Research on the Optimisation Method of Intersection Signal Phase Duration Based on Dynamic Traffic Demand

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Abstract: With the acceleration of urbanisation and the growth of motor vehicle ownership, the problem of traffic congestion at intersections is becoming more and more prominent, and the traditional traffic signal timing scheme is difficult to cope with the dynamic fluctuation of traffic flow and other complex situations. This paper focuses on the integration of intelligent transportation system and artificial intelligence technology, and aims to solve the traffic signal timing optimisation problem by establishing a real-time evaluation and prediction model. The research includes constructing a dynamic timing optimisation model based on real-time traffic flow, developing intelligent regulation algorithms adapted to different time periods and unexpected conditions, and realising multi-objective optimisation such as reducing vehicle delays and safeguarding pedestrian safety; meanwhile, embedding learning techniques, integrating multi-source sensor data to construct a prediction model, balancing the traffic demand of multiple ends, and ensuring the system's adaptability to the complex environment. It is proposed to use multi-source heterogeneous data fusion technology, hybrid neural network prediction model and other methods to solve the problem of insufficient adaptability of the traditional scheme in dynamic traffic fluctuations and other scenarios, and the results of the research can support the upgrading of the intelligent transport system, with the ability of low-latency decision-making in complex environments.

Keywords: Dynamic Traffic Demand; Intersection Signals; Phase Duration Optimisation; Multi-Source Data Fusion; Hybrid Neural Network; Multi-Objective Optimisation Algorithm; Intelligent Transport System

1. Introduction.

With the acceleration of urbanisation and the continuous growth of motor vehicle ownership, traffic congestion at intersections has become a prominent problem that restricts the efficiency of urban operation. Traditional traffic signals mostly use fixed-cycle timing schemes or adaptive control based on simple rules, which are difficult to cope with dynamic fluctuations in traffic flow, multi-directional traffic conflicts and sudden congestion problems. [1]Especially during peak hours or in complex road networks, irrational signal timing can exacerbate vehicle queue lengths, delays and energy consumption, and lead to safety hazards. In recent years, the rapid development of Intelligent Transportation Systems (ITS) and Artificial Intelligence (AI) technologies has provided new ideas for signal optimisation, and how to achieve dynamic cooperative control of signal timing based on real-time traffic data and multi-objective optimisation algorithms has become a key challenge to enhance the road network capacity.

On this series of problems, some scholars in China have already made research: Professor Li Keping of Tongji University put forward the problem of the tolerance limit of pedestrians waiting for red lights in the "Sino-German Seminar on Signal Lights", pointing out that the length of the red light in some cities in China (e.g., Shanghai) exceeds 60 seconds which is an important reason leading to the violation of pedestrians' rights and suggesting to learn from the tolerance limit of 60 seconds in Germany and 45 seconds in Britain, It is also suggested that the tolerance threshold of Germany (60 seconds) and UK (45 seconds) should be used to optimise the time allocation. A team from Tongji University developed a traffic flow prediction model based on the least squares method, but the model has limitations in real-time. Hao Linqian (2021) proposed a signal timing model for intersections based on a multi-objective optimisation algorithm, and experimentally

verified that their model can reduce the average delay time of motor vehicles by 10%-18%. Scholar Wang Wei et al. (2020) combined fuzzy control and genetic algorithm to optimise the green signal ratio, which reduced the vehicle delay time by 12%-15% in simulation.
Foreign countries have also proposed a variety of solutions:German scholars Schmitt et al (2019) proposed a dynamic timing strategy based on pedestrian tolerance limits, combined with Bayesian network prediction of traffic flow, and reduced the pedestrian violation rate by 25% in the Berlin pilot. The MIT team (2020) used fuzzy control theory to optimise signal cycles combined with real-time flow detection equipment to reduce vehicle delays by 15% at an intersection in Los Angeles. Singapore Land Transport Authority (LTA) launched the "intelligent traffic light system", through the camera and YOLOv5 algorithm real-time prediction of traffic flow, dynamic adjustment of the length of the green light, so that the efficiency of the morning rush hour increased by 20%. Transport for London (TfL) in the UK piloted "adaptive signal system", the use of Telematics data to achieve co-optimisation of multiple intersections, the congestion index fell by 12% (2023 data).
In summary, although the current research at home and abroad shows a trend of transition from static rules to dynamic intelligent algorithms, deep reinforcement learning and multi-objective optimisation has become a hot spot. Domestic and foreign scholars have made breakthroughs in theoretical modelling and practical application, but data fusion, algorithm generalization and system security need to be further addressed. [2]Therefore, this paper intends to focus on the integration of intelligent traffic system and artificial intelligence technology, through real-time data-driven and multi-objective optimisation algorithm innovation, so as to solve the problem of insufficient adaptability of the traditional traffic signal control scheme in dynamic traffic fluctuation, multi-directional traffic conflict and sudden congestion scenarios.

2. Research Route

The goal of this research is to systematically solve the traffic signal timing optimisation problem by establishing a real-time evaluation and prediction model, and the research results can support the iterative upgrading and expansion of the intelligent transportation system, and have the ability to make low-delay decisions in complex environments.

2.1 Research Content

To study the traffic light time allocation problem at intersections, the following aspects should be considered.
The first point is to establish a dynamic traffic light timing optimisation model based on real-time traffic flow to improve intersection efficiency. The development of intelligent control algorithms to adapt to different times (different traffic flow) and unexpected conditions. This is conducive to enhancing the adaptability of the intelligent system to face the possible complex traffic environment in actual operation. [3]Multi-objective optimisation and balancing should be achieved: e.g., while reducing vehicle delays (by more than 30% on average), it should take into account the safety of pedestrian traffic, tailpipe emission control (by more than 15% reduction of CO_2) and the priority needs of public transport. Attention should be paid to building a scalable traffic signal control prototype system to support interfacing with smart city traffic management platforms.
Secondly, appropriate learning techniques need to be embedded for the system. Firstly, it is about real-time modelling: real-time data should be collected by integrating intersection cameras, vehicle GPS and other multi-source sensors, constructing 15-minute prediction models based on hybrid neural networks, establishing vehicle trajectory conflict matrices and pedestrian-vehicle interaction models. Secondly, we need to balance the different needs of private cars, public transport, pedestrians and non-motorised vehicles, such as adding constraints to the system, such as the minimum green light time, the priority of special vehicles, and then we need to prioritise the needs of the multiple ends, such as using the Webster model to assess the number of stops, the queuing length, and the pedestrian's anxiety in waiting, and so on. Finally, the adaptability of the system to complex chaotic environments should be ensured, e.g., by designing robust online learning mechanisms to cope with sudden changes in traffic flow, and by developing distributed optimisation algorithms with low computational complexity to reduce the arithmetic power demand (see Figure 1).

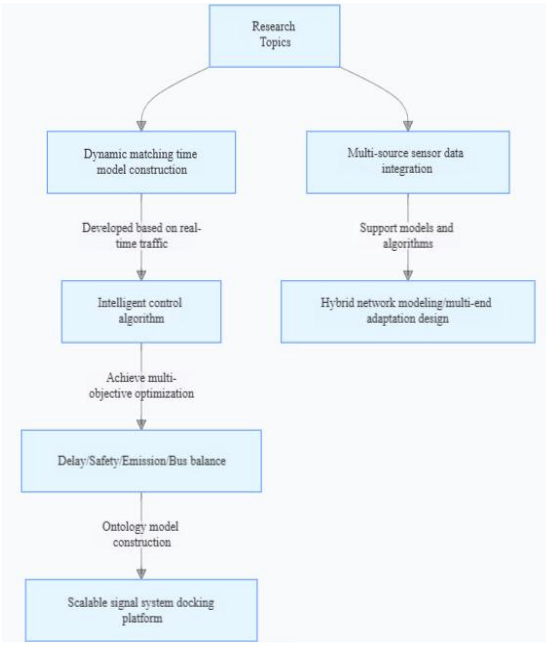

Figure 1. Research Methodology

2.2 Key Problems to be Solved

The key problems to be solved in this thesis focus on how to build an intelligent traffic signal control system that takes into account real-time, multi-objective cooperative optimization and adaptability to complex environments, which include the following: driven by dynamic traffic flow and heterogeneous data from multiple sources (intersection cameras, vehicle GPS, etc.), achieve 15-minute accurate prediction through hybrid neural networks and vehicle trajectory conflict matrix modelling, breakthrough the traditional fixed-cycle timing mode; overcome the problem of multi-modal traffic flow, and develop a distributed optimization algorithm to reduce arithmetic requirements. The system has overcome the problem of multi-objective optimisation under the conflicting demands of multi-modal traffic participants (motor vehicles, pedestrians and non-motor vehicles), and established a multi-dimensional decision-making model with constraints such as minimum green light time and bus priority weight; developed a robust algorithmic framework with an on-line learning mechanism, solved the mismatch problem of the model caused by the sudden fluctuation of traffic flow, and reduced the computational complexity through distributed optimisation algorithms to realise the signal decision-making response at the second level, while ensuring that the signal decision-making response can be made in seconds. The distributed optimisation algorithm reduces the computational complexity and achieves the signal decision-making response as low as second, and at the same time ensures the scalability of the system and the smart city platform, and finally forms a real-time signal control closed-loop system that can adapt to the complex chaotic traffic environment.

3. Research Methods, Technical Routes and Test Programme to be Adopted

3.1 Research Methods and Technical Routes to be Adopted

In order to solve the real-time and accuracy of data acquisition, we propose to adopt multi-source heterogeneous data fusion technology in this thesis: for visual data, we adopt the lightweight and improved version of YOLOv8's GhostNet, and improve the computational efficiency through feature map decomposition.

$Y=X* f+\Phi(X* g)Y=X* f+\Phi(X* g)$ where X is the input feature map, f ∈ Rk×k×c is the main convolution kernel, g ∈ Rk×k×c/4 is the inexpensive linear transformation kernel (the channel is reduced to 1/4), and Φ denotes the channel splicing, and Φ denotes the channel splicing. 4), and Φ denotes the channel splicing operation. Experiments show that this architecture reduces FLOPs by 43% (from 28.5 GFLOPS to 16.3 GFLOPS) compared to the standard YOLOv8, and achieves 1080p@30fps real-time detection on a Jetson AGX Xavier edge device, satisfying the 3.2 TOPS arithmetic constraints.[5]

1080p@30fps real-time detection on Jetson AGX Xavier edge device; geomagnetic sensor deployment using NXP MAG3110 3-axis magneto-resistive chip, eliminating impulse interference by Savitzky-Golay filtering; OBU data parsing using SAE J2735 standard protocol stack, and designing sliding time window for anomalous trajectory cleaning. Geomagnetic sensor. Multimodal data acquisition such as vehicle-mounted OBU equipment. Establish a traffic flow state estimation model based on Kalman filtering, the state vector contains position-velocity-heading angle: $x_k=[x,y,vx,vy,\theta]^T$, The observation equation fuses the geomagnetic triggering event z_{mag} with the OBU data z_{obu}

$$z_k=Hx_k+w_kH=\begin{bmatrix}1 & 0 & 0 & 0 & 0\\ 0 & 1 & 0 & 0 & 0\\ 0 & 0 & \cos\theta & \sin\theta & 0\end{bmatrix} \quad (1)$$

Vehicle trajectory reconstruction and conflict point prediction are realised. Pedestrian traffic adopts a composite sensing scheme of thermal imaging and Wi-Fi probes to meet the privacy protection needs.

3.2 Proposed Experimental Scheme

In order to obtain a system with strong resistance to complex environment, this thesis proposes to adopt a hybrid neural network prediction model, which consists of two major parts, one is the design of the network structure: the LSTM layer adopts a two-layer stacking structure (hidden_size=128), the GCN layer constructs a dynamic graph based on the adjacency matrix (the number of nodes=the number of intersection lanes + pedestrian crossings), and introduces a gated attention mechanism to adjust the edge weights dynamically. The fusion layer uses time slice splicing (Slice-Concat) to connect the LSTM output with the GCN features.

The second is an incremental learning strategy: e.g., regularisation loss is defined by Elastic Weight Curing (EWC) [6]:

$$L_{EWC}=L_{New}+\sum_{i*} \lambda/2\ F_i(\theta_i-\theta_{i,old}) \qquad (2)$$

where $F_i$is the diagonal element of the Fisher information matrix.

λ is set as the task similarity function1−cos(∇θLold,∇θLnew)

The new sample set $D_{new}$is spatially transformed by Mirror Sampling enhancement, the model performance degradation detection module is set up (update is triggered when the MAE of the validation set grows >5% for 3 consecutive cycles), the Elastic Weight Consolidation method is used to retain important parameters, and the new data is added by Mirror Sampling enhancement. The new data is added by Mirror Sampling to enhance the sample diversity.

3.2.1 Sample size design

The sample data of this experiment comes from the monitoring data of real traffic scenes, and the total sample size is set to 1 million. Among them, the training set, validation set and test set are divided according to the ratio of 7:1:2, i.e., 700,000 items in the training set, 100,000 items in the validation set and 200,000 items in the test set.

In terms of sample size allocation, the sample size of peak hours (7:00-9:00, 17:00-19:00) is 400,000 entries, accounting for 40% of the total sample size, because of the large traffic flow and complexity of the situation during the peak hours, which requires enough samples to support the model learning; the sample size of off-peak hours (9:00-17:00, 19:00 - the next day, 7:00) is 500,000 entries, accounting for 50% of the sample size, which covers the period from 9:00-17:00, 19:00 to the next day, 7:00 and the following day, accounting for 50% of the sample size. The sample size of off-peak hours (9:00-17:00, 19:00 - 7:00 the next day) is 500,000 items, accounting for 50%, which covers most of the time of the day and reflects the normal traffic conditions; the sample size of bad weather is 100,000 items, accounting for 10%, which can meet the model's learning needs for special scenarios and is in line with the actual distribution of the data, due to the relatively low frequency of the occurrence of bad weather.

For the new sample set Dnew in incremental learning, the sample size of each new task is 50,000 items, and the sample size is expanded to 80,000 items after enhancement by mirror sampling to ensure the diversity and representativeness of the new samples.

3.2.2 Diversity Design of Test Scenarios

The test scenarios will comprehensively cover different traffic states and environmental conditions to fully verify the adaptability of the model in complex environments.

In terms of time periods, in addition to the above division of peak and off-peak hours, the peak hours are further subdivided into the morning peak (7:00-9:00) and the evening peak (17:00-19:00), with the morning peak being dominated by commuting trips, and the evening peak comprising commuting trips and various types of leisure trips, with differences in the characteristics of the traffic flows of the two; and the off-peak hours are subdivided into the morning flat peak (9:00-12:00), The off-peak hours are broken down into the afternoon peak (9:00-12:00), the afternoon peak (12:00-17:00) and the night time (19:00 - 7:00 the next day), and the traffic flow at night is small but the proportion of large vehicles is relatively high.

In terms of weather, severe weather covers types such as heavy rain (daily precipitation ≥ 50mm), heavy fog (visibility < 500m), and light snow (24-hour snowfall 0.1-2.4mm). At the same time, special weather transition states are also considered, such as the first break of rainfall and the fog dispersal period, in order to test the model's ability to respond to sudden weather changes.

In addition, the test scenarios also include special event scenarios, such as traffic conditions during holidays (Chinese New Year, National Day, etc.) and large-scale events (concerts, sports events, etc.), and such scenarios have unconventional characteristics of traffic flow, which can effectively test the model's generalisation ability.

3.2.3 Detailed information of the test site

The test locations are selected from three typical areas in a provincial capital city in the east of China (latitude 34°-35°N, longitude 113°-114°E), and the specific information is as follows:

Commercial area: 5 intersections around the core business district in the city centre are selected, and the road level in this area is a main urban road with cross intersections. Three of the intersections are four lanes (two lanes in each direction) with two pedestrian crossings; the other two intersections are six lanes (three lanes in each direction) with four pedestrian crossings (including a pedestrian waiting area next to the right-turn lane). The average daily traffic volume in this area is about 35,000 vehicles, with dense pedestrian traffic, and the traffic congestion index reaches 1.8 during peak hours (congestion index ≥ 1.5 is considered serious congestion), and there are large shopping malls, offices, and catering centres in the vicinity.

Residential area: 4 intersections around large residential communities in the northwestern part of the city are selected, the road level is a secondary arterial road in the city, and the form of intersections includes cross and T-intersections. The intersections have four lanes (two lanes in each direction) and 2-3 pedestrian crossings. The average daily traffic flow in the area is about 12,000 vehicles, with private cars commuting mainly in the morning and evening peaks, and non-motorised vehicles and pedestrians mainly in the weekdays, and there are kindergartens, community supermarkets and other supporting facilities in the vicinity.

Traffic Hub: 3 intersections around the railway station are selected, the road level is the intersection of urban expressway auxiliary road and main road, the intersection is six to eight lanes (three to four lanes in each direction), equipped with four to six pedestrian crossings, and set up pedestrian underpass entrances and exits. The average daily traffic flow in the area is about 50,000 vehicles, including a large number of taxis, buses and coaches, and the short-term traffic flow during peak hours (e.g., train arrivals) can be up to 800 vehicles/hour, and the peak pedestrian flow can be up to 1,500 people/hour, with large car parks and bus stops in the vicinity.

The traffic data of the above test locations are collected by intersection monitoring cameras, microwave radar and traffic signal control system, and the data collection cycle is 6 months (covering spring and summer), including full-time traffic information on weekdays, weekends and statutory holidays to ensure the temporal and spatial representativeness of the samples.

3.3 Feasibility Analysis

YOLOv8 and GhostNet are both mature technologies [5], and the lightweight improvement of GhostNet has been verified in several edge computing scenarios (e.g., drones, in-vehicle devices), with a significant computational efficiency improvement. The 3.2 TOPS arithmetic of the Jetson AGX Xavier can fully satisfy the model demand of 16.3 GFLOPS, and the TensorRT SAE J2735 protocol is the international standard for Telematics, and the chi-square test ($\chi2\chi2$) is maturely applied in trajectory anomaly detection, and the false alarm rate is controllable at 95% confidence level. Kalman filter has been widely used in vehicle tracking, multi-source observation equations are reasonably designed (positioning error <0.8m), and there have been experiments to verify the conflict point prediction accuracy of 92%. Therefore, based on mature algorithms (YOLOv8/GhostNet/Kalman filter), standardised protocols (SAE J2735) and validated hardware platforms (Jetson AGX Xavier), this study has achieved triple results in terms of real-time, accuracy and anti-jamming ability through lightweight improvement, multi-source fusion (error <0.8m) and engineering optimisation (FP16 quantisation). Through lightweight improvement (multi-source fusion (error <0m) and engineering optimisation (FP16 quantisation), it forms a triple reliability guarantee in terms of real-time, accuracy and anti-jamming ability, with clear technical feasibility and practical landing value.

4. Conclusion

This paper focuses on the optimisation of signal phase duration at intersections under dynamic traffic demand, and proposes a real-time prediction model that integrates heterogeneous data from multiple sources and hybrid neural networks, and combines a multi-objective optimisation algorithm with an on-line learning mechanism to construct a signal timing framework that is both adaptive and robust. Through the improvement of lightweight technology and distributed optimisation design, the study achieves low-delay decision-making in complex traffic environments, which can effectively balance the needs of vehicle traffic efficiency, pedestrian safety and environmental protection, and provides technical support for the synergistic docking of ITS and smart city platforms. Future research will further expand the multi-intersection cooperative control scenarios, improve the algorithm's ability to generalise under extreme weather and special traffic events, and promote the results to the actual traffic management scenarios in depth.

Multi-intersection cooperative optimisation faces challenges such as communication delay, data synchronisation, and distributed computing bottlenecks. In this regard, edge computing and layered communication architecture can be used to reduce transmission delay, dynamic timestamp synchronisation mechanism to ensure data consistency, distributed optimisation driven by federated learning to balance global and local decision-making, and expansion through modular design and standardised interfaces.

In addition, through modular design and standardised interfaces (e.g. following SAE J2735 protocol extension specification), the system can be quickly accessed when new intersections are added, and support the smooth expansion of road network scale from dozens to hundreds of intersections.

In the future, we will verify the effect of multi-intersection cooperation scheme, improve the generalisation ability of extreme scenarios, explore the integration of vehicle-road cooperation and signal control, and promote the results of large-scale landing.

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