Knowledge-Enhanced Spatial-Temporal Routing Optimization in Last-Mile Delivery

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Abstract. Currently, last-mile delivery has become a crucial component of modern logistics because accurate planning ensures efficiency and customer satisfaction. Thus, the spatiotemporal graph neural network (ST-GNN) has been applied for traffic forecasting; however, existing methods fail to integrate external knowledge into the process of route optimization. Hence, this paper proposes a Knowledge-Enhanced ST Routing Optimization (KE-STRO) framework that improves predictions and influences route planning. Initially, the input data were collected from courier Global Positioning System (GPS) traces and delivery logs for travel times, OpenStreetMap for road network structures, and external sources to enrich knowledge-based route planning. Then, the data were preprocessed using a Kalman filter, z-score normalization, and spatial join mapping to remove outliers, scale the features, and link the external knowledge with the road network. Furthermore, a knowledge graph is constructed, and its embeddings are fused with ST-GNN outputs using an adaptive gating mechanism to predict time-dependent travel costs. Finally, these predictions were converted into dynamic arc costs and knowledge-aware constraints for the (VRPTW) which were solved using a hybrid optimization module. The proposed KE-STRO outperformed the existing Deep ST Attention Network (DeepSTA) framework in terms of mean absolute error (0.1458).

1 Introduction

In recent years, researchers have observed that rapid urbanization and the evolution of e-commerce services have increased the demand for logistics, delivery systems, and transportation factors, such as traffic congestion, weather conditions, and unexpected incidents, significantly affecting the efficiency and reliability of logistics and transportation networks [1]. Moreover. Traditional forecasting methods, such as ARIMA and moving averages, are widely used to predict delivery and traffic outcomes; however, they often fail to handle the nonlinear and dynamic nature of real-world systems [2]. Furthermore, early Machine Learning (ML) and Deep Learning (DL) models, such as Recurrent Neural Networks, Long Short-Term Memory and Convolutional Neural Networks (RNNs, LSTMs, and CNNs), improve time-series predictions but still struggle to capture the complex spatial dependencies that exist in non-Euclidean road networks [3]. Furthermore, sequential-based models for route prediction treat unfinished tasks as ordered sequences, which often cause errors such as unrealistic route decoding. However, many models treat normal and anomalous conditions equally, resulting in information loss during rare events such as epidemics, when delivery rates and traffic flows fluctuate abnormally [4]. Moreover, many traditional and early DL models struggled to capture the complex spatial dependencies that exist in non-Euclidean road networks. Roads, couriers, and districts interact with irregular structures. Furthermore, sequence-based prediction methods face difficulties because they often treat unfinished tasks as ordered sequences, leading to unrealistic route predictions and an inability to represent the evolving nature of delivery tasks [5]. In addition, a major challenge was the proper handling of anomaly events, such as epidemic outbreaks and natural disasters, where normal patterns were broken down, and prediction accuracy dropped sharply. Hence, most conventional approaches treat normal data and anomalous data equally, which causes important information about rare but critical abnormal situations to be lost during the modeling process [6].

To handle nonlinear and dynamic patterns in logistics and traffic systems, researchers have developed ST-GNN, which integrates graph-based spatial modeling with sequence-based temporal learning. Hence, the GNN was introduced to allow the representation of irregular road structures and courier interactions in an effective manner [7]. In addition, instead of relying only on sequence-based models, dynamic spatiotemporal graph frameworks are designed to capture both decision contexts and evolving task relationships, which leads to more realistic and accurate route predictions [8]. Furthermore, to manage anomaly

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events, such as epidemics and sudden disruptions, specialized modules have been proposed that separately model anomaly information by preventing the loss of critical external features during prediction. Hence, RNN and attention mechanisms are employed to encode external anomaly signals such as lockdown measures or epidemic case numbers, which improves their ability to capture abnormal delivery patterns [9]. The state-of-the-art method follows GNNs, which capture spatial correlations within non-Euclidean structures such as road networks, courier interactions, and delivery districts. Moreover, they are used to model the relationships among nodes and edges by allowing the system to learn how traffic flows, courier workloads, and regional connections influence each other over time [10]. However, GNNs have high computational costs and scalability issues, as the graph structure grows rapidly with more nodes that limit real-world applications. Memory networks are used to overcome the scarcity of anomaly-based data by storing and retrieving rare patterns from external memory [11]. Furthermore, the memory network enhanced the prediction performance during abnormal events, such as epidemic outbreaks, sudden traffic incidents, or courier absences, when the training data were limited or unavailable. Hence, Memory Networks lead to overfitting or noise accumulation if irrelevant patterns are stored, which also reduces the generalization ability in unseen scenarios [12].

The main contributions of this research are as follows:

- The proposed Knowledge-Enhanced Spatio-Temporal Routing Optimization (KE-STRO) framework is utilized to provide optimized delivery routes for ensuring efficiency in forecasting into actionable route planning.
- RDF triple-based ontology and TransE are employed for knowledge graph construction and allow for more accurate travel cost predictions that reflect real-world influences to improve the adaptability of routing decisions in dynamic delivery environments.
- A knowledge-aware vehicle routing formulation with an adaptive large neighborhood search is developed, where the dynamic costs shaped by contextual penalties guide the optimization for providing last-mile delivery solutions that minimize travel time.

The remainder of this paper is organized as follows: the existing works and their drawbacks are presented in Section 2; the overall explanation of the methodology is described in Section 3; the experimental results and discussion are presented in Section 4; and Section 5 concludes the paper.

2 Literature review

Existing studies on semantic knowledge-enhanced route planning in last-mile delivery using temporal-spatial reasoning are as follows. Wen et al. [13] introduced a dynamic ST-GNN for pick-up and delivery route prediction using a Food-PD real-world dataset to predict future food pickup and delivery routes of the driver. Subsequently, dta was preprocessed, where each task was represented as a node, and a spatiotemporal graph was constructed, such as location and service time. Feature extraction involves capturing spatial correlations using temporal correlations, graph convolution based on gated recurrent units (GRU), and worker-specific features such as load capacity, speed, and decision preference. Finally, the model was accurate and stable for predicting routes, improved delivery efficiency, and reduced misdispatched packages. However, the model has increased its complexity, high computational cost and depended on large-scale real-world data which led to limit its scalability to smaller systems. Zhou et al. [14] introduced an ST-GNN with adaptive fusion features using real-world traffic datasets to predict the flow of future traffic by removing the external factors. Subsequently, the data were preprocessed using z-score or min-max normalization to encode continuous values for humidity, wind speed, and temperature. Next, feature extraction was performed using 1D-dilation convolution to enhance the performance of the module, and sequence correlation features were extracted. Finally, GNN is suitable for different types of topologies because it can learn the structure and node feature information. Existing traffic methods capture spatial and temporal characteristics from traffic flow data to predict future traffic flows, but they ignore external factors based on traffic flow predictions.

Yi et al. [15] introduced a deep spatiotemporal attention (DeepSTA) network for timely logistics delivery rate prediction under anomalous conditions. First, real-world logistics datasets are used to calculate the correlation coefficients among couriers based on the spatial learning courier component. Subsequently, feature extraction was performed where the Graph Convolutional Neural Network (GCN) extracted features based on correlations among couriers. However, in abnormal situations, this information was difficult to collect previously because factors such as regional lockdowns made it difficult to apply those routes based on real-world arrival estimation approaches. Wu et al. [16] introduced travel route recommendations with a trajectory learning mode by collecting taxi Global Positioning System (GPS) trajectory datasets used for cleaning by removing trajectories shorter than 1 km and those with fewer than three nodes. Next, the data were preprocessed using a normalization technique, and feature extraction was performed using a position-aware GNN, which was employed to effectively learn node features. Finally, the essence of TLMR was achieved by integrating several sources of features significantly, which enhanced the model’s ability to understand users’ route-option behaviors in complex environments. However, the model faced challenges in that it did not consider the requirement for personalized recommendations, which means that the current model provides suggestions based on customized travel for various users. Baichuan Mo et al. [17] introduced route trajectories in last-mile delivery using a pair wise attention-based pointer neural network. First, the dataset was collected from the research on Amazon last-mile routing. Subsequently, feature extraction was performed using the LSTM encoder to extract the output sequence for reading one time step and the input sequences at a time to find the dimensional vector representation. Finally, the model identifies the first stop of a route that yields the lowest operational cost after training. However, the model faced challenges based on the black box, which risked to trust the routes obtained by the ML models.

3 Methodology

This research proposes a KE-STRO framework to improve the route planning by exploiting knowledge graphs and spatiotemporal predictions. This process begins with the collection of input data from courier GPS traces, delivery logs, OpenStreetMap and external sources to enhance the route planning. The collected data were preprocessed using a Kalman filter to remove outliers, z-score normalization to scale features, and spatial join mapping to link external knowledge with the road network. Subsequently, a knowledge graph is constructed, and its embeddings are fused with ST-GNN outputs using an adaptive mechanism to predict time-dependent travel costs. Furthermore, these predictions are converted into dynamic arc costs and knowledge-aware constraints for the VRPTW. Subsequently, a hybrid optimization module is employed to solve the VRPTW by generating optimized routes that incorporate both predictive modeling and knowledge-driven insights. An explanation of the proposed KE-STRO system is shown in Figure 1.

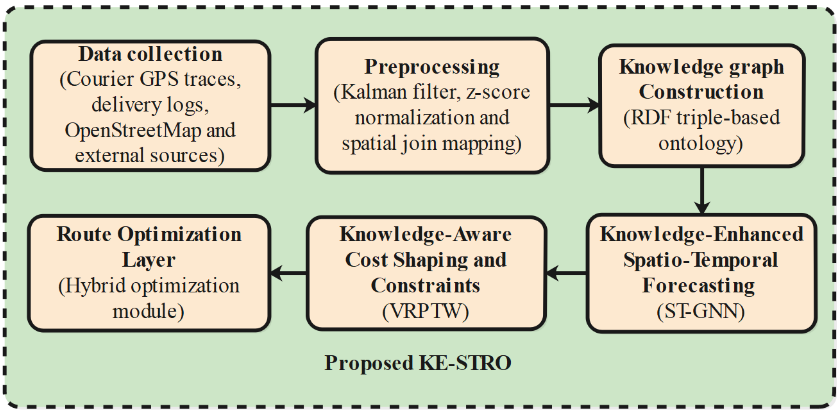

Fig. 1. Pictorial representation of proposed KE-STRO.

3.1 Data collection

The proposed KE-STRO framework for route planning optimization collected input data from multiple complementary sources to ensure that both the spatio-temporal dynamics of urban transport and the contextual knowledge required for realistic decision-making are captured [13]. Here, the courier GPS trajectories and delivery operation logs form the foundation as they provide fine-grained details about vehicle movement patterns, travel times across different periods of the day and the sequence of delivery stops. Then, the road geometry and topology are obtained from the OpenStreetMap platform to represent the structural connectivity of the transportation network which provides detailed descriptions of intersections, road categories and segment lengths which are converted into a graph structure. Also, the data is incorporated from various channels including municipal databases for curb-side restrictions, geospatial repositories for points of interest for weather conditions and special event calendars to embed external knowledge which influences delivery efficiency. These complementary datasets provide a unified basis where traffic dynamics, road connectivity and external knowledge coexist in a coherent representation. This data is crucial for prediction of time-dependent travel costs and allows the system to anticipate disruptions and plan feasible last-mile delivery routes within realistic operational environments. The collected data is further fed into preprocessing which is clearly explained in next section.

3.2 Preprocessing

The data which is collected from various sources is preprocessed to refine them into a consistent and usable form for modeling. Initially, the Kalman filter is employed for cleaning the courier trajectories and delivery logs where incomplete or noisy entries are filtered out to preserve only reliable movement information. Then, the cleaned traffic features are standardized through z-score normalization so that variations in travel speed, delivery intervals and road conditions are learned on a common scale without bias. Finally, the spatial joins are applied to connect the operational data with the transportation network so that every delivery record and contextual attribute is precisely mapped onto the corresponding nodes and edges of the road graph. The working of these techniques is clearly explained in below subsections.

3.2.1 Kalman filter

Here, the treatment of outliers within GPS trajectories and delivery logs is important where these logs distort both temporal forecasting and routing optimization. Hence, the Kalman filter technique is adopted as a probabilistic smoothing approach for estimating the true underlying state of a vehicle's movement while accounting for measurement noise. Then, the filer works through a prediction-update cycle where the predicted state at time t is expressed as Equation (1):

$$\hat{x}_{t|t-1} = A\hat{x}_{t|t-1} + Bu_t \tag{1}$$

Where, A represents state transition matrix, B defines control input matrix and u_t signifies control vector respectively. Then, the prediction is refined by using measurement z_t with an update step which is defined in Equation (2):

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t\left(z_t - H\hat{x}_{t|t-1}\right) \tag{2}$$

Where, H represents observation model and K_t defines Kalman gain respectively. This recursive adjustment ensures that the sudden deviations in GPS coordinates are identified as noise and then, corrected toward a more stable trajectory estimate. Here, the travel patterns become smoother and more consistent for providing a dependable representation of vehicle movements. The final output is a denoised dataset of courier trajectories and delivery logs that accurately reflect operational behavior.

3.2.2 Z-score normalization

Further, the z-score normalization is employed to ensure that the diverse numerical attributes of the dataset are placed on a comparable scale. Here, the z-score normalization transforms the raw values into standardized scores which reflects their relative deviation from the mean. Then, the normalized form for a given feature value x_i is expressed as Equation (3):

$$z_i = \frac{x_i - \mu}{\sigma} \tag{3}$$

Where, μ represents mean of feature and σ denotes its standard deviation respectively. Then, the measurements are adjusted to a distribution centered around zero with unit variance by applying this transformation. Also, this process makes temporal patterns more easily comparable through different delivery routes and time windows. The final output is a uniformly scaled dataset where all the operational and contextual attributes share a balanced representation to make them well-suited for integration with the knowledge graph.

3.2.3 Spatial join mapping

Further, the entity alignment ensures that contextual knowledge is accurately connected to the transportation network for later reasoning. Thus, the spatial join mapping is employed to associate external entities with their corresponding graph components. The method depends on geographic coordinates to identify overlaps and nearest relationships between delivery network elements as well as contextual datasets. For example, a point of interest like a hospital or school denoted by its latitude-longitude pair (x_p, y_p) is aligned with the closest road segment by minimizing the Euclidean distance which is given in Equation (4):

$$d(v,p) = \sqrt{\left(x_v - x_p\right)^2 + \left(y_v - y_p\right)^2} \tag{4}$$

Where, (x_v, y_v) represents the coordinates of the candidate graph node v respectively. Then, the spatial join determines whether a road edge lies within or intersects these boundaries where polygons such as restricted zones and commercial districts are considered. By systematically applying this mapping, the contextual knowledge such as regulations, event zones and weather influenced areas becomes directly linked to the structural representation of the road graph. The final output is a fully integrated dataset where operational records, graph nodes and external knowledge sources are consistently connected for effective construction of knowledge graph.

3.3 Knowledge graph construction

Here, the construction of knowledge graph allows the external knowledge to actively guide the routing optimization process. Thus, the RDF triple-based ontology modeling is combined with TransE for knowledge representation learning. The graph is constructed by representing facts in the form of triples (h, r, t) where h defines head entity, r signifies relation and t denotes the tail entity respectively. Then, the entities correspond to delivery-related components like road segments, intersections, points of interest, weather conditions and regulatory rules while relations capture their semantic and spatial connections. Once the triples are defined, the TransE is applied to learn embeddings by enforcing that for a valid fact, the embedding of the head plus the relation should be close to the tail in vector space. Then, the scoring function is expressed as Equation (5):

$$f(h,r,t) = \|e_h + r - e_t\|_2 \tag{5}$$

Where, $e_h, e_t \epsilon \mathbb{R}^d$ are entity embeddings and $r \epsilon \mathbb{R}^d$ represents relation embedding respectively. Then, the model is optimized by minimizing this distance for true triples while maximizing it for corrupted ones. The final output is a knowledge graph enriched with embeddings by providing a structured and learnable representation of contextual information to be fused with dynamic traffic predictions for adaptive route planning.

3.4 Knowledge-enhanced spatio-temporal forecasting

Further, the proposed KE-STRO framework involves in forecasting to capture both the dynamic behavior of urban traffic and the contextual influences represented within the knowledge graph. Hence, a ST-GNN with adaptive fusion gating is employed which models the spatial dependencies of the road network through graph convolution operations where the hidden representation at time t is updated as Equation (6):

$$H_t^{(l+1)} = \sigma\left(\tilde{A} H_t^{(l)} W_s\right) \tag{6}$$

Here, $\tilde{A}$ denotes the normalized adjacency matrix and W_s represents learnable weight matrix respectively. Then, the temporal dynamics are captured by using a recurrent structure like Gated Recurrent Unit (GRU) which processes sequences of traffic states and propagates them across time. Here, the embeddings which are obtained from the knowledge graph are injected into forecasting layer through an adaptive fusion gate to incorporate external knowledge. This gate determines the contribution of traffic states and knowledge embeddings by computing a weight vector which is given in Equation (7):

$$\alpha_t = \sigma(W_\alpha[z_t^{ST}||k] + b_\alpha) \tag{7}$$

Where, z_t^{ST} defines spatio-temporal feature and k signifies the knowledge embedding respectively. Then, the fused representation is used to predict the future travel costs and this integration ensures that the model learns from historical patterns and adapts to contextual constraints. The final output is a set of knowledge-enhanced and time-dependent travel predictions which provide realistic and adaptive cost estimates for route optimization.

3.5 Knowledge-aware cost shaping and constraints

Further, the obtained travel predictions are transformed into usable costs for the routing optimization module. Hence, a dynamic cost modeling with knowledge-aware penalty encoding technique is employed to refine the raw outputs of prediction stage into decision-ready values. Each edge in the delivery network is assigned a time-dependent cost based on predicted travel duration $\hat{c}_{ij}(t)$. Then, the constraints which are derived from the knowledge graph are introduced in the form of penalties or feasibility masks to embed the external knowledge. For example, if an edge passes through a restricted zone during a given interval, an additional penalty term is imposed. Then, the adjusted cost is expressed as Equation (8):

$$C_{ij}(t) = \hat{c}_{ij}(t) + \sum_{r \epsilon R} \phi_r(i,j,t) \tag{8}$$

Where, $\phi_r(i,j,t)$ represents the penalty associated with constraint r such as curb regulations, school zones or event-related disruptions. In cases of strict prohibitions, ϕ approach infinity by effectively masking the edge from the feasible solution space. This formulation helps to ensure that the resulting graph reflects historical travel efficiency and adheres to context-specific operational rules. Then, the system constructs a realistic and complaint routing environment by dynamically shaping the costs and embedding regulatory knowledge. The final output is a knowledge-aware cost matrix which encodes both predicted traffic conditions and contextual constraints by forming the basis for optimized and regulation-compliant last-mile delivery route generation.

3.6 Route optimization layer

Finally, the framework translates the knowledge-enhanced cost structures into concrete delivery routes by using knowledge-aware VRPTW solved through Adaptive Large Neighborhood Search (ALNS). Here, the delivery network is modeled as a graph where customers and delivery stops must be visited by a fleet of vehicles, each constrained by capacity and service windows. The objective is to minimize the total routing cost while respecting penalties and prohibitions derived from the knowledge graph. Formally, the optimization problem is defined as Equation (9):

$$\begin{gathered} \min_{\pi} \sum_{(i,j)\epsilon\pi} C_{ij}\left(t_{dep}(i)\right) \\ subject\ to \\ a_i \le t_{arr}(i) \le b_i \quad \forall i \epsilon V, \\ \sum_j x_{ij} = 1, \quad \sum_i x_{ij} = 1, \end{gathered} \tag{9}$$

Where, $C_{ij}(t)$ represents the knowledge-shaped travel cost, $[a_i, b_i]$ defines the service window for customer i and x_{ij} denotes whether edge (i,j) is included in the route plan. Then, the ALNS is employed to iteratively destroy and repair segments of the solution space which is guided by adaptive heuristics that learn which operators are most effective under different traffic and contextual conditions. This optimization process produces delivery schedules which helps to minimize travel time, avoid restricted zones and satisfy customer constraints respectively. The final output is the set of optimized and knowledge-aware last-mile delivery routes which helps to balance efficiency and adaptability in dynamic urban environments.

4 Experimental results

In this study, KE-STRO was presented to improve the predictions and influence the route planning of the Python package scikit-learn. Software and hardware requirements were used for the experimental analysis. The software requirements include the Windows 10 Pro operating system and hardware requirements such as Intel Core i3-8100 processor with 8.00 GB RAM and CPU 3.60GHz processing speed. To evaluate the proposed KE-STRO, Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) were used as evaluation metrics. which are expressed in Equations (10)–(12) as follows:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_i - \tilde{y}_i)^2 \tag{10}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_i - \tilde{y}_i| \tag{11}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_i - \tilde{y}_i)^2} \tag{12}$$

4.1 Performance analysis

The performance analysis of the proposed KE-STRO for improving predictions and influencing route planning was performed using various traditional models, such as the Graph Convolutional Recurrent Network (GCRN), Diffusion Convolutional Recurrent Neural Network (DCRNN), and graph wavelet net (GWN) with the help of error metrics. A graphical representation of the performance of the proposed KE-STRO system is shown in Figure 2.

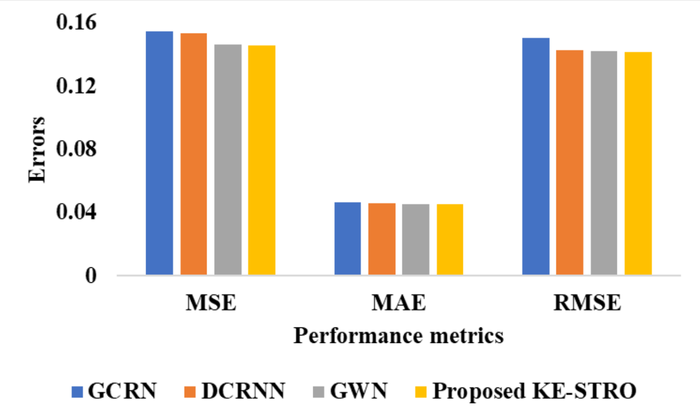

Fig. 2. Performance analysis of proposed KE-STRO.

Figure 2 shows the performance analysis of the proposed KE-STRO with various traditional models, including GCRN, DCRNN, and GWN. The proposed KE-STRO provided better results with respect to MSE, MAE, and RMSE of 0.1458, 0.0453,0.1415 respectively.

4.2 Comparative analysis

The proposed KE-STRO was estimated by comparing it with the existing DeepSTA [15] model. A comparison of the proposed DeepSTA [15] is performed with the help of the error metrics MSE and MAE, which are explained in Table 1.

Table 1. Comparative analysis of proposed KE-STRO.

Comparative analysis	MSE	MAE
DeepSTA [15]	0.1593	0.0479
Proposed KE-STRO	0.1458	0.0453

Table 1 presents a comparative evaluation of the proposed KE-STRO model with the existing DeepSTA [15] model, using evaluation metrics. DeepSTA [15] provided the best results with respect to MSE and MAE, and the results showed that the proposed KE-STRO outperformed existing models in terms of improving predictions and influencing route planning. The proposed KE-STRO achieved better results for MSE (0.1458) and MAE (0.0453) than the existing models.

4.3 Discussion

The main objective of this study was to optimize route planning and reduce delivery times by exploiting external knowledge and dynamic traffic patterns to generate more adaptive routing solutions. The results show that the proposed KE-STRO effectively overcame the existing DeepSTA [15], traditional GCRN, DCRNN, and GWN by bridging the gap between accurate prediction and actionable decision-making in last-mile delivery. The existing DeepSTA focuses primarily on anomaly aware delivery rate prediction; however, it does not extend its insights to generate optimized routes, which limits its impact on operational efficiency. Similarly, traditional GCRN, DCRNN, and GWN highlight traffic forecasting through different combinations of graph convolutions and recurrent structures, which leads to a reduction in their ability to adapt to real-world delivery constraints. Hence, the proposed KE-STRO overcomes these limitations by explicitly incorporating knowledge graph embeddings that encode contextual factors such as curb regulations, points of interest, weather disruptions, and event schedules. Moreover, these knowledge representations are combined with STGN outputs to yield more accurate and knowledge-aware travel time predictions through adaptive fusion. In addition, this study translates these enriched predictions into dynamic arc costs and integrates knowledge-driven constraints directly into a vehicle routing problem formulation to ensure that the generated routes are efficient. Furthermore, the framework reduces travel time, minimizes violations, and improves delivery reliability by unifying forecasting and optimization in a single module.

5 Conclusion

In this study, an efficient KE-STRO framework is presented to improve predictions and influence route planning. Most existing models have drawbacks in terms of traffic forecasting and route optimization. Hence, this study integrates external knowledge into the route optimization process to address the limitations of neglecting external knowledge in traditional ST-GNNs. Preprocessing techniques, such as the Kalman filter, z-score normalization, and spatial join mapping, overcome disconnected external knowledge by linking it with the road network. In addition, the construction of a knowledge graph and its fusion with ST-GNN outputs using an adaptive gating mechanism addresses the limitation of incomplete representation of dynamic arc costs. Knowledge-aware constraints for VRPTW overcome suboptimal routing decisions, and a hybrid optimization module solves VRPTW efficiently. The proposed KE-STRO established better results in terms of MSE and MAE of 0.1458 and 0.0453, respectively, compared to the existing models. In the future, this study will focus on integrating additional external knowledge sources and optimization techniques to improve the performance and generalizability of the framework.

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