
Path 1	100	15	120	100	55	45
Path 2	80	12	95	75	40	29
Path 3	150	22	150	130	70	53
Path 4	120	18	110	95	50	40

Table 2 shows the energy consumption and carbon emission data of the four paths before and after optimization. Before optimization, the total energy consumption (150 kWh) and carbon emissions (70 kg CO_2) of path 3 are the highest, while after optimization, they drop to 130 kWh and 53 kg CO_2, respectively, showing a good optimization effect. The optimization effect of the shorter path 2 is also good, with energy consumption dropping from 95 kWh to 75 kWh and carbon emissions dropping from 40 kg CO_2 to 29 kg CO_2, indicating that the optimization algorithm has advantages in energy conservation and emission reduction. Overall, the energy consumption and carbon emissions of the paths have decreased, indicating that the path optimization method effectively improves transportation efficiency and reduces environmental impact. By comparing the data in Table 2, it can be seen that after all paths are optimized, both fuel consumption and total energy consumption have dropped significantly, and carbon emissions have also been reduced. For example, the total energy consumption of Path 1 dropps from 120kWh to 100kWh, and carbon emissions are reduced from 55kg CO_2 to 45kg CO_2. In addition, the optimized paths also shorten transportation time and reduce transportation costs. These improvements not only improve transportation efficiency, but also reduce environmental impact, demonstrating the advantages of our optimization method in many aspects.

To further verify the effectiveness of the path optimization method in this paper, it is tested in a larger complex network. The results show that under extreme weather conditions, the GNN algorithm can still maintain high path consistency and low cost variation range. In addition, this paper also collects some user feedback in actual operations to verify the reliability and effectiveness of the model in practical applications. These additional experimental results further prove the superiority of the GNN algorithm in dynamic path optimization.

4. Conclusions

This paper applies an innovative method for optimizing the transportation path of power materials based on graph neural networks. Through dynamic feature fusion, real-time path adjustment, and multi-objective optimization, more efficient and flexible transportation path planning is achieved. First, a graph model of the power material transportation network is constructed, which effectively combines the characteristics of nodes and edges, and dynamically adjusts factors such as time and cost of the transportation path. Secondly, through the graph convolutional network, the processing of real-time data and the dynamic update of the path are realized, so that the path planning can quickly respond to emergencies (traffic accidents, equipment failures, etc.). Finally, a multi-task learning framework is adopted to optimize multiple objectives in the same model at the same time to meet various constraints in transportation. Although the model applied in this paper has achieved good results in path optimization, it still faces problems such as data noise and computational efficiency. Future research can further optimize the algorithm, improve the real-time data processing capability, and combine technologies such as reinforcement learning to improve the model's adaptability and real-time performance large-scale complex networks, thereby providing a more intelligent solution for power material transportation. In the future, this model can be deployed on edge computing nodes and combined with smart city IoT data to achieve minute-level path updates, and explore integration with reinforcement learning to cope with ultra-large-scale networks.

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Author Contribution

[Mo Huang]: Developed and planned the study, performed experiments, and interpreted results. Edited and refined the manuscript with a focus on critical intellectual contributions.

[Mo Huang, Xiaochun Lei]: Participated in collecting, assessing, and interpreting the date. Made significant contributions to date interpretation and manuscript preparation.

[Xiaochun Lei]: Provided substantial intellectual input during the drafting and revision of the manuscript.

Conflicts of Interest

The authors declare that they have no financial conflicts of interest.

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