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Article

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Optimized Design of Urban Road Transportation Based on Graph Convolutional Neural Network for Baltimore

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Abstract: Baltimore faces complex transportation problems that impact its growth and residents' lives. A series of measures were taken for complex transportation problems. First, a traffic network was defined as a graph. Node features were updated via time-series graph convolution operation, and multi-step time-series features were added to enhance time-series modeling. The connection of two nodes linked to a bridge was cut off, and flow was redistributed according to the law of conservation of flow. By comparing the traffic network before and after the bridge collapse, the impacts on traffic flow at various landmarks were explored, providing a basis for transportation restoration and planning. Second, a graph model was constructed with specific locations as nodes and distance and time cost as side weights. Dijkstra's algorithm was used to calculate the shortest path, and Poisson distribution was applied to simulate traffic demand, offering a multi-dimensional impact analysis for stakeholder decision-making and assessing the project's financial viability. Third, decision variables and objective functions were defined, and constraints were set. Multi-algorithm comparison and optimization were carried out, and the Graph Convolutional Neural Network (GCN) performed best in terms of accuracy, recall, precision, which improving the transportation system's efficiency and adaptability. Finally, the model's robustness was examined, and its advantages and disadvantages were evaluated.

Keywords: traffic flow model, Dijkstra's algorithm, linear programming model, ant colony algorithm (ACO), simulated annealing algorithm (SA), particle swarm optimization algorithm (PSO), graph convolutional neural network (GCN)

1. Introduction

In the process of modern urban development, the efficient operation of the transportation system is the key support for the prosperity of the city and the improvement of the quality of life of its residents. Baltimore, as an important city in the state of Maryland in the United States, its transportation system, however, faces a number of serious challenges. From the infrastructure level, aging facilities seriously affect the safety and smoothness of transportation; in terms of transportation choices, the limited options limit the convenience of travel for residents and hinder the economic development of the city . In particular, the collapse of the Francis Scott Key Bridge has exacerbated the traffic chaos in the city, making the already complex traffic problem even more difficult.

Wu C, Zhou S proposed a dynamic path planning method for congested business based on improved ant colony algorithm. The method quantifies the main attributes of urban road length, number of lanes, incoming and outgoing traffic flow, and introduces road factors for replacing the distance parameters of particle swarm optimization and ant colony algorithm. In this method, the particle swarm algorithm can effectively optimize the parameters of the ant colony algorithm, significantly improve the efficiency of the ant colony algorithm, make it more suitable for dynamic path planning applications, and greatly reduce the congestion rate of path planning. In addition, this paper selects some intersections in Beijing to conduct dynamic path planning experiments based on the improved ACO algorithm under congested road conditions. The experimental results show that the proposed dynamic path planning method can effectively reduce the average congestion rate in the range of 9.73%-13.63% compared with the ant colony algorithm based on the distance parameter[1].Li Z, Huang Jproposed an improved ant colony algorithm and combined it with virtual reality. In this paper, the traffic flow in Yangpu area is predicted based on the data obtained from the programming language Python. Comparing the simulation results with the actual results, the results show that the improved model has a better simulation effect and can utilize the allocation of traffic resources so that the traffic system can achieve a comprehensive optimization of time, cost and accident rate. Subsequently, this paper conducts a robustness test, and the results show that the virtual traffic simulation based on the improved ant colony algorithm can effectively simulate the real traffic flow, utilize the vehicle road and signal resources, and alleviate the overall traffic congestion. This paper provides suggestions for alleviating traffic congestion in old urban areas of metropolitan cities[2].

Pattanaik V, Singh M proposed an intelligent congestion avoidance technique by estimating the extent of real-time traffic congestion on an urban road network and predicting alternative shortest routes to reach the destination. The proposed system uses K-Means clustering algorithm to estimate the extent of congestion on different roads and then Dijkstra's algorithm is used to predict the shortest route. Once the user inputs the destination into the system, the system predicts the shortest route from the user's current location. The process is repeated at each intersection until the user reaches the destination[3].Ngo T G, Dao T K proposed a Dijkstra's algorithm based optimization for vehicle path analysis in urban traffic as a solution for road selection and optimization under various constraints for co-location in central metropolitan areas. Various constraints of road networks in leading metropolitan areas are considered for road condition factors and risk resistance in road planning. The analysis and implementation are validated by geocoding, network topology and network analysis. The results show that the integration of network analysis techniques with Dijkstra's algorithm

achieves optimal decision making for urban vehicle routes. Nevertheless, the improved Dijkstra's algorithm reduces the number of node visits and time complexity[4].

Amer H M, Al-Kashoash H proposed a novel dynamic centralized simulated annealing based approach for finding the optimal vehicle routes using VIKOR type cost function. The proposed method uses five attributes of traffic, namely average travel speed, vehicle density, road width, road traffic signals and road length to find the optimal route. The average traveling speed and vehicle density values can be obtained from sensors deployed in the smart city and communicated to the vehicles and roadside communication units through the vehicle self-organizing network. The performance of the proposed algorithm is compared with four other algorithms in two test scenarios: in Birmingham and in Turin city center. These results show that the proposed method improves transportation efficiency by 24.05%, 48.88% and 36.89% in terms of travel time, fuel consumption and CO2 emissions under congested conditions[5].Fan W, Machemehl R B used a simulated annealing algorithm to solve the optimal bus route network design problem (BTRNDP) at the level of distribution nodes. A multi-objective nonlinear mixed-integer model is developed for BTRNDP. The proposed solution framework consists of three main components: an initial candidate route set generation procedure that generates all feasible routes containing practical transit industry guidelines; and a network analysis procedure that assigns transit trips, determines service frequencies, and computes performance metrics; as well as a simulated annealing procedure that combines these two components, guides the candidate solution generation process, and selects a set of optimal Routes. Three experimental networks were successfully tested as pilot studies. The genetic algorithm was also used as a benchmark to measure the quality of the simulated annealing algorithm. The presented numerical results clearly show that simulated annealing outperforms the genetic algorithm in most cases where the example networks are used[6].

Currently, research for urban traffic problems has achieved some results.Zhang L ,Xu S et al proposed a traffic prediction model D-MGDCN-CLSTM based on Multi-graph Gated Dilated Convolution and Conv-LSTM.The model uses the DTWN algorithm to fill in the missing data and DWT for multi-scale decomposition in order to obtain the approximation coefficients and detail coefficients. Conv-LSTM processes the approximation coefficients to capture the long-term characteristics of the time series, while the multilayer of MGDCN processes the detail coefficients to capture the short-term fluctuations. The model was tested with 10 algorithms using the PeMSD7(M) and PeMSD7(L) datasets, and the MAE, RMSE, and ACC improved on average by 1.38% and 13.89%, 1% and 1.24%, and 5.92% and 1%, respectively. The ablation experiments, parameter impact analysis and visualization analysis demonstrate the superiority of the decomposition method in dealing with the dual features of traffic data[7]. H. Jianming, M. Qiang proposed a new method for traffic congestion identification based on vehicle trajectories in Intelligent Vehicle Infrastructure Collaboration System (IVICS). The spatio-temporal trajectory is used as an image, and autocorrelation is utilized to extract the propagation speed of congestion waves. Based on this, a congestion template is constructed in this study; through the matching algorithm, congestion and its intensity can be further recognized. Simulations on the Next Generation Simulation (NGSim) dataset verified the effectiveness of the above method[8].Wei L, Hong-Ying Dproposed a fast detection algorithm for traffic congestion on urban roads based on image processing technology. First, in order to speed up the processing speed and freely select the region of interest, a human-computer interaction vehicle region detection method is proposed. Then, using the difference in texture features between congested images and unobstructed images, a vehicle density estimation method based on texture analysis

is proposed. The energy and entropy features that can reflect the vehicle density are obtained from the vehicle area through image grayscale degradation, grayscale co-occurrence matrix calculation and feature extraction. After feature training, the decision threshold can be obtained and traffic congestion. The experimental results show that the accuracy of the algorithm is up to 99% and the processing speed can meet the real-time requirements in engineering[9] .

Our work is divided into three modules, from the data preprocessing, six-step construction of network model, experimental results and analysis in Problem 1, to the investigation and research on traffic flow model, flow analysis, cost-benefit analysis in Problem 2, from which we analyze the five key impacts it involves, and finally in Problem 3, we arrive at the solution through a three-step process of defining the decision variables, defining the objective function, and constraints, with the GCN graphical convolutional Neural Network as the optimal algorithm. The data in this article comes from the "MCM American College Student Mathematical Modeling Competition" in https://www.contest.comap.com/undergraduate/contests/mcm/previous-contests.php

2. Materials and Methods

2.1 Assumptions and Justifications

To simplify the model, the main assumptions are made in this paper.

1. travel mode choice assumption that different stakeholders in Baltimore City choose transportation modes by distance and purpose;

2. transportation infrastructure interactions assumption, where various parts of the city interact with each other, and improved transit service attracts private transportation users and reduces roadway congestion;

3. the stakeholder demand stability assumption, in which the basic transportation needs of the stakeholders are relatively stable in the short term and initial planning can be considered a fixed factor.

2.2 Notations

The corresponding meanings of the symbols are shown in Table 1.

Table 1 Symbol cross-reference

Notation	Clarification
$latitude_i$	Longitude of node i
$longitude_i$	Latitude of node i
p_i	Foot traffic on node i
BS_i	Binary characterization of whether node i is a bus stop or not
RJ_i	Binary characterization of whether node i is a roadway intersection

d_{ij}	Physical distance between nodes v_i and v_j
s_{ij}	Capacity of roads
c_{ij}	Traffic flow
$h_i^{(l)}(t)$	Hidden features of node v_i at layer l
Q	Flux
K	Intensity
V	Tempo
x_{ij}	Flow from start i to end j
T_{ij}	Travel time from origin i to destination j
C_{ij}	Travel costs from origin i to destination j
D_j	Requirements for each endpoint j
V_i	Number of vehicles that can be put into each starting point i
τ_{ij}	Pheromone concentration
p_{ij}	The probability that a citizen will next move from landmark i to landmark j
$v_i^{(t+1)}$	The velocity of particle i at the next iteration $t+1$
$gbest$	global optimum position (GOP)
$x_i^{(t)}$	Position of particle i in current iteration t
$H^{(l)}$	Node characterization matrix for layer l
$W^{(l)}$	Learnable weight matrix for layer l
$d_{in}^{(l)}$	Input feature dimensions
$d_{out}^{(l)}$	Output feature dimensions

2.3 Analysis and Modelling

2.3.1 Modeling the Impact of the Francis Scott Key Bridge Collapse on Baltimore's Transportation System

2.3.1.1 Data preprocessing

Data processing is a crucial step in the process of data analysis and model construction, ensuring that the quality of the data directly affects the subsequent analysis and model performance. Data is cleaned with the goal of standardizing the format, dealing with missing values, and cleaning up redundant information.Check for the presence of missing values or

outliers (e.g., negative values, non-numeric values, etc.). If present seek average values to fill in. Convert the data $AADT$ to traffic flow weights and normalize the annual traffic flow data.

$$AATD_{\max} = \max\left[AADT_{2014}, AADT_{2015}, AADT_{2016}, AADT_{2017}, AADT_{2018}\right] (1)$$

One of the AADT 2014-2018 data maps is shown in Figure 1 and the AAWDT2014-2018 3D color mapping surface data maps is shown in Figure 2.

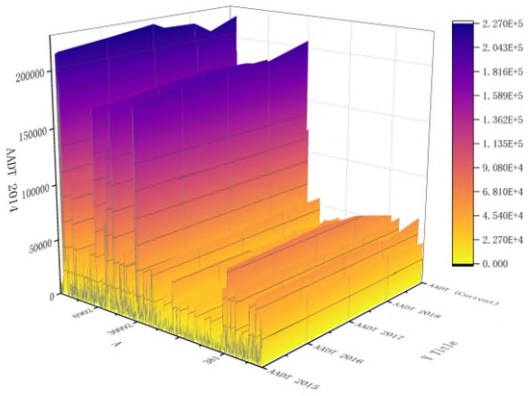


Figure 1 AADT2014-2018 3D Color Map

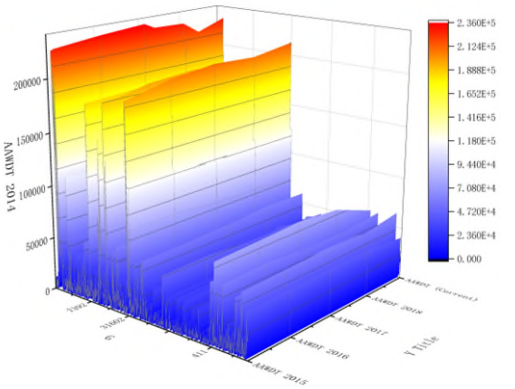


Figure 2 AAWDT2014-2018 3D Color Map

One of the 2014-2022 Nomalized_AADT data maps is shown in Figure 3.

$$Normalized_AADT_i = \frac{AADT_i}{AADT_{\max}} \quad (2)$$

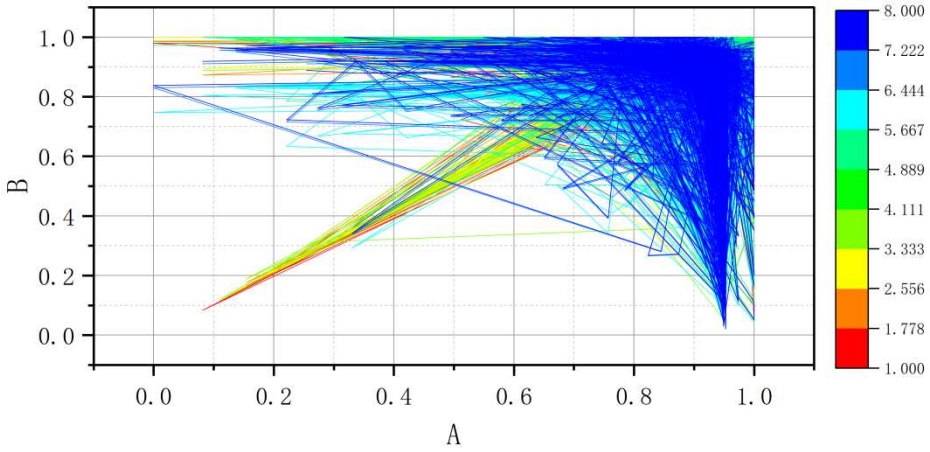


Figure 3 2014-2022nomalized Line Sequence Maps with Color Mapping

$$AADT_i \text{flow rate per unit length} = \frac{AADT_i}{GIS \text{ Shape length}} \quad (3)$$

One of the AADT 2014-2022 unit length flow data maps is shown in Figure 4.

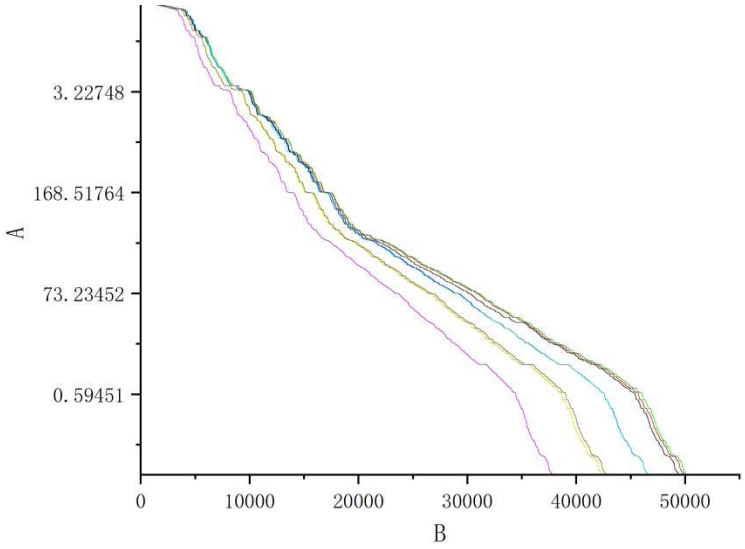


Figure 4 AADT 2014-2022 Flow Level Bridge Diagram per Unit Length

2.3.1.2 Modeling the network

In order to capture both the spatial and temporal dependencies of Baltimore City's transportation network, latitude and longitude, pedestrian flow attributes, bus stop locations, road intersections, and topological attributes of the city's roadway network are combined to

build a time-series graphical convolutional network capable of analyzing Baltimore's urban transportation[13].

1. Definition of the figure.

Let graph $G=(V,E)$ be used to represent the Baltimore city transportation network. Where the set of nodes is denoted by V, and each node v_i represents a key location in the city, such as bus stops, road intersections and other important locations; the set of edges is denoted by E, and the edge e_{ij} denotes the connectivity between nodes v_i and v_j, such as roads, routes and so on[14].

2. Definition of features of nodes and edges.

The feature vector x_i of each node v_i consists of $latitude_i$, $longitude_i$, p_i, BS_i, RJ_i, $AADT_i$, $AAWDT_i$ and can be expressed as.

$$X_i=\left[latitude_i, longitude_i, p_i, BS_i, RJ_i, AADT_i, AAWDT_i\right] \tag{1}$$

Where $latitude_i$, $longitude_i$ denote the latitude and longitude of the location of the node; p_i denotes the number of people on the node; BS_i denotes the binary feature of whether the node is a bus stop or not; RJ_i denotes the binary feature of whether the node is a roadway interchange or not; $AADT_i$ denotes the annual average daily traffic of the node v_i; $AAWDT_i$ denotes the annual average weekday traffic of the node v_i[15].

The feature vector e_{ij} of edge e_{ij} can be defined as.

$$e_{ij}=\left[d_{ij}, s_{ij}, c_{ij}\right] \tag{2}$$

Where d_{ij} denotes the physical distance between nodes v_i and v_j; s_{ij} denotes the capacity (road type) of the road; and c_{ij} denotes the traffic flow[16].

3. Time-series graph convolution operation.

In order to update the features of each node by graph convolution operation, $h_i^{(l)}(t)$ is set to be the hidden feature of node v_i at layer l and the time step is l. the feature update formula for each node at time step t is.

$$h_i^{(l)}(t)=\sigma\left(\sum_{j\in N(i)}\frac{1}{c_{ij}}W^{(l)}h_j^{(l-1)}(t-1)+b^{(l)}\right) \tag{3}$$

where $N(i)$ denotes the set of neighbors of node v_i Normalization factor.

$$c_{ij} = \sqrt{\left|N(i)\right| \cdot \left|N(j)\right|} \quad (4)$$

$W^{(l)}$ denotes the weight matrix of layer $W^{(l)}$; $b^{(l)}$ denotes the bias term; and σ is the activation function.

4. Multi-step time series features[17].

To enhance the model's ability to model changes in time series, multi-step time-series features can be introduced. Consider data from multiple time steps in history.

$$h_i^{(l)}(t) = \sigma\left(\sum_{k=1}^{K} W^{(l)} \cdot H_{t-k}^{i} + \sum_{j \in N(i)} \frac{1}{c_{ij}} \sum_{k=1}^{K} W^{(l)} H_{t-k}^{j}\right) \quad (5)$$

where H_{t-k}^{j} represents the characteristics of the node i at time $t-k$. The concept of time series is involved here, representing the characteristics of the last k time steps.

5. Global graph connectivity.

To further improve the expressiveness of the model, the features of neighboring nodes are aggregated. To integrate global information, aggregation of features of global graph nodes is introduced.

$$h_i^{(l)}(t) = \sigma\left(W^{(l)}\left[h_i^{(l-1)}(t); AGG\left(h_i^{(l-1)}(t), j \in N(i)\right)\right] + b^{(l)}\right) \quad (6)$$

where AGG is an aggregation function[18].

6. Output layer and loss function.

The output layer of the model at time step t can be set as.

$$y_t = H^{(L)}(t) W_{out} \quad (7)$$

where $H^{(L)}(t)$ denotes the node feature matrix computed at layer L (the last layer), the feature representation at time step t ; L is the number of layers of the network, and W_{out} is the weight matrix of the output layer. The loss function is chosen to be the mean square error (MSE).

$$L = \frac{1}{N} \sum_{t=1}^{N} \left(y_t - \hat{y}_t\right)^2 \quad (8)$$

7. Experimental results and analysis.The above operation combines the factors affecting the layout of the city's transportation network to obtain the transportation network of Baltimore city as shown in Figure 5.

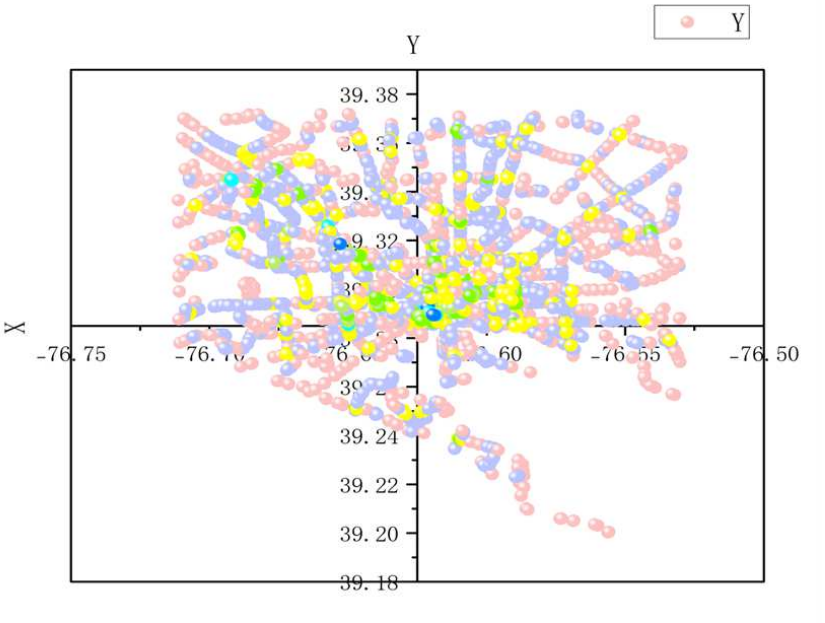
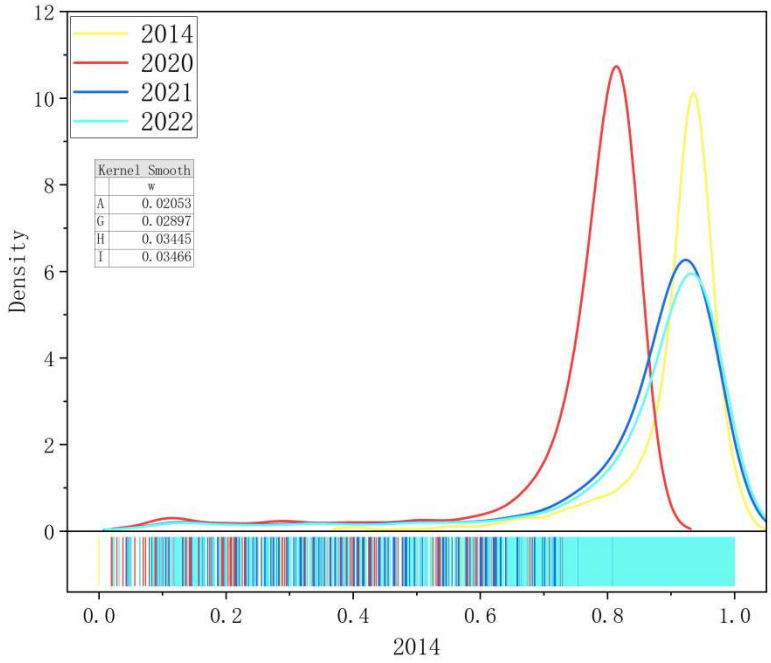


Figure 5 Transportation network in Baltimore city

Due to the collapse of the Francis Scott Key Bridge, Baltimore's transportation system has been greatly affected. Find the two transportation nodes connecting the Francis Scott Key Bridge, remove the connections between the nodes, and re-route the flow of people and traffic on Baltimore City's transportation network.



Which 2014 2019-2022nomalized data graphs are shown in Figure 6.

Figure 6 2014-2022nomalized distribution map + shaft whiskers

One of the AADT 2014-2016 3D mapped surface data plots for the unit length flow band projection is shown in Figure 7.

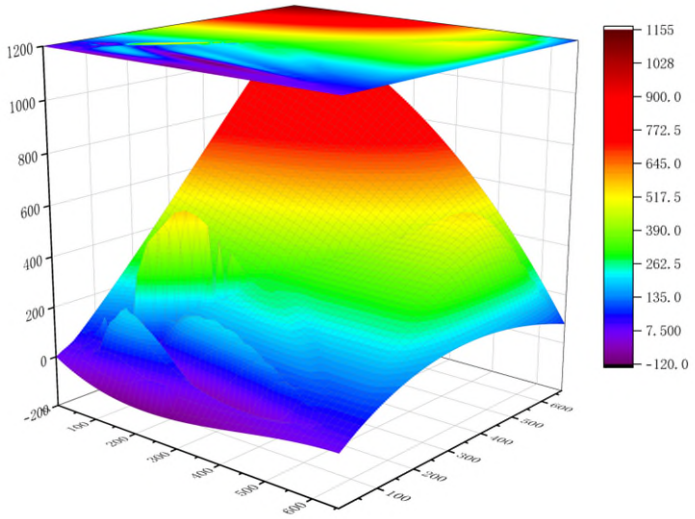


Figure 7 AADT 2014-2016 3D Mapped Surface Maps for Unit Length Flow with Projections

Assuming that an edge (u,v) is removed, identify the two traffic nodes u and v connected to the Francis Scott Key Bridge, denoting the collapse of the Francis Scott Key Bridge, and participate in the adjustment of the traffic through the law of conservation of flow.

Obtain the flows $SumFlows_u$ and $SumFlows_v$ from nodes u and v on both sides of the bridge, which are redistributed to be transferred to other neighboring nodes. The proportion of neighboring node traffic can be calculated for redistribution.

1. get the flow $SumFlows_u$ before and after the side (u,v) is removed.

$$SumFlows_u = \sum_{j \text{ is a neighbor of u}} p_j \tag{9}$$

2. reassign to neighboring nodes x and y .

$$p'_x = p_x + \frac{p_u}{SumFlows_u} \cdot flow_{uv} \tag{10}$$

$$p'_y = p_y + \frac{p_v}{SumFlows_v} \cdot flow_{uv} \tag{11}$$

3. the new Baltimore City transportation network structure is generated again by the graph convolutional neural network model.

The AADT 2020-2022 unit length flow XYAM vector data plots is shown in Figure 8.

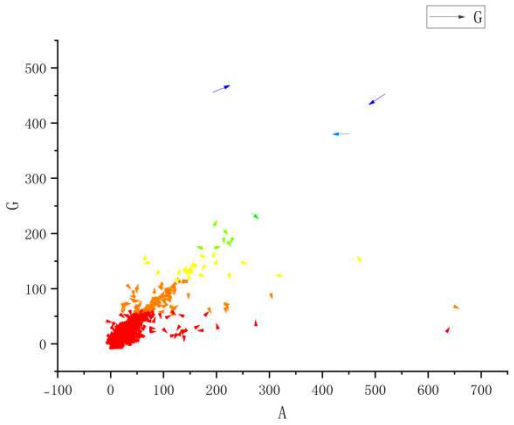


Figure 8 AADT 2020-2022 Flow per unit length XYAM Vectors

4. The gap between the forecast and the true value using the mean square error.

$$Loss = \frac{1}{N}\sum_{i=1}^{N}\left(p_i' - p_i\right)^2 \tag{12}$$

The flow data before and after the bridge collapse obtained by constructing the network model is shown in Table 2 below.

Table2 Plot of flow data before and after bridge collapse

Annual traffic flow	**Before(million vehicles)**	**After(million vehicles)**
Upper (highway)	10374.6	10878.9
Medium (Tunnel)	6732.1	6971.0
Down (Bridge)	1149.2	0

The changes in road flow between nodes in the city are shown in Figure 9 below.

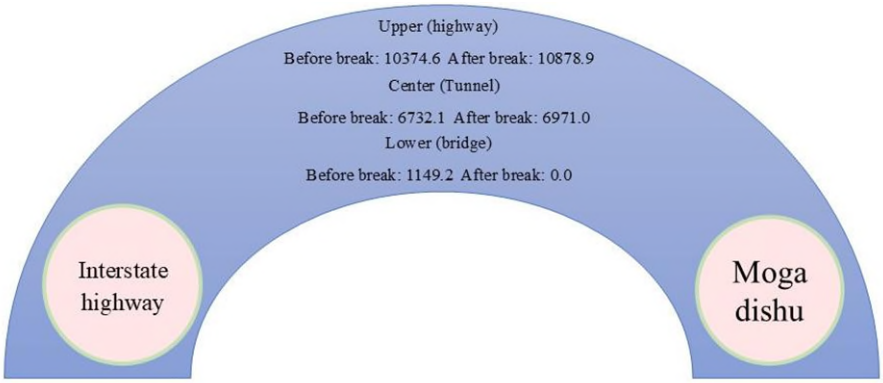


Figure 9 Map of road flow changes between nodes in the city

With regard to the impact of stakeholders, the analysis of the data yielded the following table 3.

Table 3 Stakeholder impact

Daily traffic flow / Spot	Before the Broken Bridge (2022)	After the Broken Bridge (now)
Airport 1 (684495620)	21871	23532
Airport 2 (37831627)	9572	11180
Nearest transportation link to the bridge Hub (602433660)	38453	36010
Nearest transportation link to the tunnel Hub (631298010)	13093	6310
The largest transportation hub in the lower right corner(373144337 37575437)	75343	76080
The largest transportation hub in the city center(49461313 49461547)	22581	24302
with the largest transportation hub in the NW cities Hub (443520870)	54301	57452
The largest transportation hub with the northern cities (664286830)	2702	2500

3.1.2 Modeling and Solving Transit System Projects in Baltimore City

3.1.2.1Model building

In modern urban transportation management and planning, traffic mobility and walkability are key factors in ensuring sustainable urban development[19]. Here, this group launches a discussion of projects on public transit systems, with in-depth studies on traffic flow models, flow analysis, and cost-benefit evaluation to help decision makers understand and optimize the structure and function of transportation networks[20].

1. Traffic flow model

First construct a graph model with residential neighborhoods, shopping centers, bus stops, and parks as nodes V , and distance d and time cost t as the weights of edges E . Calculate the shortest path using the $Dijkstra$ algorithm. initialize the distances of all nodes to infinity, and the distance of the starting node to 0. Use a priority queue to select the node with the smallest current distance[21]. For each neighboring node of the current node, calculate the distance to the neighboring node through the current node.

$$new_dis\tan ce = current_dis\tan ce + edge_weight \tag{13}$$

If the new distance is less than the known distance, it is updated.

$$dis\tan ce[neighbor] = \min\left(dis\tan ce[neighbor], new_dis\tan ce\right) \quad (14)$$

Repeat the above steps until the shortest path for all nodes is determined.

2. Flow analysis

The flow model is an important tool for describing traffic flow and consists of three key parameters[22]. flow Q , density K , and speed V . flow Q represents the amount of traffic passing through a node per unit of time, usually expressed in units of (people/hour); density 555 represents the amount of traffic per unit of length, expressed in units of (people/meters); and speed V refers to the speed of traffic flow, often expressed in units of (m/ hour) is expressed. There is a close relationship between these three parameters, which can be described by the basic formula, in which the relationship between flow, density and speed can be expressed as.

$$Q = K \times V \quad (15)$$

This formula shows that under certain flow conditions, when the density or speed changes, it will inevitably affect the overall performance of the traffic flow, which provides an important theoretical basis for the monitoring and optimization of traffic flow.

Which busdopXY latitude and longitude Y data color mapping of the waterfall data map is shown in Figure 10.

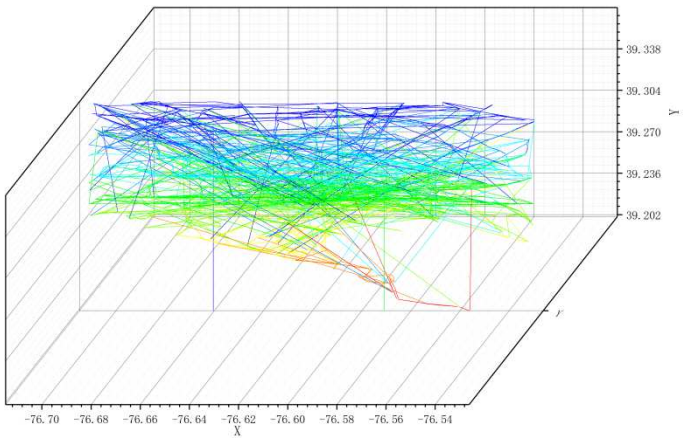


Figure 10 aterfall plot of busdopXY latitude/longitude Y data color mapping

Transportation demand is modeled by Poisson distribution, assuming that the demand for public transit obeys a Poisson distribution with parameter λ (average arrival rate) in a given time period, the probability of arrival in time t is[23].

$$P\left(X=k\right)=\frac{e^{-\lambda}\lambda^{k}}{k!} \tag{16}$$

where X is the number of passengers arriving within time t and k is the specific number of arrivals.

The Poisson distribution can be used to predict the flow in different time periods[24]. The Poisson distribution is suitable for describing the occurrence of random events in a fixed time period, and its parameter λ indicates the average arrival rate in the time period, so the expected number of arrivals $E\left[X\right]$ can be expressed by the following equation:

$$E\left[X\right]=\lambda \tag{17}$$

3. Cost-benefit analysis

Firstly, the cost-benefit model is constructed, in which the construction cost C_{bulid} includes the costs of infrastructure construction, materials, labor, etc. The cost-benefit model can be expressed as follows It can be expressed as.

$$C_{bulid}=C_{materials}+C_{labor}+C_{\inf rastucture} \tag{18}$$

Operating Costs $C_{operate}$ Includes routine maintenance, management costs, etc. Can be expressed as[25].

$$C_{operate}=C_{ma\,\mathrm{int}enance}+C_{staff}+C_{fuel} \tag{19}$$

Time Savings T_{saved} The average travel time reduction through the new system can be calculated using the flow model and shortest path algorithm. Assuming an original travel time of $T_{original}$ and a new travel time of T_{new}, the time savings are.

$$T_{saved}=T_{original}-T_{new} \tag{20}$$

The financial metric for evaluating an investment in a pedestrian trail system project or financial decision by calculating Net Present Value NPV, the NPV formula is.

$$NPV=\sum_{t=0}^{n}\frac{R_t-C_t}{\left(1+r\right)^{t}} \tag{21}$$

where (R_t indicates the benefits in year t (e.g., cost of time saved, revenue from increased ridership); Ct indicates the costs in year t (construction and operating costs); r indicates the discount rate; and n indicates the total number of years of the project[26]. If NPV is greater than 0, it means that the project is expected to generate revenues in excess of the investment costs, indicating that the project is a viable investment option; if NPV is less than 0, it indicates that the project may result in losses and is not recommended for investment.

3.1.2.2 Impacts of Various Baltimore Stakeholders

The traffic modeling, flow forecasting, and cost-benefit analysis will enable an understanding of the impacts of mobility and walkability on the city's transportation system, provide data and decision-making for project implementation, and assess project feasibility, economic benefits, and impacts on stakeholders. The project's network modeling has the following key impacts on Baltimore stakeholders.

Traffic management. can optimize traffic signals and allocate resources rationally.

Citizens and commuters. improve travel experience and reduce traffic accidents.

Businesses and merchants. analyze customer flow and optimize logistics.

Urban planners and policy makers. provide data for infrastructure construction and policy making.

Among them, BUS_STOP traffic heat map data is as follows Figure 11.

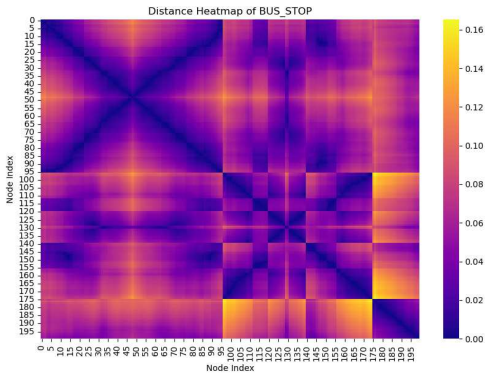


Figure 11 BUS_STOP traffic heat map

Environmental protection organizations. conduct environmental impact assessment.

In short, this project positively influences various stakeholders and provides data support in traffic forecasting, promotes scientific and modernized traffic management, and helps build an efficient, safe and sustainable urban transportation system.

3.1.3 Optimization Modeling and Solving for Transportation Network Projects in Baltimore City

3.1.3.1 Model building

In order to enhance the efficiency of the transportation system, minimizing travel time and reducing operating costs are considered as important objectives. The reduction of travel time enhances the operational efficiency of the entire transportation network, which is important for reducing traffic congestion and shortening passenger waiting time. On the other hand, for transportation operators, cost reduction means being able to increase profitability while maintaining service quality. Through the use of optimization models, resources can be allocated rationally to find the lowest-cost travel solution, thus maintaining an advantage in the fierce market competition.

1. Define decision variables.

Before building an optimization model, it is important to first define the decision variables to reflect the factors that need to be controlled and adjusted during the optimization process. Specifically, the relevant decision variables in the optimization model include. Traffic flow x_{ij} . represents the flow rate from the starting point i to the ending point j in vehicles per hour. By controlling the flow rate on each path, the operation status of the whole transportation network is manipulated.

where AADT2014-2022 data plots for flow per unit length are shown in Figure 12.

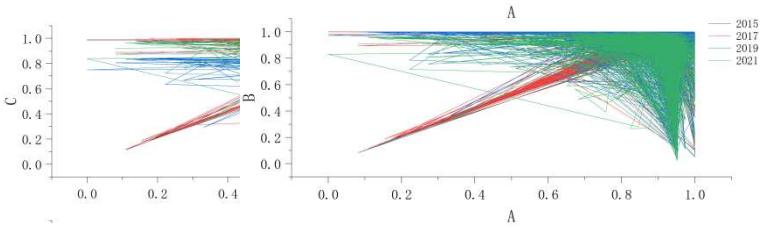


Figure 12 AADT2014-2022 data up and down bridge diagrams for unit length flow rates

Travel Time T_{ij} . Travel time from origin i to destination j , usually determined by distance and vehicle speed.

Travel Cost C_{ij} . the cost of travel from the origin i to the destination j , which includes a number of aspects such as fuel costs and labor costs.

Demand D_j . the amount of demand at each end point j that determines the baseline for traffic flow distribution.

Available Vehicles V_i . refers to the number of vehicles that can be put into use at each starting point i , limiting the maximum value of traffic flow.

2. Define the objective function.

Minimize travel time.

In order to achieve the goal of minimizing travel time, our objective function can be expressed as follows.

$$MinimizeZ_T = \sum_{i,j} T_{ij} \cdot X_{ij} \tag{22}$$

Travel time T_{ij} can be further calculated by distance L_{ij} and average speed $V_{avg,ij}$.

$$T_{ij} = \frac{L_{ij}}{V_{avg,ij}} \tag{23}$$

Thus the final objective function can be expanded as.

$$Z_T = \sum_{i,j} \left(\frac{L_{ij}}{V_{avg,ij}} \right) \cdot X_{ij} \tag{24}$$

This objective function emphasizes the relationship between traffic flows and corresponding travel times from each origin to destination, using flow allocation to optimize travel efficiency.

Minimization of costs.

In pursuing the goal of minimizing operating costs, our objective function can be expressed as follows.

$$Minimize Z_C = \sum_{i,j} C_{ij} \cdot X_{ij} \tag{25}$$

The C_{ij} here includes the cost of vehicle operation, maintenance and other related expenditures. Overall operating costs can be effectively reduced by rationalizing the distribution of traffic on each path.

3. Constraints

Flow Balance Constraints

The flow balance is an essential element of the optimization model. For each endpoint j, a balance between inflows and outflows must hold.

$$\sum_i X_{ij} - \sum_k X_{jk} = D_j \quad \forall \mathrm{j} \tag{26}$$

Network capacity constraint.

The flow on each path is constrained by the maximum transportation capacity, a condition that can be expressed in the following way.

$$x_{ij} \le C_{ij,\max} \quad \forall (i,j) \tag{27}$$

This ensures that traffic is distributed appropriately and does not exceed its actual carrying capacity.

Vehicle quantity constraints,Between the vehicle input and the flow rate at each starting point i, the constraints of available vehicles need to be satisfied.

$$\sum_j X_{ij} \le V_i \quad \forall i \tag{28}$$

This ensures efficient travel by avoiding traffic bottlenecks due to lack of vehicles.Non-negative constraints.All traffic variables must be non-negative, which reflects the logic that traffic cannot be negative in reality.

$$X_{ij} \geq 0 \quad \forall (i, j) \tag{29}$$

3.1.3.2 Multi-Algorithm and Model Comparison Optimization

Algorithm 1. Ant Colony Algorithm (ACO)

The Ant Colony Algorithm is a heuristic search algorithm for solving combinatorial optimization problems[27]. In the problem of planning urban transportation routes, the ACO algorithm can be used to find urban transportation routes that promote business development and improve the quality of life for residents, workers, and tourists[28]. Following are the detailed steps for planning urban transportation routes using Ant Colony Algorithm[29].

1.Pheromone initialization.

Initialize the pheromone matrix τ_{ij} :

$$\tau_{ij} = \tau_0, \quad \forall \mathrm{i,j} \tag{30}$$

where τ_0 is a small positive number.

2.Pheromone update.

Each ant (representing one possible transportation route scenario) updates the pheromone based on path quality after completing a trip (traversing the transportation route from start to finish). Path quality can be measured in several ways, e.g., for residential trips, it can be green parks, residential houses, and recreational facilities and leisure places, etc.; for tourists, it can be the number of attractions visited and the total travel time[30].

3.Heuristic information:

Heuristic information can be based on commute times and population flows between two locations. For example, $\frac{1}{d[i][j]+s[i]}$ is used as a heuristic[31].

4. selection rules.

In order to derive the optimal transportation planning route for the city of Baltimore[32], mathematical modeling of ACA can be performed based on pheromone concentrations and heuristic information. Let p_{ij} be the probability of the citizen's next step from landmark i to landmark j, then we have.

$$P_{ij} = \frac{\left(\tau_{ij}\right)^{\alpha} \cdot \left(\eta_{ij}\right)^{\beta}}{\sum_{k \in allowed} \left(\tau_{ik}\right)^{\alpha} \cdot \left(\eta_{ik}\right)^{\beta}} \tag{31}$$

where τ_{ij} is the pheromone concentration, η_{ij} is the heuristic information, $allowed$ is the set of landmarks that the citizen expects to choose next , $allowed = \{1, 2, \cdots N\}$; s is the desired target location, and β is the weighting parameter.

5.Pheromone update:

Update the pheromone after each iteration:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \Delta\tau_{ij} \tag{32}$$

where $\Delta\tau_{ij}$ is the pheromone increment generated by the access path, usually proportional to the fitness of the path.

Average transportation route length is shown in Figure 13.

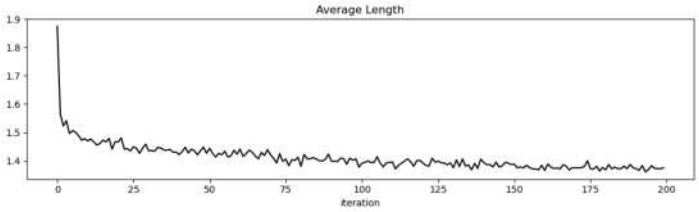


Figure 13 Average transportation route length

Optimal transportation route length is shown in Figure 14.

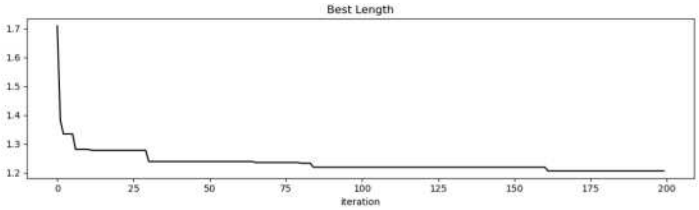


Figure 14 Optimal transportation route length

Algorithm 2. Simulated Annealing Algorithm (SA)

In addition to the above ACO algorithm used for calculations, the simulated annealing algorithm can also be used for calculations and then compared with it, the following are the detailed steps for planning the transportation routes in Baltimore City using the simulated annealing algorithm[33].

Iterative equation. according to the *Metropolis* criterion, the probability of cooling with an energy difference of dE for a system temperature of T is:

$$p(dE) = e^{dE/KT} \tag{33}$$

This equation then states that the higher the temperature, the higher the probability of a single cooling with an energy difference of dE ; the lower the temperature, the lower the probability of a cooling[34]. Again, since dE is always less than 0 (because the process of annealing is a gradual decrease in temperature), $0 < p(dE) < 1$. using that cooling probability as a basis, the state transfer probability $p(\Delta f)$ is used to express the tolerance of the worse state.

$$p(\Delta f) = e^{\Delta f/T} \tag{34}$$

where f is the state generating function and hence the corresponding equation is.

$$\Delta f = f(x_{new}) - f(x_{old}) \tag{35}$$

The constant k is neglected by changing the range of values of the temperature T, i.e., T in Eq. (36) is equivalent to T in Eq. (37).There are two types of acceptable solutions in the process of finding the most value.

a better solution - BS (a state closer to the optimum than the current state);

a tolerant solution - TS (a solution further away from the optimum than the current state)[35].

The former has an acceptance probability of 1 and the latter has an acceptance probability of state transfer probability $p(\Delta f)$, which must be guaranteed $p(\Delta f) \in (0.1)$.

Find the minimum value.

$$\begin{cases} \Delta f < 0 \to BS \to 1 \\ \Delta f \geq 0 \to TS \to p(-\Delta f) \end{cases} \tag{36}$$

Find the maximum value.

$$\begin{cases} \Delta f < 0 \to BS \to 1 \\ \Delta f \geq 0 \to TS \to p(\Delta f) \end{cases} \tag{37}$$

If $f(x_{new}) \leq f(x_{old})$, the move is always accepted; if $f(x_{new}) > f(x_{old})$, the move is accepted with a certain probability, and this probability decreases over time.

Traffic Route Map Simulated by Simulated Annealing Algorithm is shown in Figure 15.

Algorithm 3. Particle Swarm Optimization Algorithm (PSO)

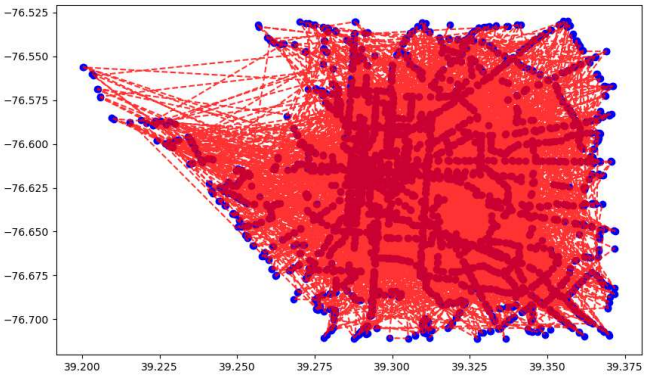


Figure 15 Traffic Route Map Simulated by Simulated Annealing Al-gorithm

In addition to the above two algorithms, particle swarm optimization algorithm also has better results in solving urban traffic path planning problems. Particle Swarm Optimization (PSO) algorithm is an optimization algorithm based on group intelligence, which is inspired by the bird flock foraging. The algorithm finds the optimal solution by simulating the flight behavior of particles in the search space, each particle represents a potential solution and adjusts the flight direction through experience. The process of particle swarm algorithm is as follows Figure 16.

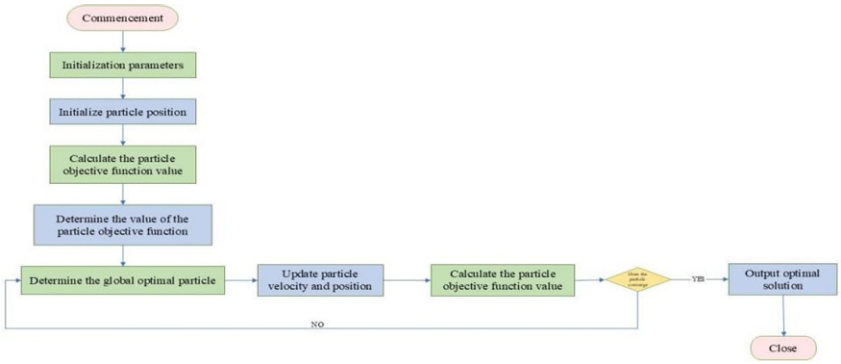


Figure 16 Particle Swarm Optimization Algorithm Flowchart

Particle Swarm Optimization (PSO) algorithms find optimal solutions by simulating group behaviors such as foraging by flocks of birds in nature. In PSO, each particle represents a potential solution and they update their velocity and position based on individual experience and group experience to explore the global optimal solution.

The velocity update of the particles follows the following equation[36].

$$v_i^{(t+1)} = w \cdot v_i^{(t)} + c_1 \cdot r_1 \cdot \left(pbest_i - x_i^{(t)} \right) + c_2 \cdot r_2 \cdot \left(gbest - x_i^{(t)} \right) \tag{38}$$

where. $v_i^{(t+1)}$ is the velocity of particle i in the next iteration i ; ω inertia weight, which controls the degree of retention of particle velocity and affects the global search ability of the algorithm; $v_i^{(t)}$ is the velocity of particle i in the next iteration t ; c_1 and c_2 are acceleration coefficients, which represent the individual learning factor and the social learning factor, respectively, and control the degree of convergence of particles to the individual optimum and the global optimum; r_1 and r_2 are the random numbers in the interval of $[0,1]$, which increase the randomness for the algorithm to add randomness; $pbest_i$ is the individual optimal position

found so far by particle i ; $gbest$ is the global optimal position found so far by the whole particle swarm; $x_i^{(t)}$ is the position of particle i in the current iteration t .

The position update of the particles follows the following formula:

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \qquad (39)$$

where. $x_i^{(t+1)}$ is the velocity of particle i at the next iteration $t+1$; $x_i^{(t)}$ and $v_i^{(t+1)}$ are the position of particle i at the current iteration and the velocity at the next iteration, respectively.

Implementation steps[37].

1. Initialize the particle swarm.

Assign random initial positions and velocities to each particle. These positions and velocities should be within the defined problem space.

Initialize the individual best position ($pbest$) of each particle as its initial position and the global best position ($pbest$) as the best position in the whole particle swarm.

2.Evaluate particle performance.

For each particle, the performance at its current position is evaluated using an objective function.

If the current position performs better than $gbest$ for that particle, update $gbest$ for that particle.

If the current position performs better than $gbest$ for that particle, update $gbest$ for that particle.

3. Speed and location of updates.

The velocity of each particle is updated based on $pbest$, $pbest$, the current velocity, and two learning factors (individual and social learning factors).

Updates the position of each particle.

4. Repeat or terminate.

The algorithm is stopped if the termination condition is satisfied (maximum number of iterations reached or improvement of $gbest$ is less than a threshold).Otherwise, repeat steps 2 and 3.

Traffic Route Map Simulated by Particle Swarm Algorithm is shown in Figure 17.

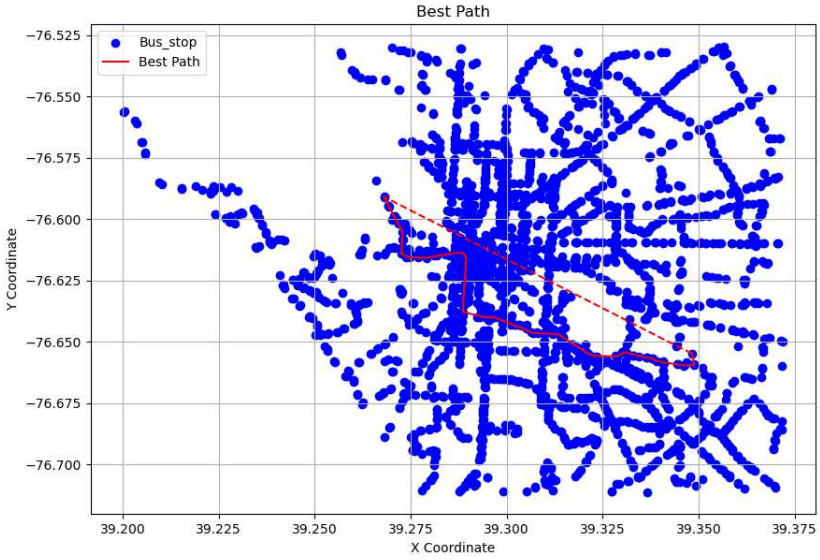


Figure 17 Traffic Route Map Simulated by Particle Swarm Algorithm

Algorithm 4. Graph Neural Network (GNN) and Graph Convolutional Neural Network (GCN)

Graph Convolutional Network (GCN) is a deep learning model specialized for processing graph-structured data[38]. Its core idea is to update the representation of nodes by aggregating the information of neighboring nodes to capture the local structural features in the graph.The model formulation method of GCN is mainly based on the theory of Fourier Transform in Graph Signal Processing, which converts the node features in the graph to the frequency domain for processing[39].

The data of urban residential areas, shopping centers, bus stops, parks, etc. are known[40].Let the number of layers of the graph convolutional network be 3,represent the data as adjacency matrix A and node feature matrix $H^{(1)}, H^{(2)}, H^{(3)}$ for each layer.Let the set of points with building coordinates be $P = \left\{ p_i \middle| i = 1, 2 \ldots n \right\}$ and the building coordinates be $p_i = \left(x_i, y_i \right)$ .Use the NearestNeighbors algorithm to find the neighbors of each point p_i .For each point p_i calculate the distance d_{ij} from the other point $p_i \left(i \neq j \right)$ .The distance between two points $p_i = \left(x_i, y_i \right)$ and $p_j = \left(x_j, y_j \right)$ in Euclidean space can be expressed as $\sqrt{\left(x_i - x_j \right)^2 + \left(y_i - y_j \right)^2}$ .The modeling formula for GCN is[41].

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} W^{(l)} \right) \tag{40}$$

where $H^{(l)}$ is the node feature matrix of layer l ; σ is the $\tanh$ activation function[42].

$$H^{(l)} = \frac{e^{Z^{(l)}} - e^{-Z^{(l)}}}{e^{Z^{(l)}} + e^{-Z^{(l)}}} \tag{41}$$

$\tilde{A} = A + I$ is the adjacency matrix with added self-connections (A is the initial adjacency matrix and I is the unit matrix); $\tilde{D}_{ii} = \sum_j \tilde{A}_{ij}$ is the degree matrix of $\tilde{A}$; and $W^{(l)}$ is the learnable weight matrix for layer l [43].

$\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{(l)}$ implements the aggregation and updating of node features. The features of neighboring nodes are aggregated to the central node and then normalized by $\tilde{D}^{-\frac{1}{2}}$ to ensure that nodes of different degrees have the same contribution[44]. The new feature representation of a node is computed layer by layer by continuously propagating forward through the model formulation, and the $H^{(l)}$ output of each layer is processed by an activation function. For the weight matrix $W^{(l)}$ at layer L, its dimension depends on the input feature dimension $d_{in}^{(l)}$ and the output feature dimension $d_{out}^{(l)}$, i.e[45].

$$W^{(l)} \in \square^{d_{in}^{(l)} \times d_{out}^{(l)}} \quad (42)$$

During model training, the weight matrix is updated by minimizing the loss function L with the update formula[46].

$$W^{(l)} = W^{(l)} - \alpha \frac{\partial L}{\partial W^{(l)}} \quad (43)$$

Where α is the learning rate, denotes the step size of each update, and the partial derivative $\frac{\partial L}{\partial W^{(l)}}$ denotes the rate of change of the loss function L to the weight matrix $W^{(l)}$. Finally, the accuracy of the training results is evaluated by calculating Accuracy, Recall, and Precision to continuously optimize the performance of the model on the data.

Figure Convolutional neural network first multi-round result plot are shown in Figure 18.

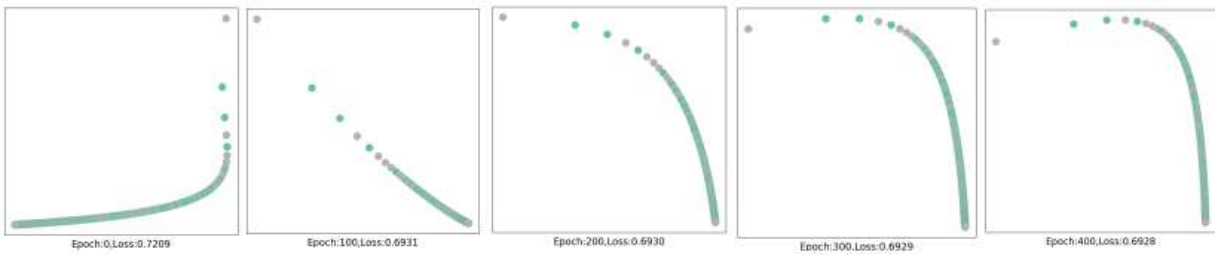


Figure 18 Figure Convolutional neural network first multi-round result plot

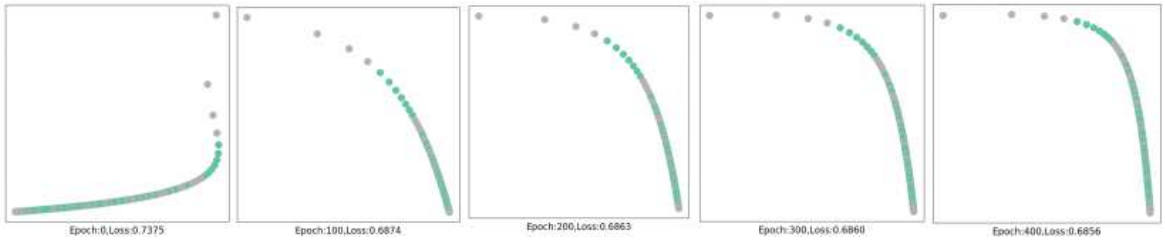


Figure Convolutional neural network second multi-round result plot are shown in Figure 19.

Figure 19 Figure Convolutional neural network second multi-round result plot

Bus_stop location heat map is shown in Figure 20.

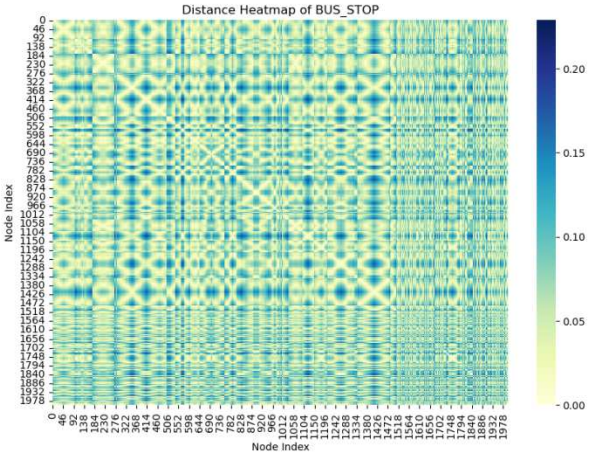


Figure 20 Bus_stop location heat map

Traffic Route Map for GCN Simulation is shown in Figure 21.

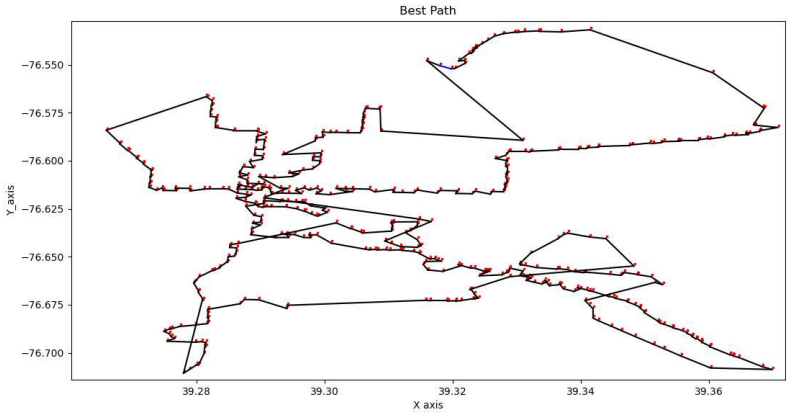


Figure 21 Traffic Route Map for GCN Simulation

Combining these four algorithms to get the most suitable algorithm for this problem solving - graph convolutional neural network, the clustering structure of the graph neural network is very clear, with similar nodes tightly clustered and dissimilar nodes dispersed.

The graph convolutional neural network model can automatically learn the complex features of transportation hubs and paths, and can learn the type of hubs, busyness, road congestion, as well as the length of paths, road conditions, and passable traffic modes, and integrate these features into route planning. Through multi-layer convolutional operations, high-level features can also be gradually abstracted to more accurately evaluate the advantages and pressure within Baltimore City, and also help promote the synergistic development of the regional economy.

3.Results

Analysis of safety in the transportation system

Baltimore City faces traffic safety issues in a number of ways that severely impact residents' daily travel and overall quality of life. First, the lack of effective connections between highways and urban neighborhoods causes many residents to face safety hazards when traveling to and from the city. The existing public rail system mainly serves suburban areas, while most of the transportation facilities in urban areas are focused on meeting the needs of tourists and cannot effectively reach inter-city residents, increasing the frequency of reliance on motorized travel. In addition, aging infrastructure has increased the risk of traffic accidents. Meanwhile, improper driving behavior due to traffic congestion exacerbates the threat of crashes.

In terms of improving transportation infrastructure development, the reconstruction of the Francis Scott Key Bridge needs to adopt modern design standards, emphasize safety features, and ensure adequate pedestrian and bicycle access. At the same time, the design of traffic intersections should be optimized and the connection between highway exits and urban communities should be strengthened to shorten residents' commuting time and improve travel efficiency.

In optimizing the public transport system, the focus should be on expanding public transport coverage and enhancing public transport services in urban areas in order to improve and expand the transport network. In addition, the number and frequency of buses should be increased according to residents' needs, especially during peak hours, to ensure that residents can reach their destinations conveniently and quickly.

Finally, in terms of optimizing the traffic signal and management system, scientific data analysis can accurately set the switching cycle of traffic lights according to the changes in traffic flow at different times of the day, to ensure that vehicles and pedestrians in all directions can pass safely and smoothly. In addition, tidal lanes are introduced on roads with large changes in pedestrian flow at different times of the day, so as to flexibly adjust the use of lanes according to changes in traffic peaks and troughs, and to increase the capacity of lanes in specific directions during peak hours, thereby effectively easing congestion.

In summary, through comprehensive improvement of transportation infrastructure, optimization of public transportation, implementation of intelligent traffic management, and enhancement of public education on traffic safety, Baltimore City can effectively improve the safety of the transportation system, ensure the safety and convenience of residents' travel, and lay a solid foundation for the sustainable development of the city.

Funding

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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