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# Traffic flow allocation during urban important bridge construction based on mixed graph convolution

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**Abstract**

Bridge construction often leads to sudden changes in the original traffic network topology, a sharp drop in the capacity of key nodes, and difficulty in accurately allocating traffic flow. Therefore, conducting research on traffic flow allocation during the construction of important urban bridge based on mixed graph convolution. Firstly, by constructing a sandwich structure prediction model and utilizing multi-channel spatial modules to capture static and dynamic spatial dependencies. Secondly, based on the predicted results, a probability model for non-equilibrium traffic flow allocation is established, and the optimal strategy is solved to achieve reasonable flow allocation. Finally, genetic algorithm is used to optimize path selection, while ensuring travel efficiency and alleviating traffic pressure in the construction area. The experimental results show that the path flow allocation balance of the proposed method is stable at 78% -82%, and the probability of choosing a detour path remains at 90.45%-93.56%.

*Keywords - bridge construction, traffic flow, mixed graph convolution, probability model for non-equilibrium traffic flow allocation, genetic algorithm, optimize*

## 1. Introduction

The accelerated process of urbanization has led to the continuous expansion of the road network, and urban bridges, as key nodes of the transportation network, bear the growing demand for traffic. Bridge construction often occupies road resources and changes the original traffic organization, leading to a sudden increase in traffic pressure on the surrounding road network [6, 4]. The decrease in traffic capacity in the construction area can lead to systemic negative effects such as traffic congestion, increased delays, and rising emissions. A scientifically reasonable traffic flow allocation plan can effectively alleviate the impact of construction on the operational efficiency of the road network and ensure a smooth transition of the urban transportation system [11]. The current research on traffic management during the construction period mainly focuses on the design of temporary traffic plans at the micro level, lacking exploration of the mechanism of traffic flow redistribution from the macro road network perspective. Traditional traffic allocation models often overlook the dynamic changes in road network characteristics caused by construction activities, making it difficult to accurately reflect actual traffic behavior patterns. Building a refined traffic flow allocation system for construction scenarios has important theoretical value and practical significance for minimizing construction impact and maximizing road network efficiency [1, 9, 3].

Yue et al. [13] proposes an iterative weighted algorithm for static traffic flow allocation based on congestion space queuing, considering regret psychology and perceptual differences in travel decisions, and constructing path selection probability models under different levels of rationality. This model integrates factors such as road capacity and queuing effects, proposes a method for correcting traffic flow, and analyzes the dissipation pattern of vehicles through incremental allocation. Although behavioral economics factors have been taken into account, actual decision-making is still influenced by dynamic factors such as cognitive biases and information asymmetry. Long et al. [7] travelers, considering the regret psychology and perceptual differences in travel decisions, and constructing probability models for path selection under different levels of rationality. This model integrates factors such as road capacity and queuing effects, proposes a method for correcting traffic flow, and analyzes the dissipation pattern of vehicles through incremental allocation. Although behavioral economics factors have been taken into account, actual decision-making is still influenced by dynamic factors such as cognitive biases and information asymmetry. Han et al. [2] proposes a traffic flow allocation method based on CAV autonomous parking behavior, considering regret psychology and perceptual differences in travel decisions, and constructing path selection probability models under different levels of rationality. This model integrates factors such as road capacity and queuing effects, proposes a method for correcting traffic flow, and analyzes the dissipation pattern of vehicles through incremental allocation. Although behavioral economics factors have been taken into account, actual decision-making is still influenced by dynamic factors such as cognitive biases and information asymmetry.

During bridge construction, the sudden change in road network topology disrupted the original traffic balance, triggering a chain reaction. The decrease in critical node traffic capacity forces traffic flow to be redistributed, and this mandatory path transfer leads to a cascading effect in the surrounding road network, resulting in a clear nonlinear characteristic of the entire system's traffic state. The frequent changes in temporary traffic control measures further exacerbate the uncertainty of the system, and emergencies are more likely to cause widespread congestion when the redundancy of the road network is reduced. Therefore, a traffic flow allocation method for urban important bridge construction period based on mixed graph convolution is proposed. Propose a mixed graph convolution model, combined with spatiotemporal feature prediction and game theory optimization, to achieve precise traffic allocation for construction bridges. Extracting temporal features through multi head attention and optimizing path selection with genetic algorithm effectively alleviates traffic congestion in construction areas.

## 2. Traffic flow prediction during the construction of important bridges in cities using mixed graph convolution

The mixed graph convolution based traffic flow prediction model is a multi-channel spatiotemporal traffic flow prediction model based on mixed graph convolution. The model extracts static topological features and dynamic flow features of the construction impact area through parallel graph convolution channels, overcoming the limitations of single graph structure modeling [8]. The traffic flow prediction model is shown in Figure 1.

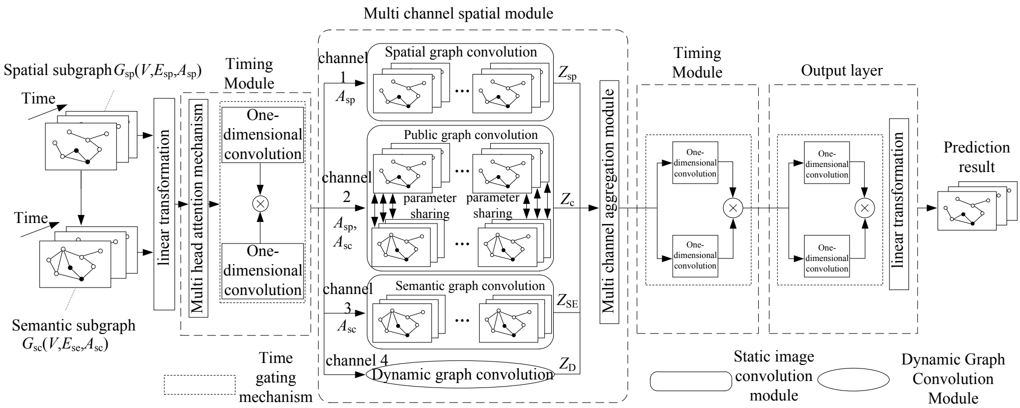



Fig. 1 - Traffic flow prediction model

As shown in Figure 1, the model consists of two time modules, a multi-channel spatial module, and an output layer. Among them, the model adopts a sandwich structure (i.e. a multi-channel spatial module in the middle and time modules on both sides). The input of the model is historical traffic data $X_{in}$, spatial neighbor subgraph $G_{sp}$, and semantic neighbor subgraph $G_{se}$ during the construction of important urban bridges, and the output is the predicted traffic flow during the construction of important urban bridges.

### *2.1. Timing module*

In the time module of this model, a multi head attention mechanism is used to extract global time features during the construction of important urban bridges, and a time gating mechanism is used to extract local time features during the construction of important urban bridges. The traffic data $X_{in}$ during the construction of important urban bridges is first linearly transformed and mapped to a high-dimensional space to enhance the fitting ability of the model:

$$X=X_{in}W+b \tag{1}$$

In the formula, $X_{in}\in R^{T\times N\times D}$, $T$ refers to the time interval length corresponding to historical observation data, $N$ represents the total number of nodes, and $D$ represents the total number of features, $W\in R^{D\times P}$, $P$ represents the high-dimensional spatial dimension values obtained after mapping processing, $b\in R^{1\times 1\times P}$.

For the architecture of single head attention mechanism, when the input is $X^{t-T+1:t}=\left[X^{t-T+1},X^{t-T+2},...,X^{t}\right]\in R^{T\times N\times D}$, it can be abbreviated as $X$. Then, using linear transformation, the input matrix is transformed into three matrices, namely matrix $Q\in R^{N\times d_q}$, matrix $K\in R^{N\times d_k}$, and matrix $V\in R^{N\times d_v}$. Among them, $W^Q$, $W^K$, and $W^V$ belong to three trainable parameters, which can be expressed as:

$$Q=\mathrm{X}W^Q,K=XW^K,V=XW^V \tag{2}$$

The attention output is:

$$Attention(Q,K,V)=\mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{3}$$

In the multi head attention mechanism, different weight matrices linearly map input features to different data subspaces, and complete the same attention calculation in each subspace to fully learn the time series. The $i$-th head attention calculation process is as follows:

$$head_i=Attention(Q_i,K_i,V_i) \tag{4}$$

In the formula, $Q_i=XW_i^Q$, $K_i=XW_i^K$, $V_i=XW_i^V$.

Finally, concatenate the different heads in sequence and perform a re projection operation to obtain the output of the multi head attention mechanism

$$\text{MultiHead}(Q,K,V)=Concat(head_1,head_2,...,head_h)W^O \tag{5}$$

In the formula, $W^O \in R^{hd_v \times d_{model}}$ and h represents the number of bulls [12].

The multi head attention architecture performs well in mining the overall dependency characteristics of time series. To further explore local temporal correlations, time gating techniques will be introduced to capture temporal features. The time gating method uses convolution operation to extract local temporal features in parallel. Firstly, the input sequence is processed through one-dimensional convolution, and then it is split into two branches. One branch is transformed by Sigmoid function, while the other branch remains unchanged. Finally, the results of these two branches are multiplied to obtain the final output. The calculation formula is:

$$h(X)=(X*W+b)\times\sigma(X*W+c) \tag{6}$$

In the formula, $W$, $V$, $b$, and $c$ are trainable parameters, * represents convolution operation, and $\sigma(.)$ represents activation function [10].

*2.2. Multi channel spatial module*

The spatial dependence of traffic flow during the construction of important urban bridges is closely related to the spatial structure. To extract the spatial characteristics of different spatial structures during the construction of important urban bridges, a multi-channel spatial module was designed [5, 15].

(1) Static image convolution module

The static graph convolution module covers three categories: spatial dimension graph convolution, semantic information graph convolution, and shared graph convolution. For the spatial convolution part, its core operation is to perform feature extraction on the spatial neighborhood subgraph. The operation result of the $l$-th layer in this part is represented as:

$$Z_{sp}^{(l)}=\text{ReLU}(\widetilde{D}_{\text{sp}}^{-1/2}\widetilde{A}_{\text{sp}}\widetilde{D}_{\text{sp}}^{-1/2}Z_{sp}^{(l-1)}W_{sp}^{(l)}) \tag{7}$$

In the formula, $W_{sp}^{(l)}$ corresponds to the weight matrix parameters involved in the $l$-th layer, ReLU(.) represents the activation function, and $Z_{sp}^{(0)}$ in the initial state is taken from the output result processed by the first time module. When $\widetilde{A}_{\text{sp}}=A_{\text{sp}}+I_{sp}$, $I_{sp}$ takes the form of an identity matrix, $\widetilde{D}_{sp}$ is the diagonalization matrix corresponding to matrix $\widetilde{A}_{\text{sp}}$, and the output of the last level of the spatial graph convolution is denoted as $Z_{sp}$.

During the semantic graph convolution operation, feature extraction is performed on adjacent semantic subgraphs, and the output result of the $l$-th level is presented as follows:

$$Z_{se}^{(l)}=\text{ReLU}(\widetilde{D}_{\text{se}}^{-1/2}\widetilde{A}_{\text{se}}\widetilde{D}_{\text{se}}^{-1/2}Z_{se}^{(l-1)}W_{se}^{(l)}) \tag{8}$$

In the formula, it refers to the weight matrix parameters corresponding to the $l$-th layer, while the output of the final level of semantic graph convolution is identified by $Z_{SE}$.

Using public graph convolution techniques to extract node information from spatially adjacent subgraphs:

$$Z_{csp}^{(l)}=\text{ReLU}(\widetilde{D}_{\text{sp}}^{-1/2}\widetilde{A}_{\text{sp}}\widetilde{D}_{\text{sp}}^{-1/2}Z_{csp}^{(l-1)}W_{c}^{(l)}) \tag{9}$$

In the formula, $Z_{csp}^{(l-1)}$ corresponds to the output result of the $l$-1-th layer node, $Z_{csp}^{(0)}$ represents the output data processed by the first time module, and $W_c^{(l)}$ refers to the weight matrix configured by the $l$-th layer of the common graph convolution.

To achieve the goal of extracting shared information, when using the common graph convolution method to extract node information from semantic neighbor subgraphs, the model uses the same weight matrix $W_c^{(l)}$ for sharing in each layer of the common graph convolution operation. The expression is:

$$Z_{cse}^{(l)}=\mathrm{ReLU}(\widetilde{D}_{\mathrm{se}}^{-1/2}\widetilde{A}_{\mathrm{se}}\widetilde{D}_{\mathrm{se}}^{-1/2}Z_{cse}^{(l-1)}W_c^{(l)}) \tag{10}$$

The shared weight matrix can filter out shared features from two subgraphs. According to different input graphs, two outputs $Z_{CSP}$ and $Z_{CSE}$ can be obtained, and finally the common information $Z_C$ is obtained:

$$Z_C=(Z_{CSP}+Z_{CSE})/2 \tag{11}$$

(2) Dynamic Graph Convolution Module

The key idea of the dynamic graph convolution module is to dynamically assign different weights to different nodes [14]. For node $i$, calculate the weighted sum of all other node information in the graph:

$$Z_i^{(l)}=\sum_{j\leq N}\alpha_{i,j}\cdot Z_j^{(l-1)} \tag{12}$$

In the formula, $\alpha_{i,j}$ is used to represent the importance attention score that node $j$ has for node $i$, while $Z_i^{(l)}$ represents the embedding representation corresponding to the $i$-th node in the $l$-th layer.

Adopting self-learning node embedding and hidden state connection, and using scaled dot product method to calculate attention:

$$o_{i,j}=\frac{\langle W_q\left(Z_i^{l-1}\|e_i\right),W_k\left(Z_j^{l-1}\|e_j\right)\rangle}{\sqrt{d}} \tag{13}$$

In the formula, $\langle . \rangle$ represents the inner product operation, $e_i$ represents the node embedding vector corresponding to node $i$, which is randomly set to an initial value and gradually optimized with training. $W_q$ and $W_k$ are the key matrix and query matrix, respectively.

Calculate the attention score using formula (14):

$$\alpha_{i,j}=\frac{\exp(o_{i,j})}{\sum_{\mathrm{k}\leq\mathrm{N}}\exp(o_{i,j})} \tag{14}$$

After obtaining the attention score, update the node information according to formula (12). The output of the $l$-th layer of the dynamic convolution module is:

$$Z_D^{(l)}=\left[Z_1^{(l)},Z_2^{(l)},\ldots,Z_N^{(l)}\right]^{\mathrm{T}} \tag{15}$$

In the formula, $N$ represents the number of nodes.

(3) Multi channel aggregation module

This study proposes to use attention mechanism to aggregate multi-channel information, where the outputs of the static graph convolution module are $Z_{SP}$, $Z_C$, $Z_{SE}$ in sequence, and the output of the dynamic graph convolution module is $Z_D$. By using attention mechanism $att(Z_{SP},Z_C,Z_{SE},Z_D)$, the importance level $(\alpha_{sp},\alpha_c,\alpha_{se},\alpha_d)$ corresponding to the output results can be explored. The expression is:

$$(\alpha_{sp},\alpha_c,\alpha_{se},\alpha_d)=att(Z_{SP},Z_C,Z_{SE},Z_D) \tag{16}$$

In the formula, $\alpha_{sp}$, $\alpha_c$, $\alpha_{se}$, and $\alpha_d\in R^{n\times 1}$ represent the attention values of $n$ nodes $Z_{SP}$, $Z_C$,

$Z_{SE}$, and $Z_D$, respectively.

As for node $i$, its corresponding embedding in $Z_{SP}$ is represented as $z^i_{SP} \in R^{1\times h}$, and h serves as the output channel produced by the last layer of graph convolution. Firstly, a non-linear function is used to perform a transformation operation on the embedding, and then the shared attention vector quantity $q \in R^{1\times h'}$ is used to obtain the attention value, as follows:

$$\omega^i_{SP} = q^T \cdot tan\mathrm{h}(W \cdot (z^i_{SP})^T + b) \tag{17}$$

In the formula, $W$ represents the weight matrix and $b$ represents the bias vector.

Similarly, the attention values $\omega^i_C$, $\omega^i_{SE}$, and $\omega^i_D$ corresponding to node $i$ in embedding matrices $Z_C$, $Z_{SE}$, and $Z_D$ can be calculated separately. Subsequently, the softmax function is used to normalize these attention values and obtain the final weights:

$$\alpha^i_{SP} = softmax(\omega^i_{SP}) \tag{18}$$

The larger the $\alpha^i_{SP}$ value, the more significant the corresponding embedding criticality. According to this logic, $\alpha^i_C$, $\alpha^i_{SE}$, and $\alpha^i_D$ related results can be derived. For $n$ nodes, the learned weights are $\alpha_{sp}$, $\alpha_{sp}$, $\alpha_e$, and $\alpha_d$ respectively, while setting $\alpha_{SP} = diag(\alpha_{sp})$, $\alpha_C = diag(\alpha_c)$, $\alpha_{SE} = diag(\alpha_{se})$, and $\alpha_D = diag(\alpha_d)$. Integrate the four outputs to obtain the final output of the multi-channel spatial module:

$$Z = \alpha_{SP} \cdot Z_{SP} + \alpha_C \cdot Z_C + \alpha_{SE} \cdot Z_{SE} + \alpha_D \cdot Z_D \tag{19}$$

### *2.3. Output layer*

Finally, a time gating mechanism and a linear transformation are added as the output layer to directly predict the future $M$-step traffic flow during the construction of important urban bridges, in order to avoid the error accumulation caused by inaccurate predictions during the construction period. Set the number of output channels of the linear transformation layer as the step size $M$ to obtain the desired output $\hat{y}$ during the construction of important urban bridges. Use Huber loss as the loss function to measure the performance of the model during the construction of important urban bridges:

$$L(Y,\hat{Y}) = \begin{cases} \frac{1}{2}(Y-\hat{Y})^2, |(Y-\hat{Y})| \leq \delta \\ \delta |(Y-\hat{Y})| - \frac{1}{2}\delta^2, \text{other} \end{cases} \tag{20}$$

In the formula, $\hat{Y}$ and $Y$ represent the predicted and actual values, respectively, and $\delta$ represents the hyperparameter.

## 3. Consider traffic flow allocation for the shortest path

### *3.1. Establishment of probability model for unbalanced traffic flow allocation*

During the construction of important bridges in cities, a simulation method is used to establish a probability model for multi-path unbalanced traffic allocation. By simulating the route selection behavior of each traveler during the construction of important bridges in cities, and proportionally allocating the number of trips in each traffic area to multiple feasible routes, the problem of travelers only choosing a single route during the construction of important bridges in cities is avoided. The probability of travelers choosing route $r$ from feasible subsystems during the construction of important urban bridges is:

$$p(r) = \frac{exp(\theta \cdot t_r)}{\Sigma exp(-\theta \cdot t_i)} \tag{21}$$

In the formula, $t_r$ represents the duration of travel on route $r$, and $\theta$ represents the parameter values in the traffic flow process.

Obtain a probability model for multi-path unbalanced traffic allocation through equation (21), and then use the shortest path game method to obtain the optimal path allocation strategy during the construction of important urban bridges.

### *3.2. Game based allocation of traffic flow*

Set A to describe a set of OD pairs, where each OD pair satisfies the $(a,b)\in A$ condition. If there are n bridge construction detours between a→b, then $\{f_1,f_2,...,f_n\}$, and this combination is considered as one of the main decision-makers, that is, a set of path selection schemes for travelers. Assuming that the OD quantity is allocated to $f_1,f_2,...,f_n$, the traffic capacity of the urban road network will also change accordingly. If the road network situation is $b_1,b_2,...,b_n$ at this time, then the combination of traffic flow allocation methods during the construction period is $\{b_1,b_2,...,b_n\}$. To this end, a game problem road network is established to obtain the time loss matrix of travelers, that is:

$$H=\begin{array}{c} \\ b_1 \\ b_2 \\ \vdots \\ b_n \end{array}\begin{bmatrix} f_1 & f_2 & \cdots & f_n \\ a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{22}$$

$x_{ij}$ describes the travel duration function of each route when the traveler flow $OD$ is allocated to all available routes. According to the user equilibrium theory in game theory, formula (22) presents:

$$\max_i \min_j x_{ij} = \min_j \max_i x_{ij} = x_{c,l} \tag{23}$$

In the formula, $l$ and $c$ are two different transportation routes.

If formula (23) holds, it indicates that there is a pure strategy equilibrium solution to the game problem, where $f_{l,b_c}$ is the optimal traffic allocation state, that is, the travel flow $OD$ is reasonably allocated to the critical path $c$. If formula (23) does not hold, there is no pure policy equilibrium solution, and the problem will have a mixed policy equilibrium solution. This mixed strategy solution can be characterized as the probability distribution of travel flow allocation on each alternative path during the construction period. The traffic allocation problem can be transformed into a linear programming problem in the following form:

$$\begin{gathered} LP{:}\max Z=\textstyle\sum_j e_j' \\ \textstyle\sum_j x_{ij}e_j' \le 1, e_j' \ge 0 (i,j=1,2,...,n) \end{gathered} \tag{24}$$

In the formula, $Z$ describes the objective function, $Z=\frac{1}{\chi}$, and $\chi$ describes the quantity corresponding to the traffic allocation plan during bridge construction, that is, the average time delay of travelers, $\chi_{ij}$ describes the key parameters of the time loss matrix for this problem, $e_j'=\frac{e_j}{\chi}=e_jZ$, $e_j$ is the probability of travelers choosing the detour path $f_i$, which can also be regarded as the traffic flow allocation ratio of the construction area's alternative path $f_i$. The schematic diagram of the road network is shown in Figure 2.

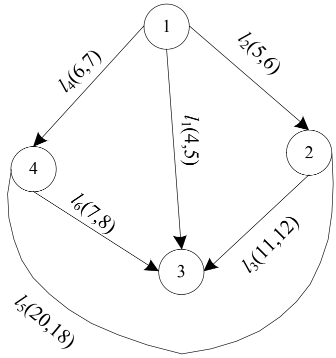



Fig. 2 - Schematic diagram of partial road network

In Figure 2, each construction affected road section is labeled with a $l_i(x,b)$ style. Among them, $i$ is used to explain the selection scheme of the detour path, $x$ is used to illustrate the travel time delay caused by the traffic flow not being allocated to the critical path $i$, and $s$ is used to represent the travel time consumption caused by the traffic flow being allocated to the alternative path $i$. Construct a time loss matrix for travelers based on game theory, as follows:

$$H^{'}=\begin{array}{c} \\ \varphi_1 \\ \varphi_2 \\ \varphi_3 \\ \varphi_4 \end{array}\begin{bmatrix} \delta_1 & \delta_2 & \delta_3 & \delta_4 \\ 39 & 16 & 14 & 14 \\ 29 & 21 & 17 & 14 \\ 29 & 19 & 21 & 16 \\ 29 & 16 & 16 & 19 \end{bmatrix} \tag{25}$$

By applying the superior methods covered by the game theory to simplify formula (25), the final result is:

$$H^{''}=\begin{array}{c} \\ \varphi_2 \\ \varphi_3 \\ \varphi_4 \end{array}\begin{bmatrix} \delta_2 & \delta_3 & \delta_4 \\ 21 & 17 & 14 \\ 19 & 21 & 16 \\ 16 & 16 & 19 \end{bmatrix} \tag{26}$$

According to formula (26), it can be seen that the first column and first row are in an optimized state, that is, in the mixed strategy solution, the component values of the first column and first row are both 0. Based on this and referring to formula (24), the countermeasure problem is transformed into a linear programming problem to be solved. The specific process is as follows:

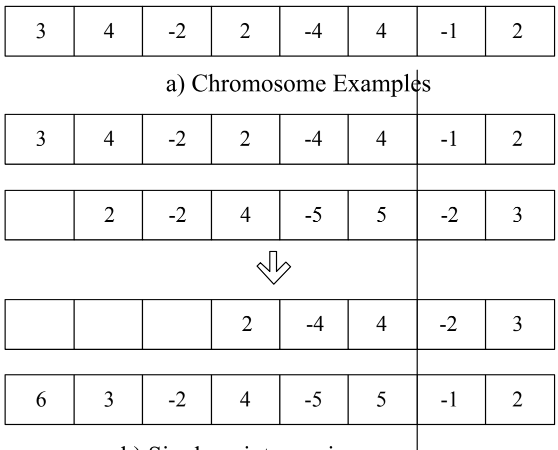
$$\begin{cases} 21e_2^{'}+17e_3^{'}+14e_4^{'}\leq 1 \\ 19e_2^{'}+21e_3^{'}+16e_4^{'}\leq 1 \\ 16e_2^{'}+16e_3^{'}+19e_4^{'}\leq 1 \\ e_2^{'},e_3^{'},e_4^{'}\geq 0 \end{cases} \tag{27}$$

The solution of formula (27) is: $e_2^{'}=0.1987$, $e_3^{'}=0.0078$, $e_4^{'}=0.0394$. The equilibrium value reached in this traffic allocation game is $v=\frac{1}{(0.1987+0.0078+0.0394)}$. Based on this, the flow allocation proportions of each detour path can be obtained as $e_2=80.8\%$, $e_3=3.1\%$, $e_4=17.1\%$. Considering that Route 1 in the construction area has been surpassed by other alternative routes, its allocation proportion can be reduced as appropriate, while correspondingly increasing the allocation probability of other routes to encourage more travelers to scientifically choose alternative travel routes.

Based on the above analysis, multiple detour route options are available for travelers during bridge construction. Subsequently, a genetic algorithm is used to find the optimal traffic flow allocation plan that meets travel needs.

*3.3. Shortest path game traffic flow allocation*

Genetic algorithms can be classified as stochastic algorithms and have highly directional characteristics. When performing optimization search tasks, this algorithm achieves the allocation goals of minimizing pedestrian paths and optimizing traffic flow by using selection, crossover, and mutation operation mechanisms. Chromosomes are presented using numerical encoding, with each chromosome consisting of the number of vehicles that need to be adjusted for each road segment. For example, there are 8 alternative paths from the starting point to the endpoint, and the schematic diagram of chromosome changes is shown in Figure 3.




a) Chromosome Examples

b) Single point crossing process

Fig. 3 - Schematic diagram of chromosome changes

Figure 3a) presents a chromosome that characterizes the traffic flow allocation scheme that needs to be adjusted (increased/decreased) for the road sections affected by construction. In the initial stage of genetic algorithm, a large number of chromosomes are randomly generated to form the initial population. Each chromosome represents a traffic flow regulation strategy, and the quality of each strategy is evaluated by the fitness function. The fitness function is set as follows:

$$f=\frac{1}{1+\alpha\cdot C+\beta\cdot T} \tag{28}$$

In the formula, $C$ represents the congestion level indicator of the construction impact path, $T$ represents the average travel time of the detour route, $\alpha$, $\beta$ are dynamic weight coefficients used to balance the impact of path congestion and travel delays on fitness during construction. The larger the $f$ value, the better the traffic flow allocation strategy during bridge construction.

By using selection operators to eliminate low-quality individuals within the population, the higher the individual $f$ value, the higher the probability of inheriting it to the next generation of the population, On the contrary, the smaller the individual $f$ value, the lower the probability of inheriting it to the next generation population. Based on this, the roulette wheel selection operation is used to determine the probability of any individual being selected. The specific calculation is as follows:

$$p=\frac{f_i'}{N} \tag{29}$$

From formula (29), it can be seen that the probability of an individual being selected is positively correlated with their fitness value. Then generate new chromosomes based on the single point crossover algorithm. If two chromosomes are paired, a crossover position is set on their corresponding coding sequences, and then the crossover position on each chromosome is exchanged to generate a new chromosome. The entire process is shown in Figure 3 (b).

The mutation operator replaces the gene values at a specific locus in each chromosome coding sequence with other alleles at that locus, resulting in a completely new individual. This method can effectively address the local optimization problem of genetic algorithms and prevent premature convergence. Review each mutation site in the coding sequence of each chromosome in order, and replace the original gene value with a value selected from the range of gene values based on the mutation probability $p$.

If the -1 marker of a chromosome corresponds to a gene that is a mutation site, the range of chromosome variation is limited to the construction influence coefficient $[U_{min},U_{max}]$ interval. After uniform mutation processing, a new traffic allocation scheme individual (optimized detour route scheme) can be obtained. The gene value of the mutation site corresponding to this new individual is the detour time adjustment coefficient $U_{min}+g\cdot(U_{max}-U_{min})$, and the path selection probability $g$ is a random parameter in the [0,1] interval.

## 4. Test experiment

### *4.1. Experimental environment and data*

The experiment used ArcGIS mapping tools to collect data on the road network around bridge construction, including the length of alternative construction detours, topological changes caused by bridge closures, and path selection schemes for construction control zones. Excel was used for cleaning and format conversion, Run Matlab software and write algorithm code based on shortest path game algorithm (simulating driver detour decisions), particle swarm algorithm (optimizing traffic diversion in construction areas), and ant colony algorithm (dynamically adjusting detour paths) to meet the special traffic flow allocation requirements during bridge construction, and debug and optimize them, Using GameTheoryToolbox to simulate the game behavior of different entities (traffic management departments, drivers, etc.) during the construction period, Use SUMO traffic simulation tool to construct bridge construction scenarios, simulate road network traffic flow allocation under different traffic control schemes, and obtain key parameters such as bypass path flow distribution and construction zone delay time, Finally, Matlab was used to import simulation results and visualize the impact characteristics of bridge construction on regional road network traffic flow.

The road network structure of the experimental example is shown in Figure 4.

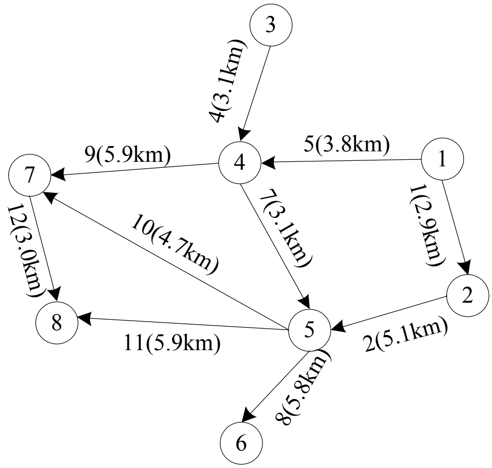



Fig. 4 - Schematic diagram of experimental road network structure

This network is built around important bridge construction areas in the city, consisting of 8 key nodes (1-8) and 11 line segments affected by construction. Nodes 1 and 3 are the main traffic starting points including bridge entrances, while nodes 6 and 8 are the main diversion endpoints after bridge closure, forming four typical OD pairs: 1-6, 1-8, 3-6, and 3-8, The values in parentheses after encoding each road section represent the actual travel distance of the construction detour path (considering the detour increment caused by construction). Table 1 details the dynamic traffic demand changes of each OD pair during different periods of construction, particularly highlighting the redistribution characteristics of commuting traffic caused by bridge closures during peak hours in the morning and evening.

Tab. 1 - OD demand generated by each point

| | O1D1<br>1→6 | O1D2<br>1→8 | O2D1<br>3→6 | O2D2<br>3→8 |
|---|---|---|---|---|
| 2s | 18 | 11 | 10 | 19 |
| 4s | 21 | 17 | 13 | 16 |
| 6s | 18 | 11 | 12 | 17 |
| 8s | 19 | 21 | 9 | 12 |
| 10s | 24 | 21 | 25 | 19 |
| 12s | 35 | 31 | 29 | 27 |
| 14s | 36 | 37 | 32 | 20 |
| 16s | 21 | 24 | 27 | 25 |
| 18s | 19 | 21 | 23 | 25 |
| 20s | 18 | 17 | 19 | 26 |

### *4.2. Experimental plan and indicators*

Using the accuracy of traffic flow prediction, balance of path flow allocation, and probability of detour path selection as indicators, this method is compared and tested with the method in Yue et al. [13] and Long et al. [7].

Traffic flow prediction accuracy: refers to the accuracy of the method in predicting the traffic demand in the construction affected area, reflected in the estimation error rate of the OD matrix during the time period. This indicator measures the degree of agreement between traffic generation predictions and measured values, which directly affects the rationality of diversion schemes. High precision prediction can effectively avoid overloading or resource waste of the surrounding road network in the construction area, and is the basis for optimizing traffic organization.

Balance degree of path flow allocation: describes the reasonable distribution of traffic flow caused by construction closure on alternative paths. This indicator is evaluated by the deviation between the actual flow of each detour path and the theoretical optimal allocation, reflecting the efficiency of road network resource utilization. A low balance degree can lead to increased congestion on some alternative paths, while other paths are underutilized.

The probability of choosing a detour path: characterizes the driver's tendency to choose a specific alternative path when facing construction closures. This indicator is influenced by path attributes (distance, time), information induction, and personal preferences, which directly determine the diversion effect. Studying this probability can help optimize traffic sign placement and navigation strategies, and improve overall traffic organization efficiency.

### *4.3. Experimental results*

#### 4.3.1. Accuracy of traffic flow prediction

High precision prediction can accurately reflect the changes in travel behavior and regional road network load transfer characteristics caused by bridge closure, providing quantitative basis for formulating reasonable traffic control plans and resource allocation strategies. Insufficient prediction accuracy will directly lead to the failure of the diversion plan, which may cause chain congestion in the surrounding road network of the construction area and affect the overall operational efficiency of the urban transportation system. Accuracy testing can verify the adaptability of the model to special construction scenarios, ensuring the reliability of subsequent flow allocation and path optimization schemes. The accuracy results of traffic flow prediction using the three methods are shown in Table 2.

Tab. 2 - Accuracy results of traffic flow prediction

| Number of tests | Accuracy of traffic flow prediction/% | | |
|---|---|---|---|
| | Proposed method | Yue et al. [13] method | Long et al. [7] method |
| 1 | 98.45 | 72.34 | 68.79 |
| 2 | 97.89 | 71.56 | 67.45 |
| 3 | 99.12 | 73.21 | 69.12 |
| 4 | 98.76 | 70.98 | 66.87 |
| 5 | 99.03 | 72.67 | 68.34 |
| 6 | 98.54 | 71.89 | 67.98 |
| 7 | 99.21 | 73.45 | 69.56 |
| 8 | 98.34 | 70.56 | 66.45 |
| 9 | 99.01 | 72.78 | 68.89 |
| 10 | 98.67 | 71.23 | 67.12 |

From the data in Table 2, it can be seen that the traffic flow prediction accuracy of our method is significantly better than that of the comparative methods. In 10 tests, the accuracy of our method consistently remained in the high-level range of 97.89% to 99.21%, and the prediction results were stable and excellent. The accuracy range of Yue et al. [13] is only 70.56% to 73.45%, while the Long et al. [7] has a lower accuracy range of 66.45% to 69.56%. Both methods have significant fluctuations and lower values. This gap fully demonstrates that the method proposed in this article can more accurately reflect the changes in travel behavior and the characteristics of road network load transfer caused by bridge closure, providing a more reliable quantitative basis for the formulation of traffic control plans and resource allocation.

4.3.2. Balance degree of path traffic allocation

The balance test of path flow allocation can evaluate the reasonable distribution of traffic flow on alternative paths, avoiding the phenomenon of resource waste where some detours are overloaded while other routes are idle. Low balance can lead to increased congestion in local road networks, lower overall traffic efficiency, and increase safety hazards. By quantitatively analyzing the balance of traffic allocation, it can provide decision-making basis for dynamically adjusting control measures and optimizing induction schemes, ultimately achieving coordinated operation and maximum resource utilization of the construction area transportation system. The balance results of path traffic allocation for the three methods are shown in Figure 5.

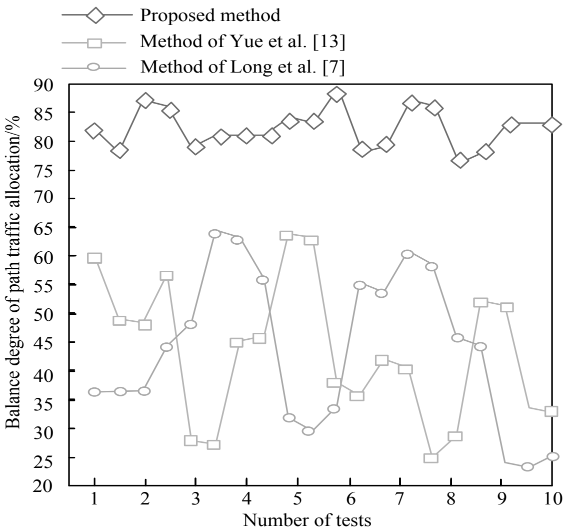



Fig. 5 - Results of path traffic allocation balance

From the data in Figure 5, it can be seen that the method proposed in this paper has a significant advantage in the balance of path traffic allocation. In the 10 tests, the balance value remained stable at around 80% or above, with small fluctuations (such as a slight decrease from 80% to 78% and then a rebound). The method described in Yue et al. [13] exhibits significant fluctuations, with the equilibrium degree dropping as low as 28% in the third attempt and reaching 65% in the fifth attempt. The overall mean is low and discrete. The method in Long et al. [7] also fluctuated violently, with the first time reaching about 36%, the fourth time rising to 65%, and the ninth time dropping sharply to 24%. This method can more stably maintain a high degree of balance, effectively avoid imbalanced distribution of traffic flow, improve the efficiency and safety of road network traffic, and provide more reliable support for optimizing the transportation system. It far exceeds the comparative methods in terms of balanced flow allocation, ensuring coordinated operation of the system, and resource utilization.

4.3.3. Probability of choosing a detour path

The probability test of detour path selection can reveal the decision-making rules of travelers under construction closure conditions and quantify the differences in attractiveness of different detour schemes. By understanding the true selection tendencies of drivers, targeted optimization of traffic guidance sign settings and navigation strategies can be achieved to avoid imbalanced path selection caused by information asymmetry. This study provides a behavioral basis for dynamically adjusting regulatory schemes and plays a decisive role in improving the acceptability and implementation effectiveness of diversion schemes. The probability results of the three methods for selecting detours are shown in Table 3.

Tab. 3 - Probability results of detour path selection

| Number of tests | Probability of choosing a detour path/% | | |
|---|---|---|---|
| | Proposed method | Yue et al. [13] method | Long et al. [7] method |
| 1 | 92.34 | 58.67 | 53.21 |
| 2 | 90.78 | 57.45 | 51.89 |
| 3 | 93.56 | 59.89 | 54.67 |
| 4 | 91.23 | 56.78 | 50.45 |
| 5 | 92.89 | 58.12 | 52.78 |
| 6 | 91.67 | 57.98 | 51.34 |
| 7 | 93.21 | 60.23 | 55.12 |
| 8 | 90.45 | 56.34 | 49.89 |
| 9 | 92.78 | 58.45 | 53.67 |
| 10 | 91.89 | 57.12 | 50.78 |

From the data in Table 3, it can be seen that the method proposed in this paper has significant advantages in terms of the probability of choosing a detour path. The results of 10 tests show that the selection probability of our method consistently remains in the high range of 90.45% to 93.56%, demonstrating a stable high-level performance. In contrast, the selection probability of the method in Yue et al. [13] is only 56.34% to 60.23%, while the method in Long et al. [7] has a lower probability of 49.89% to 55.12%. This significant difference indicates that the method proposed in this paper can more accurately reflect the true choice tendency of drivers, better reveal the travel decision-making rules under construction closure conditions, provide more reliable behavioral basis for optimizing traffic guidance sign setting and navigation strategies, and play an important role in improving the implementation effect of diversion schemes.

## 5. Conclusion

During the construction of important urban bridges, traffic flow allocation faces complex challenges such as network mutations and decreased node capacity, making accurate prediction and dynamic regulation a key challenge. The hybrid graph convolution framework proposed in this study effectively captures the evolution of traffic flow under the influence of construction by integrating temporal feature extraction and multi-scale spatial dependency modeling, providing a new approach for traffic flow allocation in unbalanced road networks. Experimental verification shows that this method exhibits significant advantages in prediction accuracy, allocation balance, and path selection reliability, especially in dealing with sudden congestion and cascading effects. It can quickly generate traffic allocation schemes that balance efficiency and fairness through game theory driven dynamic optimization mechanisms.

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# Real time positioning method for autonomous vehicles considering network delay attacks

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**Abstract**

To reduce the network transmission delay and positioning error of positioning information, this paper proposes a real-time positioning method for autonomous vehicles considering network delay attacks. Firstly, by constructing virtual fence boundaries, additional reference information is provided for real-time vehicle positioning, improving the accuracy and reliability of positioning. Then, considering network latency attacks, the time difference is eliminated and the transmission delay of the sensor network is reduced through multi-sensor clock synchronization processing, and the sensor network is then used to collect vehicle location information. Finally, the HMM map matching algorithm was used to correct the positioning error, effectively improving the positioning accuracy and reliability of autonomous vehicles. The experimental results show that after applying this method, the end-to-end transmission delay of the vehicle position signal is always set within 0.8s, and the average positioning error increases from 0.09m to 0.15m.

*Keywords - autonomous vehicles, real time positioning, virtual fence, sensor network, network latency*

## 1. Introduction

With the rapid development of technology, autonomous driving has become a research hotspot in the field of transportation. Accurate real-time positioning is a key prerequisite for autonomous vehicles to achieve safe and efficient driving [17]. This technology aims to enable vehicles to determine their position at any time in complex dynamic environments, just as humans can quickly locate themselves in unfamiliar surroundings, thereby providing a foundation for subsequent path planning and decision-making. Real-time positioning of autonomous vehicles is crucial within the framework of intelligent transportation systems [1]. On one hand, traffic congestion is becoming increasingly severe, and traditional traffic management methods are unable to meet current demands. Autonomous driving is expected to optimize traffic flow efficiency and improve road capacity through precise positioning. On the other hand, enhancing traffic safety is a pressing societal need. Accurate real-time positioning can reduce accidents caused by human error and ensure safer travel [19]. However, the real-time positioning of autonomous vehicles currently faces many challenges. Road environments are complex and varied—for example, high-rise buildings in urban areas may block signals, while tunnels often suffer from poor signal reception, both of which can degrade positioning accuracy. Additionally, regional differences in geography and climate further complicate the task [11]. Moreover, dynamic factors such as vehicle speed and steering during operation impose even higher demands on real-time positioning. Therefore, in-depth research into real-time positioning methods for autonomous vehicles holds significant practical importance and urgency.

Tang et al. [15] designed an autonomous vehicle positioning method based on 3D laser point cloud, which uses 3D laser scanning technology to capture dynamic road scenes and generate multi-dimensional image data. After mapping point cloud data to a high perspective single view, extract view features using any two-dimensional function, combine map element compilation functions with road scene coupling information, and optimize complex views to achieve the localization function of large-area scenes. However, when compressing and mapping a 3D laser point cloud to a 2D high perspective single view, the spatial geometric relationships of the original point cloud will suffer irreversible information loss due to projection transformation. Especially in complex dynamic scenes, 2D views cannot preserve 3D topological constraints, resulting in systematic errors in subsequent feature extraction and map compilation functions. Guo et al. [5] designed a vehicle localization method based on InEKF and deep learning, which introduced a wheel speed measurement model as the basis and constructed a deep neural network architecture based on autoencoder, aiming to restore the true value of vehicle speed. Then, based on the InEKF principle, a filtering algorithm was designed with SE (3) as the state variable, which integrates multiple information sources to accurately estimate the position of the vehicle. Although autoencoder networks can recover vehicle speed, their black box nature makes it impossible to quantify error distribution, and the InEKF algorithm strongly relies on accurate noise statistical characteristics. When the output error of the deep learning model is directly input into the SE (3) filtering framework, it will break the mathematical optimality assumption of the Kalman gain, leading to the accumulation of positioning errors. Sheng et al. [12] designed a vehicle positioning method based on visual technology and roadside units. This method communicates distance measurement between roadside units and vehicles, combined with visual cameras, to obtain the lateral distance between vehicles and road routes. Then, the error state Kalman filtering algorithm is used to determine the vehicle position based on the obtained data. This method relies on visual technology to obtain the lateral distance between road lines and vehicles, which may lead to a sudden drop in data reliability in complex road environments such as low light, severe weather, or blurry road markings.

In response to the shortcomings of traditional methods mentioned above, this study proposes a real-time positioning method for autonomous vehicles that considers network latency attacks. The design concept of this method is as follows:

(a) The parallel line algorithm is used to generate virtual fence boundaries to improve the accuracy of autonomous driving positioning. The translation direction is determined by calculating the unit normal vector of the boundary line segment, and the boundary line segment is translated along the normal vector direction to form an inwardly contracted polygon. The initial translation distance is set to coordinate system unit 1, and adjusting the multiplier can control the distance size. The boundary points are arranged counterclockwise to ensure inward translation. The core of the algorithm lies in orthogonality calculation and normal vector derivation, ultimately constructing a virtual fence boundary line parallel to the boundary of the research area, providing additional reference for vehicle positioning.

(b) Utilizing wireless sensor networks to obtain real-time position signals of autonomous vehicles, eliminating multi-sensor network delays through clock synchronization mechanisms, and constructing a spanning tree hierarchy using MTS algorithm to achieve time deviation calibration between nodes. Based on the beacon node strategy, select the three nodes with the best signal quality, combine linear regression and weight calculation to determine the distance between the vehicle and the beacon node, solve the coordinate intersection point through the positioning weight factor, and finally derive the precise position coordinates of the vehicle. The entire method achieves centimeter level real-time positioning accuracy through signal strength analysis and distance weight filtering.