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An integrated intelligent intersection management and control system design

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Abstract. While a fair amount of study has been done recently on integrated management and control models for large-scale traffic systems, there is comparatively little information available regarding the design of management and control systems for small-scale intersections. This study aims to create the structural diagram of a management system for intersections and control technologies. It does this by designing three distinct systems: congestion prediction, traffic signal timing, and congestion flow dredging. This study searches the current state of common technology and chooses the intersection integrated management system by means of comparison. Fuzzy TOPSIS algorithm and ADP adaptive dynamic programming are chosen as the calculation techniques of signal lamp timing, while BP neural network and ATT-GCN network are chosen as the key algorithms of congestion prediction after thorough investigation. In the end, conventional traffic management techniques like forbidding left turns are used to direct cars that haven't arrived at the busy crossroads beforehand. This paper aims to select the best model for an intersection management system currently available from the common technologies. The idealized management system and its structure diagram are designed in a straightforward manner, and they will serve as a guide for future road and vehicular intersection design.

Keywords: Intersection integrated, congestion prediction, traffic signal timing, congestion flow dredging.

1. Introduction

These days, there are a lot of integrated traffic management systems in place, thus there aren't as many distinct intersection road traffic control systems. Instead, management system research focuses on the large model building part of the system, which needs to take into account a variety of geometric conditions of the road, including overpasses, ramps, and other roads [1, 2]. Many academics are currently studying the prediction of traffic congestion utilizing deep learning, big models, and related methods. In addition, it is crucial to maintain a reasonable flow of traffic during periods of traffic congestion. This calls for actions such lane changes that are signaled in advance, real-time updates, and road reconstruction prior to intersections. Simultaneously, the signal light control system is especially significant when discussing intersections. Moreover, choosing an effective dynamic transformation signal timing algorithm and control system is highly beneficial to the dynamic traffic flow during peak traffic hours.

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In order to provide some guidance for the future development direction, this article will synthesize the three systems mentioned above: the intersection congestion prediction system, the traffic flow guidance system, and the signal light dynamic timing system. It will also compare the overall performance of each system's current technologies, summarize and summarize the technology with good results, and thoroughly design an intersection traffic control system that is currently understudied.

2. System Overall Design Scheme

Three technologies are integrated to create a bidirectional intersection in the figure 1 below.

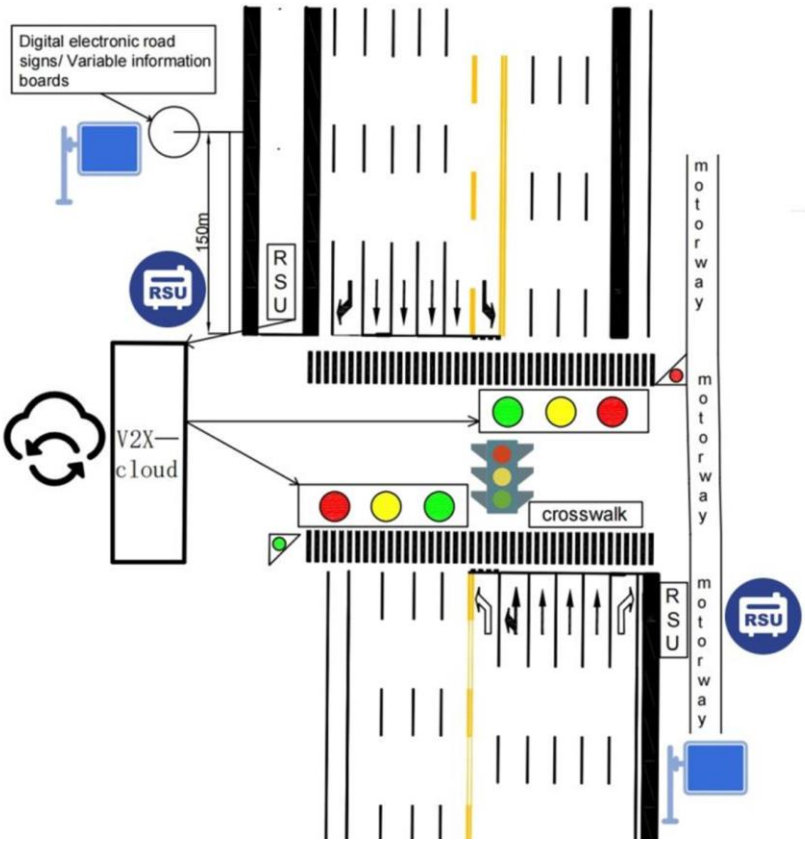

Figure 1. System overall structure (Picture credit: Original)

The vehicle networking technology serves as the primary hardware and software carrier. To receive vehicle guidance information and produce comprehensive road information, the RSU side unit and the traffic flow status sensor are respectively established at the road test at the intersection. Following computation and processing, a forecast of the traffic flow congestion is produced. Furthermore, the intersection's intelligent traffic light system receives the real-time signal cycle timing and uses it to adjust the signal lamp's green and red times in real time by utilizing the best possible algorithm. Using road information (such as tidal lane changes, no left turns, etc.), the variable information board, which is positioned 150 meters from the intersection, is intended to show the geometric changes of the road ahead of the car.

3. Intersection Traffic Congestion Prediction System

Currently, there are various methods for intersection congestion prediction. After investigation, it is found that the following methods are more frequently used: Auto-Regressive Integrated Moving Average (ARIMA), Double Exponential Smoothing, BP Neural Network method, and Translation Nested Network model. To date, deep learning technology has become the mainstream.

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3.1. Basic Theory of Congestion Prediction

There are a variety of existing prediction models. However, after summarizing their characteristics and application scenarios, they can be roughly divided into several categories. The following introduces and analyzes the three most widely used algorithm models.

3.1.1. Auto-Regressive Integrated Moving Average Model (ARIMA)

The ARIMA model (autoregressive integral Moving average model) is a time series model used to analyze and model data that changes over time [3]. The model captures patterns in the data and predicts future values by combining autoregressive, moving average, and differential components.

The basic idea of the model is that the data sequence shown by the forward movement of the target to be predicted is arranged in the order of time, and the corresponding mathematical model is used to simulate and describe the data sequence. With the corresponding algorithm, once the model is identified, the historical observation data can be used to make predictions about future data.

3.1.2. Translation Nesting Algorithm

Current traffic congestion prediction mainly utilizes deep learning algorithms such as RNN, LSTM, and GRU, and applies the translation nesting method to judge traffic conditions. Based on the data of time, space, weather, and history, this method adopts PI values of grid connections to establish prediction models [4]. By using deep learning to calculate the spatiotemporal characteristics of intersection traffic, this method can obtain the result of traffic jam prediction. In general, this algorithm is combined with various deep learning algorithms and is more effective in alleviating traffic jam than using any single deep learning algorithm.

3.1.3. Neural Network Series

It is worth noting that in recent years, several deep learning algorithms have been extensively applied to traffic congestion prediction, such as BP neural networks and GCN fusion models [5].

BP Neural Network: Due to the dynamic nature of transportation systems, linear trend models often fail to accurately capture their changing patterns. To address this challenge, BP neural networks, known for their strong non-linear fitting capabilities, are widely utilized. The BP neural network operates by minimizing the network error through an iterative process of weight adjustment between neurons. This learning process involves continuously updating weights to optimize network performance. BP neural networks exhibit two fundamental characteristics: firstly, every neuron in each layer connects to neurons in the preceding layer. Then, secondly, there must be at least one hidden layer between the input and output layers, resulting in a multi-layer feedforward neural network model [6].

GCN Network: GCN stands for Graph Convolutional Network, introduced in 2017. Since data in traffic networks are graph data, which are difficult to compute using CNN convolutional neural networks, using GCN networks, a tool for processing graph data, facilitates traffic congestion data computation and prediction. GCN networks are characterized by local connectivity, which can reduce the network's computational complexity to some extent, enhancing the efficiency of real-time traffic congestion prediction [5].

The CNN VS. GCN is shown in figure 2.

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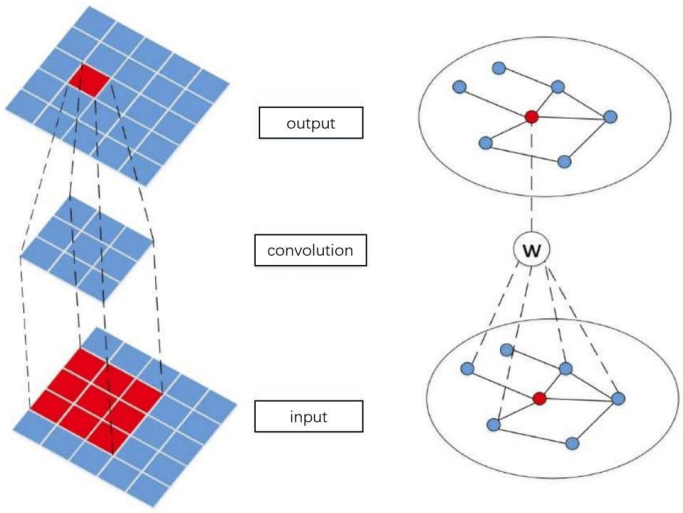

Figure 2. CNN VS. GCN [5]

3.2. Related Theoretical Application Examples

Many scholars have conducted additional study using the traffic congestion prediction systems outlined above.

3.2.1. Practical Application Examples

Zhang Fuqiang used K-means clustering and ARIMA prediction technologies to identify the traffic situation. A transportation volume time series was used to calculate the standard BIC value, which came out to be 2.334. First-order moving average, second-order differencing, and zero-order autoregression were used to build the model. Transportation volume, average speed, traffic density, delay index, average braking times, and average braking length were all measured in this way. High prediction accuracy was demonstrated by the results of each experiment, which showed a high similarity between the actual observed values and the model fitting values [3].

A deep learning model for ATT-GCN fusion was created by Zhang Lifan. The notion of an attention mechanism (ATT) from the field of visual technology was incorporated into the model, expanding upon the GCN network. By successfully blurring the non-key road sections, this improved the time-fitting capabilities and resolved the issue of regular models' inability to store historical data for extended periods of time. The attention mechanism had an impact on the model, which led to a significant improvement in the prediction accuracy of main road congestion at the expense of branch road congestion [5]. This is especially useful for intersections with only main road crossings, as it can improve the intersections' capacity to predict congestion.

In order to simulate the Beijing North Third Ring Road to the North Fourth Ring Road portion, Wang Liwei used a translation-embedding model and includes a variety of traffic phase structures, such as crossings. When compared to other deep learning techniques, the researcher's LSTM2L-GRU model showed a noticeably greater PI value (as stated in the theoretical part above) prediction capabilities during peak traffic periods [4].

Based on current technologies, study on the aforementioned methodologies demonstrates that traffic congestion prediction accuracy has been substantially enhanced. Some directional shortcomings still exist, though. For example, the translation-embedding model's prediction performance is weaker than that of standard deep learning algorithms at intersections where traffic flow is both smooth and rapidly changing, and the mean absolute error of the ARIMA method for average speed reaches 6.7%. The ATT-GCN model is also unable to predict smaller branch roads with any degree of accuracy or to adapt to highly complex intersections.

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3.2.2. BP Neural Network Prediction Method's Examples

In order to confirm that BP neural networks are feasible for predicting traffic flow during periods of congestion, Liu, ZB et al. created a short-term traffic flow prediction model for a single intersection and used a variety of techniques [7]. Ma, QF successfully carried out simulation and created a short-term traffic flow prediction program based on the BP neural network technique of enhanced particle swarm optimization. The software's simulation data will be utilized to inform future predictions of intersection congestion as well as the prevention and management of traffic-related environmental pollution [8]. Qin, En conducted research on BP neural network, established the short-term traffic flow evaluation model of BP neural network based on MATLAB software code, and generated guiding data for traffic flow prediction in the simulation. The model was also applicable to the prediction of traffic flow congestion [9]. Hu Xinze et al. identified 10 influencing factors, including new drivers, road construction, and morning and evening rush hours, based on their analysis of the traffic system. These factors were then screened using the principal component analysis method, BP neural network was used, and an urban traffic congestion prediction model was created. The thorough model may be broadly applied and has a high degree of accuracy. It has a specific use case [10].

In the current stage of traffic congestion prediction, BP neural network is a fundamental technique worth selecting due to its good performance and universality as a popular application algorithm.

4. Traffic light dynamic timing system

In the field of dynamic timing of signal lights, there are many popular research methods. Researchers focus on the professional knowledge of traffic timing such as minimum red-light time, and take vehicle-road collaboration technology, approximate dynamic programming (ADP), floating vehicle data analysis and other related technologies as the background technology for further algorithm development, model establishment, timing optimization evaluation and other work.

4.1. Basic Theory of traffic light's dynamic timing system

Regarding particular signal light dynamic timing technologies, this paper will introduce the more sophisticated ones in turn: fuzzy TOPSIS algorithm, adaptive dynamic programming (also known as approximate dynamic programming, or ADP), and more conventional signal light timing algorithms in the traffic domain.

4.1.1. Approximate dynamic programming system

Approximate dynamic programming (ADP), sometimes known as "adaptive dynamic programming," is a potent technique for resolving difficult sequential decision-making issues. Over time, ADP algorithms' performance is enhanced by experience. The evaluator, actuator, and model are the three elements that make up the ADP framework. After evaluating the actuator's plan, the evaluator calculates the associated value function [11]. The actuator then uses the evaluator's estimates to optimize its plan of action. To direct the learning process, the model produces training signals.

Werbos' research indicates that heuristic approximation dynamic programming (HDP) is a well-liked ADP algorithm. Neural network-based HDP is a fast-converging ADP technique that does not rely on models and can learn from data directly [12]. Since HDP can handle complicated traffic problems with elaborate models and large volumes of data, it is frequently utilized in the design of dynamic traffic signal lights.

4.1.2. Fuzzy TOPSIS algorithm

The fuzzy TOPSIS algorithm blends the fundamental TOPSIS method with the fuzzy algorithm. Technique for Order Preference by Similarity to Ideal Solution is referred to as TOPSIS. It seeks to identify the best and worst options for a given problem. The algorithm determines each alternative's weighted Euclidean distance from both the positive and negative ideal solutions. The alternatives are then assessed based on how close they are to the ideal answer. For the first time, Chen defined the Euclidean distance between two fuzzy integers and extended TOPSIS to the domain of fuzzy decision

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making [13]. Furthermore, fuzzy values rather than precise values were used in the analysis because of issues like fuzziness and uncertainty in the data in the analysis scenario. The main concept is to sort and then choose the best value. TOPSIS algorithm is a powerful multi-criterion decision-making method. It is widely used in various fields, including signal lamp timing optimization.

4.1.3. Traditional traffic timing algorithm

The first is the floating automobile data analysis approach, which operates on the basis of gathering pertinent driving data from vehicles and combining it with deep reinforcement learning to perform unstable and dynamic real-time timing at intersections [14]. The multi-mode joint optimization signal timing model is the second. The purpose of the so-called multi-mode joint is to combine the five fundamental parameters of traffic capacity, saturation, delay time, queue length, and stop periods in order to optimize the system fully [15]. The multi-period division model, which divides periods using the K-means clustering algorithm and assigns the duration of the red and green signal lights within a suitable amount of time for each period using the signal phase matrix [16].

4.2. Related Theoretical Application Examples

The relevant study findings for each of the aforementioned theories will then be listed, examined, and chosen.

4.2.1. Practical Application Examples

In the context of adaptive dynamic programming system technology, Di Liu et al. created a switch-based control formula for a multi-intersection, multiphase traffic light system using heuristic approximate dynamic programming. A macroscopic method of modeling traffic flow was proposed in related works. The vehicle traffic improvement effect of the system is also reflected in the simulation data [11]. This method is helpful for the creation of a traffic signal operation optimization system based on model and handover under adaptive dynamic programming (ADP) architecture.

For traffic signal timing control systems, Hakim, Galang P. N., et al. presented a fuzzy TOPSIS algorithm based on the number of cars in real-time and vehicle classification. Vehicle metrics, such as vehicle length in this study, were used to determine which vehicles should be prioritized based on the algorithm. Automobiles rank third in importance. The maximum passing time of a single vehicle for each type of vehicle is then determined by computing the coefficient; for example, 2.771552 seconds for trucks, 2.581965 seconds for buses, and 1.862602 seconds for cars. Setting the duration of traffic lights at junctions is guided by the calculated time [17]. The main formula of traffic light timing equation generated by Fuzzy TOPSIS is shown in the final formula (1)

$$T = \sqrt{2(\sum_{i=1}^{n} L_i}\,.\,\alpha.CCi \tag{1}$$

Where i = 1,2,3,4 …n, T means proper timing's seconds for different vehicle. Transform maximum passengers' comfortable acceleration threshold as other component a= 0.93. L_i means total all vehicle length. CCi means closeness coefficient

In order for the deep learning framework to extract the traffic state from floating vehicle data and make real-time predictions and adjustments to signal lamp timing, Chen Qade proposed an adaptive optimization of signal lamp timing technology. This involves learning the data evolution law and operation mechanism of the floating vehicle method in the field of traffic [14]. Using the multi-joint optimization timing approach, CAI Jinde et al. established the hierarchical structure model and judgment matrix with the goal of increasing traffic capacity, decreasing delay and queue length, and obtaining good simulation results using VISSIM [15]. Following the division of the route into several phases, Li Yanan and colleagues separated the arriving intersection's phase, created a phase matrix, and employed a genetic algorithm to solve the problem. It was done to time the signal phase flow according to various periods. Following simulation, the technique was able to cut the total latency by 9.1% [16].

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4.2.2. Analysis and evaluation based on algorithm examples

The fuzzy TOPSIS algorithm is more visually appealing, has obvious stages and a reasonable level of complexity, and produces more logical and reference-worthy timing results for the multi-dimensional traffic elements, according to a search of simulation data and the literature's calculation process. Furthermore, the method may be used to construct the coefficient system, which can adjust to crossings with various types and flows of traffic. The approach is generally applicable to signal timing systems with different types of intersections.

The primary benefit of the handover-based approach described in this paper for the ADP algorithm system is that it eliminates the need for the cyclic average flow approximation, which is a common feature of mainstream methods currently in use, and allows the system to choose whether to activate a particular type of signal timing model at a given time point for a given duration based on traffic conditions. Furthermore, the framework does not require synchronization requirements in order to manage varying cycle times at intersections. Under certain traffic demand conditions, the minimum residency time constraint can be explicitly enforced, allowing the signal light to be timed to suit the minimum green or minimum red time of each phase.

In summary, there are a few issues with the dynamic signal lamp timing approach in comparison to the standard signal lamp timing, including high computing complexity, challenging modeling, and significant time costs. The system setup and implementation costs have not been calculated, which is a consideration. Additionally, this method needs to be combined with deep learning and other technologies, or its implementation requires road hardware basis and road geometry basis based on vehicle-road collaboration [18]. In contrast to the two aforementioned algorithms, the single computation model's system implementation stability is greater and its cost is more unknown.

5. Traffic flow dredging system

Following a search and summary, it is discovered that the primary techniques for removing traffic flow congestion may be examined using the following formulas.

In order to reach the saturation traffic flow occupying one route, Li Xiaoyan uses the node-diverting approach to gather OD data and the Dijstra shortest path algorithm to direct certain vehicles to alternate routes with lower decircuit costs beforehand [19]. A grey-fuzzy road network dredging decision-making model based on road network equilibrium was created by Ren Qiliang and his colleagues. Selective choice dredging was chosen after comparison with four traffic dredging method models [20]. Tan Xiaojie of Southeast University combined data mining, data warehousing, and decision support techniques. She thoroughly examined the factors contributing to congestion, which could be summed up as high traffic demand, traffic load, etc., in order to create a model that would specifically address the aforementioned factors and improve traffic flow [21]. Using Tianjin City as an example, Liu Heng also utilized the technique of gathering road network data. He then created a dredding traffic Q calculation model and a decision-making model to ascertain the beginning and ending points of the induced diversion as well as the choice of dredding path [22]. The most fundamental traffic flow diversion control strategy, however, was put forth by Liu Shuqing of South China University of Technology. It included boosting the capacity of the intersection entrance, restricting the amount of traffic that can enter downstream intersections from upstream intersections, and capping the rise in traffic demand at downstream intersections. He made the deliberate choice to forbid making left, right, or U turns, and he made vehicles choose alternate routes based on traffic demand, which caused the flow of traffic to be diverted [23].

This study finds that the main idea is to either force the cars to take the alternative way with the lowest consumption cost or allow them choose it on their own after a thorough analysis of pertinent approaches. While there are algorithms that can calculate the course ahead of time, the most efficient approach to guarantee diversion is to limit the phase of road crossings by forbidding left turns during rush hours. This approach can simultaneously avoid algorithm complexity and lower intersection management system layout costs (the system load is significant due to the other two systems' relatively

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high algorithmic complexity). Consequently, it is best to notify drivers in the opposite direction of the road's closure during rush hour just prior to the intersection.

6. Conclusion

The existing intersection management system's traffic demand is thoroughly examined in this study, and the system as a whole is broken down into three components: the traffic flow dredging system, the traffic light dynamic timing system, and the intersection traffic congestion prediction system. Based on pertinent research, the primary models, algorithms, and strategies of these three systems are examined. In addition to analyzing the relevant algorithms' underlying principles and actual research instances, this paper offers design recommendations and technique selections for each system in the comparison and selection of experimental data or algorithm features.

Initially, the author discovered in the Intersection Traffic Congestion Prediction System that the BP neural network application performs well in real-world scenarios. As a result, the BP neural network method is incorporated into the complete system. The ATT-GCN algorithm model may also efficiently realize the precise forecasting of traffic congestion at sizable crossroads.

This paper examines the pertinent data analysis in the traffic light dynamic timing system and conclude that the fuzzy TOPSIS algorithm and ADP approximation dynamic programming can be employed as the main methods for dynamic timing of signal lights. Implementing the features of real-time-changing signal lamp timing at crossings is incredibly accurate and efficient. It is important to note that the ADP approximate dynamic programming system can enforce the minimum green and red-light times at intersections under unconstrained conditions, while the fuzzy TOPSIS algorithm can generate customized minimum passage times at various intersections for various vehicle types. As a result, there is less needless green time during periods of low traffic.

The author finally outlines the ultimate structure of the idealized large-scale integrated intersection by summing the previously chosen methodologies and the author's structural diagram of the intersection management system, which is mentioned in Part 2.

Conveniently, the data transmission occurs in real-time and the management system is configured based on vehicle-road coordination. First, at the sides of four phases of intersections, respectively, RSU side units and sensors for traffic flow status monitoring are set up. These devices are used to capture data like the number of vehicles, the proportion of models, and the traffic flow in a specific period of time. The collected data is then uploaded to the cloud system of V2X-cloud of the vehicle-road cooperation system. The variable information board displays no left turn or other instructions at 150 meters before the intersection (this distance can be changed according to the intersection geometry). The cloud computer then uses the ATT-GCN algorithm or BP neural network algorithm to calculate reasonable traffic congestion queuing time, total delay, queue length, and other data. It then implements reasonable road traffic flow diversion measures and uploads the instructions to the variable information version. Finally, it clears the congested traffic flow based on the selected section and the path of least cost detour. The green and red-light durations (or ADP approximation dynamic programming) are then determined using the fuzzy TOPSIS algorithm in accordance with the characteristic data, such as the vehicle proportion. Every time a period occurs during peak and congestion periods, the real-time signal length is computed. During off-peak hours, the signal light's predetermined time period is adopted and delivered to the light for precise display to allow traffic to proceed.

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