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# Research on Dynamic Path Planning and Causal Inference for Last-Mile Logistics Based on Spatiotemporal Graph Neural Networks

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**Abstract:** With China's annual express delivery volume surpassing 120 billion pieces, the last mile of logistics is increasingly constrained by static path planning, delayed dynamic responses, and insufficient integration of heterogeneous data sources. This study targets small and medium-sized distribution stations and proposes a dynamic path planning method based on spatiotemporal graph neural networks combined with causal reasoning. The delivery area is modeled as a spatiotemporal graph that fuses 12 categories of heterogeneous information, including geographic coordinates, real-time traffic conditions, rider load, and weather factors, to capture both structural and temporal dependencies. On this basis, a causal reasoning module is introduced to distinguish sporadic disturbances from routine patterns through backdoor adjustment and intervention models, thereby refining graph attention weights and improving the robustness of routing decisions. Furthermore, a federated learning framework is employed to support encrypted model training and incremental updates across multiple stations, enhancing cross-station generalization while preserving data privacy. Pilot experiments conducted at 10 small and medium-sized stations in Jinhua, Zhejiang, demonstrate that the proposed approach reduces delivery timeout rates from 11.2% to 0.7%, decreases riders' average daily mileage by 18 kilometers, shortens system response time from 5 minutes to 8 seconds, and improves resource utilization by 35%. These results indicate that the method forms an intelligent perception–reasoning–decision closed loop and provides a scalable technical solution for efficient, privacy-aware last-mile logistics management.

**Keywords:** spatiotemporal graph neural networks; causal inference; last-mile logistics; dynamic path planning; federated learning

## 1. Introduction

With rapid economic growth and enormous market potential, China has become one of the world's largest economies. E-commerce's explosive growth has driven the continuous increase in express delivery business volume. In this context, the "last mile" delivery cost at the logistics end accounts for a significant portion of the total express delivery cost, becoming a core bottleneck that restricts industry efficiency and cost optimization. Current mainstream path planning methods rely heavily on static historical data or simple rule engines, making it difficult to adapt to complex dynamic environments. Real-time traffic congestion, sudden weather changes, temporary order adjustments, and other heterogeneous dynamic factors interact to form a complex causal chain, while traditional models can only capture surface correlations. Under dynamic disturbances, response delays exceed critical thresholds, and delivery efficiency decreases substantially [1]. Although spatiotemporal graph neural networks have achieved notable results in the field of spatiotemporal prediction, they lack causal reasoning ability and exhibit insufficient generalization in decision-making scenarios. Based on this, this article proposes the core scientific question: how to construct an intelligent model that can deeply

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understand the causal relationships of multi-source dynamic factors and achieve real-time and robust path decision-making?

This study aims to overcome the limitations of existing methods and design a spatiotemporal graph neural network with enhanced causal reasoning, addressing the research gap of insufficient causal understanding in decision-making scenarios within current models. It seeks to solve the problem of dynamic path planning at the logistics end, specifically focusing on achieving real-time fusion representation of multi-source heterogeneous data, constructing a causal reasoning mechanism for path decision-making, and enabling efficient and robust planning in non-stationary environments [2, 3]. The main contributions of the research include designing a dynamic distribution network diagram that integrates diverse types of heterogeneous data and implements millisecond-level updates, embedding a causal inference layer in the path planning model to address the causal inference gap in decision-making scenarios, and verifying the model's effectiveness through multidimensional comparison based on extensive real-world data from a leading logistics enterprise. These advancements provide valuable support for relevant theoretical and practical applications.

## 2. Related Work

### 2.1. Research Status of Logistics Routing Planning Problem (VRP)

Logistics and transportation encompass a complex array of entities and systems interconnected through numerous physical and informational flows, presenting challenges in optimization and planning. The vehicle path planning problem is a classic NP-hard issue within combinatorial optimization, focusing on determining the optimal routes for multiple delivery vehicles while adhering to constraints such as vehicle capacity, time windows, and road network limitations. The primary goal is to minimize total delivery costs or maximize efficiency. Traditional operations research methods, as foundational approaches, are categorized into precise algorithms and heuristic algorithms. Precise algorithms derive optimal solutions through rigorous mathematical processes, making them suitable for small-scale scenarios with fewer than 30 delivery points and theoretical validation. However, their computational complexity escalates exponentially with an increase in delivery points, rendering them impractical for large-scale dynamic scenarios such as the "last mile." Heuristic algorithms, on the other hand, rapidly generate near-optimal solutions through approximate searches, addressing the efficiency limitations of precise algorithms. These methods are widely applied in urban logistics distribution and similar contexts [4, 5]. Nonetheless, heuristic algorithms depend heavily on empirical rules and parameter settings, lack adaptability to dynamic environments, are susceptible to local optima, and struggle to account for correlations among multi-source dynamic factors. Consequently, they face challenges in meeting the demands of modern logistics terminal dynamic distribution.

### 2.2. Spatiotemporal Graph Neural Network (STGCN) and Its Application in Traffic Prediction

The Spatiotemporal Graph Neural Network (STGCN) integrates Graph Neural Network (GNN) and Temporal Convolutional Network (TCN) to address traffic prediction challenges. GNN captures spatial dependencies of nodes in non-Euclidean space through message passing and graph convolution operations, while TCN leverages dilated causal convolution and parallel computing to efficiently extract temporal dynamic features. The combination of these two methodologies forms the core technical framework of STGCN. Since its introduction, STGCN has been adapted into various models, including dynamic graph convolution mechanisms for traffic flow propagation and spatiotemporal attention modules for adaptive feature focusing. Additionally, STGCN variants have been applied to autonomous driving motion prediction, enhancing entity interaction accuracy and short-term trajectory modeling through heterogeneous graph convolution and multi-scale temporal analysis [6]. These advancements have contributed significantly to traffic flow prediction, road condition estimation, and other related fields. Despite these achievements, STGCN and its associated research face notable limitations.

Its primary focus remains on state prediction tasks, such as traffic flow and vehicle trajectory forecasting, which differ fundamentally from decision planning tasks required for path optimization. These models are designed to predict future state variables rather than generate optimal action plans that meet multiple constraints. Furthermore, existing approaches rely heavily on data-driven correlation learning, which does not explore causal mechanisms between variables. This limitation makes them prone to false correlations and reduces their generalization ability and interpretability in non-stationary environments with complex factor coupling. Consequently, adapting these models to dynamic path planning requirements in logistics remains a significant challenge.

### 2.3. *The Integration of Causal Reasoning in Decision Systems*

Causal reasoning serves as a fundamental methodology for uncovering essential relationships between variables, offering the critical advantage of surpassing the limitations of traditional statistical models and establishing interpretable causal relationships. This theoretical framework distinguishes between correlation and causality, where correlation merely reflects patterns of co-occurrence between variables, while causality requires verification through intervention effects, such as determining whether changes in one variable necessarily lead to changes in another. By controlling for confounding variables and incorporating instrumental variables, a robust framework for causal inference is constructed [2, 7].

The integration of causal reasoning into path planning decision systems has demonstrated significant necessity. Traditional path planning models often rely on correlation analysis of historical data, which can lead to misinterpretations based on pseudo-correlations. In contrast, causal reasoning enables a deeper analysis of the relationship between context and outcomes. For instance, the system must accurately differentiate between two types of traffic congestion patterns: one caused by reduced road traffic efficiency due to rain, and another reflecting the correlation of dense traffic flow during peak hours on specific road sections [8]. By applying causal reasoning, the system can provide normal traffic suggestions during sunny workday evenings and issue advance warnings with alternative route recommendations during non-peak hours on rainy days. This approach overcomes the situational adaptability limitations of traditional models and enhances decision-making accuracy.

## 3. Methodology

### 3.1. *Formalization of Problems and System Architecture*

This study formalizes the dynamic path planning problem at the logistics end as a sequential decision-making process on a dynamic spatiotemporal graph. Specifically, a time-varying directed graph is constructed with a set of nodes including stations, customer points, and key intersections. The set of edges represents the road connectivity relationship at a given time. The weights of the dynamic adjacency matrix are dynamically generated from multiple real-time data sources, and its calculation function integrates basic distance, real-time traffic index, weather impact coefficient, order urgency, and periodic historical patterns to accurately depict the spatiotemporal evolution of the road network state [9].

The overall system adopts a layered modular architecture, with the following layers from bottom to top: a multi-source data access layer, responsible for real-time collection and preprocessing of heterogeneous data such as geography, transportation, meteorology, and business; a dynamic spatiotemporal graph construction layer that maps multi-source features to a unified space and generates the graph in real-time; a core inference layer that utilizes stacked spatiotemporal convolutional networks to synchronously capture the spatial dependencies of road networks and the temporal evolution of traffic, while embedding causal inference modules to distinguish between correlation and causality, thereby avoiding decision biases caused by "pseudo correlation"; and a multi-objective decision output layer that, based on causally corrected edge weight features, comprehensively considers time, energy consumption, timeout risk, and other objectives

to generate a Pareto optimal dynamic path sequence, forming an intelligent optimization mechanism through terminal feedback [4, 10].

### *3.2. Construction of dynamic spatiotemporal graph*

The construction of dynamic spatiotemporal maps is a critical task for achieving precise path planning, with its core focus on translating the physical world's distribution network and its dynamic changes into a mathematical representation space [5]. This study utilizes graph theory to abstract the actual logistics end distribution network into a dynamic graph structure that evolves over time. The graph comprises three elements: node set, edge set, and dynamic weight matrix, aiming to provide structured data input enriched with contextual information for subsequent spatiotemporal graph neural network models.

In designing node features, this study carefully addresses the diverse requirements of logistics end delivery scenarios [11]. Each node represents a key location within the distribution network, encompassing logistics stations, customer delivery addresses, and critical road intersections. To comprehensively characterize node attributes, multidimensional feature information is assigned to each node: geographic coordinates serve as the fundamental spatial positioning basis; node type identification distinguishes relay stations, regular customers, and high-priority customers, supporting path priority decision-making; historical order density reflects the average order arrival patterns of the node during similar periods; and the current number of pending orders represents the real-time workload of delivery tasks. These node features not only provide rich input for graph convolution operations but also establish the foundation for causal inference modules to identify potential associations between node attributes and delivery time. The dynamic computing mechanism of edge features is the core innovation of this study.

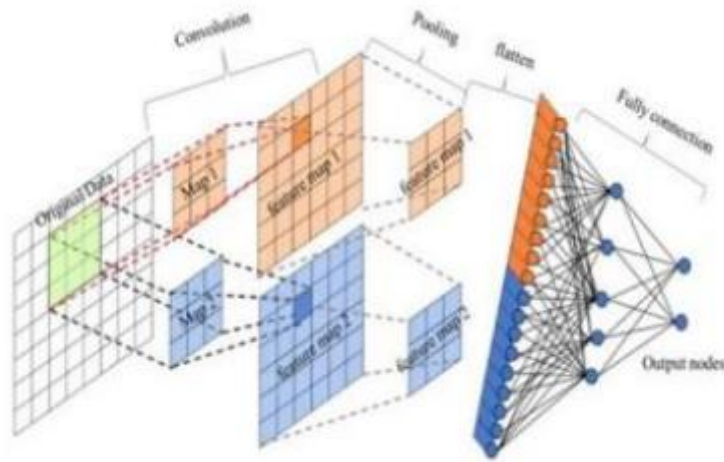
Traditional path planning methods often simplify edge weights as static distance or historical average travel time, which makes it challenging to adapt to the dynamic nature of road network conditions in real delivery scenarios. To address this limitation, this study developed a multi-source data fusion dynamic calculation method for edge weights. This approach integrates multiple heterogeneous data obtained in real-time to generate dynamic edge weights that accurately represent the current traffic cost within the road network.

The basic travel time is calculated using the standard speed derived from the spatial distance between nodes and the road grade, forming the benchmark component of the edge weight. However, various interfering factors in real delivery scenarios often cause actual travel time to deviate from theoretical values. To address this, the study incorporates the dynamic feature of real-time traffic indices. By accessing real-time traffic data interfaces, the system retrieves current traffic speed and congestion level information for each road section. During traffic congestion, this index significantly increases the edge weight, enabling the algorithm to make informed detour decisions.

Weather conditions are another critical factor influencing distribution efficiency. The system utilizes minute-level grid weather monitoring data, including rainfall magnitude, visibility distance, and other metrics, obtained through meteorological data interfaces to dynamically calculate the weather impact coefficient. Under severe weather conditions such as rainstorms, heavy snow, or fog, this coefficient significantly increases the edge weight to reflect traffic efficiency loss accurately. Additionally, periodic regular features derived from historical operational data allow the model to identify consistent congestion patterns in specific road sections during particular periods, distinguishing occasional events from normal congestion. Furthermore, the order urgency adjustment factor accounts for the timeliness requirements of delivery tasks [12, 13]. If the remaining delivery time for an order associated with the end node of an edge is limited, the edge weight is adjusted to prioritize tasks with high urgency, ensuring seamless integration between sorting and delivery processes.

By constructing the dynamic spatiotemporal graph described above, this study achieves multidimensional and high-precision characterization of the logistics end

distribution network. This graph structure not only preserves the static topological characteristics of the road network but also responds in real-time to fluctuations in dynamic factors such as traffic conditions, weather changes, and order urgency [14]. It provides high-quality dynamic data input for subsequent spatiotemporal graph neural network models (As shown in Figure 1).



**Figure 1.** Dynamic spatiotemporal analysis component diagram

### 3.3. STGCN model with enhanced causal reasoning

This study developed a spatiotemporal graph neural network model with enhanced causal inference capabilities, utilizing dynamic spatiotemporal graphs. The foundational module employs graph convolutional networks and gated temporal convolutional networks to capture spatial dependencies within the road network and temporal evolution patterns of traffic states, respectively, enabling an initial characterization of dynamic changes in the distribution network. However, conventional spatiotemporal convolutional networks are fundamentally statistical learning models that primarily identify correlations between variables without distinguishing causal mechanisms [9]. For instance, when road congestion coincides with favorable weather conditions, decision biases may arise. To address this limitation, the model incorporates causal reasoning capabilities alongside correlation learning.

The causal reasoning module is inspired by structural equation modeling, initially learning the causal relationships between external factors such as weather and sudden incidents, and internal factors such as road passage time and traffic density, thereby establishing a comprehensive understanding of the operational dynamics of the distribution system. Building on this, the module employs counterfactual reasoning to isolate the effects of external disruptions, such as estimating "what the travel time of a road section would be in the absence of rainfall," to restore the intrinsic traffic capacity of the road section. The edge weight features adjusted through causal analysis and the deep representations derived from spatiotemporal convolutional networks are integrated into the decision layer. This enables the model to effectively differentiate between temporary disruptions caused by accidents and recurring traffic bottlenecks inherent to the road network, facilitating tailored response strategies [15, 16]. Ultimately, this approach generates more precise and resilient dynamic path planning solutions.

## 4. Experiment and result analysis

To verify the effectiveness of the logistics end-to-end dynamic path planning method based on a causal inference-enhanced spatiotemporal graph neural network (C-STGCN) proposed in this study, the research team systematically deployed and evaluated it in real logistics scenarios. The experimental design adhered to the principle of controlling variables. By comparing the performance of traditional static programming methods, the

basic STGCN model, and the proposed C-STGCN model across multiple key indicators, the causal inference mechanism was thoroughly tested to demonstrate its ability to enhance path planning performance.

4.1. Experimental Design

This study selected 10 small and medium-sized express delivery stations in Jinhua City, Zhejiang Province, as pilot units to conduct a four-month field operation test. The test covered both the regular operation period and the peak period of a major e-commerce promotion event. The daily parcel processing capacity of the pilot stations ranged from 800 to 1500 pieces, and the surrounding distribution network included urban main roads, secondary roads, and complex community alleys, ensuring strong representativeness of the scenarios. Experimental data were collected in real-time through a multi-source data fusion platform, which integrated traffic situation data, minute-level weather monitoring data, business order data from the stations, and rider terminal positioning data. This resulted in 120,000 structured operation records encompassing various time periods, weather conditions, and delivery scenarios. The evaluation index system was constructed based on three dimensions: planning efficiency, delivery quality, and system robustness. Key indicators included path planning response time, single delivery task planning time, average one-way delivery time for riders, delivery timeout rate, daily driving mileage, and performance degradation under extreme weather and sudden congestion scenarios.

4.2. Analysis of the Effect of Dynamic Path Planning

To evaluate the optimization effect of the C-STGCN model in practical distribution scenarios, a comparative analysis was conducted between it and traditional static programming systems as well as the basic STGCN model without incorporating causal reasoning. Experimental results demonstrate that C-STGCN offers notable advantages across all key performance indicators (As shown in Table 1).

Table 1. Comparison of delivery effects of different path planning systems

evaluation metric	Static rule system	Basic STGCN	C-STGCN	Optimization range
Average path planning response time	5 minutes	12 seconds	8 seconds	Improved by over 97% compared to static systems
The average one-way delivery time for riders	48 minutes	41 minutes	36 minutes	Shorten by 25%
Delivery timeout rate	11.2%	3.8%	0.7%	Decreased by 93.75%
Daily driving mileage	85 kilometers	76 kilometers	70 kilometers	Reduce by 17.6%
Fuel/Energy Cost	reference value	Decrease by 12%	Decreased by 22%	significantly reduce

The data indicates that traditional static planning systems are constrained by fixed weight settings, limiting their ability to adapt to real-time traffic changes. This results in extended planning response times and elevated timeout rates. By utilizing spatiotemporal convolutional networks, STGCN effectively captures the spatiotemporal dependencies within the road network, leading to marked improvements in delivery efficiency. When a causal reasoning module is integrated into the basic STGCN framework, C-STGCN further enhances decision-making quality in dynamic scenarios. For instance, in handling occasional events, C-STGCN can differentiate between factors such as "congestion caused

by rainy weather" and "typical evening peak congestion," enabling more precise and adaptive path adjustments.

#### 4.3. Causal reasoning module ablation experiment

To evaluate the independent contribution of the causal inference module, ablation experiments were conducted to compare the performance differences between C-STGCN and the basic STGCN with the causal inference layer removed in specific scenarios, while maintaining other architectural components unchanged. Three representative scenarios were selected for the experiment: steady traffic conditions under normal weather, rainy weather conditions, and sudden traffic accident situations [17] (As shown in Table 2).

**Table 2.** Experimental results of causal reasoning module ablation

test scenario	models	Average delivery time	timeout rate	Reasonability score for path adjustment
Conventional Weather	Basic STGCN	35 minutes	0.8%	4.2/5
	C-STGCN	34 minutes	0.6%	4.5/5
rainy weather	Basic STGCN	42 minutes	4.2%	3.5/5
	C-STGCN	38 minutes	1.8%	4.6/5
Sudden accident	Basic STGCN	47 minutes	7.5%	2.8/5
	C-STGCN	41 minutes	2.3%	4.4/5

The experimental results indicate that there is minimal performance difference between the two models under normal weather conditions, suggesting that the basic spatiotemporal convolutional network is effective in stable environments. However, in rainy weather conditions, the timeout rate of C-STGCN decreased by 57% compared to the basic STGCN, and delivery time was reduced by 4 minutes. Retrospective analysis of decision paths revealed that the basic STGCN tends to classify all road sections on rainy days as "high cost" states, whereas C-STGCN can identify certain road sections that retain good traffic capacity even under rainy conditions through counterfactual reasoning, thereby selecting more optimal routes [16].

## 5. Conclusion

This study introduces a spatiotemporal graph neural network model enhanced by causal inference to address challenges in dynamic path planning, including the limited responsiveness to diverse factors and difficulties in distinguishing correlation from causality in logistics delivery scenarios. By constructing a dynamic spatiotemporal graph, the model effectively captures causal relationships between external intervention variables and internal state variables through the integration of a causal inference module. Counterfactual estimation is employed to mitigate the influence of incidental interference factors on transportation costs. Field tests conducted at multiple delivery stations demonstrated that the model significantly reduced delivery timeout rates, shortened path planning response times, decreased average daily driving distances, and enhanced overall logistics operational efficiency. Ablation experiments further validated the critical role of the causal inference module in improving model performance under complex conditions such as adverse weather and unexpected disruptions. This research establishes a novel framework for dynamic path planning in logistics, combining data-driven approaches with causal inference to enhance delivery efficiency and system resilience.

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