Machine Learning for Autonomous Vehicle Traffic Signal Prediction and Coordination

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1. Introduction to Autonomous Vehicles and Traffic Signal Coordination

Recent research-grade literature posits developing novel traffic control policies that could better accommodate both human-driven vehicles and CAVs [1]. In addition to the traffic control strategies selected based on the general traffic characteristics, personalized traffic signal control strategies and timing policies may be determined according to the requirements of the CAVs waiting at the intersection in future smart cities. It is not clear how reinforcing the importance of informed platoon signal control can reduce the conflict of vehicles. By quantifying how traffic signal schedule feeds back the expected number of vehicles in a network, the threshold rates are derived, which demonstrate the importance of synergy between the left-turn movement and the platoon signal at an unsignalized intersection; a competitive characteristic exists between the through movement and left-turn movement at the signalized intersection; the majority of drivers may choose to rejoin the queue lane.

Human Machine Symbiosis in Traffic Signal Coordination [text_start] Smart cities and intelligent transportation systems (ITS) are future urban designs in modern civil engineering and transportation domains. Incorporating advances in traffic control and communication technology, connected and automated vehicles (hereafter referred to as CAVs) are developing rapidly. Aiming to enhance safety, reduce environmental impacts, and avoid traffic congestion, CAVs have been evolving from representation of development plans to new practice scenarios [2]. Nevertheless, one indispensable component of urban transport—the conventional, human-controlled, signalized intersections—may hinder the transition of the entire transportation system to the new era where all vehicles are automated. With greenwaves and vehicle-to-everything technology, vehicles run smoothly in every condition. In fact, to maximize urban transport performance under different traffic conditions and to reduce the congestion index of road traffic due to the conflict effects caused by intersections, microscopic models are essential for both the control of traffic signal lights and for the planning of decision making modules in intelligent vehicles [3]. [text_end]

1.1. Overview of Autonomous Vehicles

The state of the art in machine learning (ML) algorithms gives accurate and complete predictions, improves design performance, and in general provides appropriate functioning of traffic signal controllers [4]. Nevertheless, in the context of controllers, ML can stand for century-old tools like neural networks (NNs) or decision trees, or more modern approaches like the deep Q-learning that are based on reinforcement learning. The latter are the main focus of this article. Besides the data-driven nature of the approach, one of the key features behind ML is the adaptation complexity which means that agents require historic data to operate. Consequently, an unexpected input, such as a construction zone, can severely degrade the traffic network's performance. Though such retraining frequency for updating Q-table can be defined as a matter of time (with a predefined heuristic) or event, it can be argued that our current transportation systems are gradually facing new and unexpected situations frequently and it can be very costly to retrain agents after each single new setup [5]. This is in fact important because constructing a sufficiently large and efficient dataset may impose further effort in comparison to more classical models; as a result their generalization will be significantly limited. Therefore it is indispensable, to look into the adaptability of the system will pave the way to solve numerous contemporaneous problems.

Traffic signal coordination, route prediction, and driver assistance systems have been widely studied in the context of autonomous vehicles (AVs). In these domains, there is a wide range of methods including traditional mathematical optimization and machine learning algorithms [6]. Recently, large-scale traffic systems are equipped with both human-driven vehicles (HVs) and AVs. The presence of mixed traffic flow provides another level of thoughtfulness to achieve the reasonability of traffic control and coordination. For this purpose, AVs should communicate timely with each other and with the infrastructure, which has led to a growing interest in the traffic signal–AV coordination and prediction subject.

1.2. Importance of Traffic Signal Prediction and Coordination

The traffic signals should be predicted and verified, because the initial phase (orange light or green light) setting is the initial information for the intersection passing flow for the spatial string in our model, which is affected by many factors such as the phase order, traffic flow, and driving decision methods. How to arrange the initial phase of the initial traffic lights in advance to make the traffic lights play the greatest role and help the vehicle navigation safely and efficiently through the intersection has become a hot spot of current research work. Due to the impact of road attributes such as intersection structure, traffic flow size, and road network layout on traffic signal field, the initial signal light setting of the field traffic light signal also has a great impact on its traffic efficiency. Therefore, it is of great significance to predict the signal status in the future based on the real-time observations of the traffic departments in real time to provide historical traffic operations, calculate transportation-global optimal traffic signal setting, solve real-time solution operation and algorithm to solve the optimal solution, simulation optimization, and expected operation. In addition, smart traffic signal system facilitates the smooth passing of vehicle flow by predicting the signal status and adjusting travel plan in advance, which can effectively reduce the waiting time of vehicles on the intersection waiting. In this model, multiple signals can be combined and cooperated at any time, and flexible traffic rights are decorated.

[7] There is a high-priority need for developing smart traffic signal systems to enhance urban mobility [9, 29]. The research community has made significant progress in advanced signal control algorithms based on vehicle-to-vehicle communication, vehicle-to-infrastructure communication, and the sensor and camera information of road infrastructure [13, 50]. Despite the research achievements, the performance of current traffic signal control systems can still be greatly improved. First, if the observation data of a traffic signal with a priority of vehicles are not taken into account, the phase setting of the signal is not beneficial for AI transportation-unified spatial-temporal, customized space-time-varying confirmation intelligent service and appreciable volume of traffic intersection. The interaction of the priority vehicles in the customized space-time-varying road, space-time-varying environment, and in the customized space-time-varying road attributes.

2. Fundamentals of Machine Learning in Traffic Engineering

The use of machine learning in real scenarios has been proved to be effective in optimizing urban road links, helping the system to be able to predict traffic problems, but this method cannot be directly applied in the scenario of traffic signal control and coordination. The real-time traffic control system is more complicated than the road link traffic optimization problem, integrating the information of multiple intersections and lanes, as well as more innovative techniques, removing unnecessary links or intersections, and keeping the continuity of traffic can imate traffic conditions more effectively and accurately. Therefore, effective traffic prediction and coordination issues are very important. The prediction model for traffic signal control scenario based on machine learning can effectively predict future traffic states so that the signal control algorithm can take measures in advance to deal with potential problems and improve many traffic security limits [8].

[9], [10] The advent of autonomous vehicles, smart cities, and Internet of Things technologies has made real-time traffic signal control, reasonable road resource allocation, and flow coordination increasingly popular and important topics in the field of traffic optimization and control. Traffic signal optimization is an effective method to solve the traffic congestion problem to a certain extent. Improving traffic signal coordination is a hot topic in the research and practice of traffic management and control. Various optimization algorithms have been proposed for urban traffic signal coordination and control. However, these algorithms are difficult to satisfy the fluctuating traffic environment. Machine learning can effectively analyze complex road traffic issues by extracting the potential relationships between historical traffic data and provide valuable traffic iron for optimization decisions. Researchers have tried machine learning in traffic signal control, which also shows its potential in solving traffic prediction problems.

2.1. Supervised Learning Algorithms

The key for this solution is to predict the speed and the traffic light ahead of time. The methods used for speed prediction have all been influenced by the traffic flow prediction field [10]. Traffic flow prediction has developed through three fields. Originally, traffic flow prediction began with classical statistical models. As traffic data eventually grew more complex, machine learning was adopted and thus began a whole new era for traffic flow prediction. The machine learning algorithms commonly used for traffic prediction include KNN,K-means, SVM, Bayesian network, ANN, etc. Traffic flow prediction in the present day is becoming an even more complex subject because methods employing multimodal data for prediction targeting road network systems have been developed. The traditional data processing methods for traffic light prediction have been K-means, time series prediction, and machine learning, mainly for predicting delay and control. More recent methods have employed deep learning and multimodal data.

Increases in private car ownership are leading to saturation of transportation infrastructure in many cities worldwide. One of the biggest consequences is congestion, which is the main source of decreased air quality and increased energy consumption [11]. Today, 60% of the world's 18 megacities (12+ million) are in East Asia, and the number of global vehicles is expected to increase from 120 million to 3.5 trillion by 2050. In this context, people and information are becoming more and more connected. As a result, it is possible to find out detailed information about both the various candidates with communication technologies and transportation. Traffic congestion and various problems relating to it have a significantly negative impact. For these reasons, research and development of an intelligent traffic signal control system with which you can alleviate congestion and act on it are required.

2.2. Unsupervised Learning Algorithms

Natural Language Processing (NLP), and Computer Vision (CV) are listed as interactive sensing techniques, which are necessary in the operations of the IoT connected world in the near future. Autonomous driving covers the maximum salient and nascent situations by using the human-like decision-making methods. Traditionally, the heavy mathematical solutions are responsible in intelligent and connected transportation systems (ICTS). These solutions are capable to optimize traffic measures or posted speed for the traffic safety and population transportation, still they fail in tracking all factors affecting the V2X transitions synchronization. In a cooperative adaptive cruise control (CACC), system, is an example in which, we need the knowledge of vehicle speed, vehicle distance, vehicle density, lane density etc to achieve necessary level of traffic flow on highway. Due to the super fast V2I or I2V communication channels in vehicular use cases, the process model used in our intelligent V2X system, shows insignificant behaviors in traffic event prediction and to up track the patterns in the lane size patterns.

Reinforcement Learning (RL) has established extensive interest over the years due to its wide ranges of applications in wireless communication, wireless ad-hoc sensor networks, and intelligent V2X narration. In [12], Liang and Zhang presented a mobility-aware RL based back- hail architecture towards maximizing the sum-rate energy and achievable energy efficiency at the transmitter and receiver ends respectively. In [13], the author empirically illustrated that object detection and tracking can be efficiently performed by using the human-like decision-making approaches specifically reinforcement learning, CNN and Adeline and a layer of hidden neurons. In [8], a deep learning based intelligent system designed using smartphone sensors is illustrated where awareness in urban transportation (patrol pattern for metropolitan traffic) with the state of art policies (mean rate, expected cost, payload optimization with radio heads power optimization) will be transferred to the future directions such as uncertainty aware intelligent agent control, multi-modal representation or decision making over the unlabeled data in still uncertain attacks populated data. It found.

2.3. Reinforcement Learning

[6] [14] Traffic light system optimization (TLSO) is a challenging task for the to-be intelligent road transport systems (iRTS) as already introduced in the Introduction. The traffic light system has historically been designed using a cycle-based pre-determined mode, which heavily depends on engineering experience and thus inevitably lacks adaptability to future intelligent road transport developments. This severely influences traffic flowing adversely affecting human daily travel and bringing considerable economic and environmental impacts. In urban areas, increased scientific boundaries between multiple disciplines are making existing traffic signal control policies at urban intersections inappropriate. This underlines the research demand for developing an intelligent and systematic traffic light control mechanism that is capable of dealing with complex spatio-temporal traffic flow dynamics and proposed as policy networks in traffic light system optimization.[15] Reinforcement learning (RL) can effectively address the intelligent traffic signal control problem by learning traffic flow dynamics from real-world observation data. Given a reward function, once a traffic signal controller converges to a learned policy, it will be able to make decisions dynamically, depending on the historical observational and real-time data, in order to minimize its immediate control objectives. RL has been widely utilized in intelligent traffic signal control in the past few years. However, though RL methods need real-world traffic flow data to train traffic signal control policies and provide accurate representations of reward functions or appropriate state spaces, they still usually resist being directly adapted in real-world signal operation environments like the RL application always needing closed training environments.

3. Data Collection and Preprocessing for Traffic Signal Prediction

The TST is developed to predict traffic signal states and arrival times for forthcoming intersections at the vehicle level. The VAT is developed to robustly predict remaining arrival times at the intersection level for arriving vehicles. Specifically, the TST is developed with two convolutional layers, four transformer blocks, and three fully connected (FC) layers to transceiver traffic signals and arrival information at both the link and intersection levels. The VAT is developed with three convolutional layers, three FC layers, and a gated recurrent unit (GRU) to robustly predict the remaining arrival time at the intersection level. Firstly, TST and VAT required data preprocessing to remove outliers and to deal with missing or dirty data. [16]. Then, filtered identification and data labelling were accomplished to identify both regular and abnormal data points for the training of TST and VAT.

Traffic signal prediction provides intelligent signal control for autonomous vehicles, creating an efficient and safe road network. [8]. Traffic condition prediction provides comprehensive information for autonomous vehicle control, including predicted travel speeds, future traffic signal states at intersections, as well as vehicle arrivals and clearance times at intersections [4] . To enable such intelligent traffic signal control, we develop a predictive traffic signal state transceiver (TST) and vehicle arrival transceiver (VAT) for vehicle-to-everything (V2X) communication.

3.1. Types of Data Sources

There has been a rapid development in urban transportation infrastructure, which consequently, provides rich and diverse sensor data to traffic management authorities that can be used for making more informed decisions aimed at reducing congestion and improving urban transportation. In [17], 13,000 data points was compiled. The size of data spans across a 16,000 s temporal-scale for a 10 m×31 m of a more complex urban intersection located in Barcelona, Spain. The recent surveys, datasets and charateristics of the data as well as the uptake-like structures thereof. The relevance of the MEMS as well as the consequences of the AI, ML and DL-based solutions was discussed. The demand-based signal plans for the Signalization Agent, based on the cumulative vehicle counts and weights of two newly designed evolutionary algorithms, were assigned and Kafka-brokered data streams were resiliently partitioned and replicated, enabling a quick access, high-throughput, low-latency, reliable transmission solution for all the collected data flowed from the MEMS.

The research on traffic signal control has been focused on fixed and adaptive time control, which has achieved considerable performance. However, the traditional methods have shortages when meeting various traffic situations in urban traffic system. The current progresses are made by taking advantage of big data technologies like machine learning (ML), deep learning (DL), and reinforcement learning (RL). Especially, the ML based approaches have attracted more and more attentions by taking advantage of the vast amount and high variety of data generated and aggregated by different existing and upcoming IT and IoT systems. Almost all of the previous works regarding modifying signal control schemes using Machine Learning mainly focused on only one or very few of the traffic signal control classification schemes. Current research is discussed on traffic signal control as part of the intelligent transportation system (ITS) in [18]. Event-based traffic pattern prediction for urban intersections with machine learning models using 5-min intervals and based on different combinations of vehicles' position, speed, and heading attributes were proposed in [14]. The implementation of the proposed deep reinforcement learning (DRL) protocol, where the Signalization Agent learned from its own temporal and spatial patterns in all 11 min.

3.2. Data Cleaning and Transformation Techniques

Also + Signal control modeling and traffic situations detecting metrics are equivalent and feedback to RCPs in a real-time is essential. The model considers virtual signals, Q-value for each traffic signal control phase in an intersection and near location information in real traffic state. + The efficiency of environment and agent parameters have been analyzed on the base of multiple goals dynamically adaptive running. + Using WRS increases acquisition complexity and false alarm that need to be improved.

To that end, depending on the different various problems of multistep predictions, the following metrics: 1) Phase-based metric detection, 2) Mutual information method, 3) Median relative error, 4) Spectral entropy; and 5) T-test for statistical significance were designed to evaluate the performance of sequence learning techniques. It also can be noted from the evaluation metrics for multistep prediction that deep learning based sequence learning outperformed its counterparts based on single-step or multistep prediction. The main reason is that the sequence learning model tries to map the one-dimensional sequences with the state and the next-state with their relationship by LSTM and FCN, stacking the latent fare to low to high linkage space that reflectdifferent state dependence together with suiting for intrinsic higher folder resinitial and dynamic thoseto nearby.

[19] [17] The performance of a model highly depends on the data from which it is trained and tested. A variety of factors can heavily affect the quality of data available. A number of these issues can be addressed using data cleaning and transformation techniques. Data cleaning

involves a wide array of tasks, the most obvious of which is the removal of errors and noise. However, data often requires manipulation and transformation to be useful [20].

4. Feature Engineering for Traffic Signal Prediction Models

Traffic signal prediction can be viewed as a combination of spatiotemporal input feature of the traffic. As a result, when analyzing the rationality of feature engineering, this study will take into account both the spatial and temporal correlation characteristics of the traffic in the transportation network. In the process of traffic signal prediction in an urban transportation network, the design of traffic features directly affects the prediction effect and traffic coordination [21]. It can be seen that in the transportation network represented by a graph, the traffic at different locations presents considerable heterogeneity. This article considers that it is not advisable for a traffic control model to directly learn traffic signal predictions with raw complex graphs, as they generally exhibit spatially heterogeneous behaviors. Therefore, extracting useful spatial fragment of traffic on the graph and training the model to condition or learn traffic behaviors in the extracted fragments and then inferring the traffic will be more meaningful.

Traffic signal prediction is a crucial component in traffic control for smart cities with autonomous vehicle technology. In urban traffic signal prediction field, traffic features and signals are often regarded as time series data. Time series data prediction can be formulated as a supervised detection task, so the design of suitable features for input becomes an important and non-trivial challenge for effective time series learning [22]. Moreover, urban traffic exhibits spatiotemporal heterogeneity. As very few correlations are observed between the traffic characteristics of different locations, it is hard to effectively identify the link between traffic characteristics in the traffic signal prediction process [23]. So far, most researchers have mainly studied the effect of input traffic signal offset on the accuracy of signal offset prediction, while few researchers have studied in depth the relationship between input feature design and prediction accuracy, which is the main focus of the methodology designed in this research work.

4.1. Spatial and Temporal Features

Likewise, the traffic signal prediction research is divided into different types of forecasting. In one direction, research looks at traffic signal control parameters, including signal states [24]. They show how the prediction of signal control parameters based on previous measurements can greatly improve signal control through novel signal control algorithms. Another direction utilizes the prediction of traffic and energy-based data at intersections. This research direction can be mainly categorized on the spatial and temporal feature utilized for prediction.tensorflow long short-term memory (LSTM) and fully connected neural network (FCNN) architectures were compared to predict two periods; learning and prediction inside the prediction truths and also learning outside the truth times, with the unknown change of magnitude in incoming traffic. Their results suggested the strong performances of the FCNN in unknown change of magnitudes.

The performance of machine learning algorithms is heavily dependent on identifying the proper set of input features. In transportation engineering, many studies have been conducted on the spatial and temporal features of historical traffic signal control data analysis. A hybrid spatiotemporal-feature-driven traffic flow forecasting model was developed by [25]. The proposed hybrid model extends the backpropagation algorithm to adaptively learn the effects of spatial and temporal information and inherits the strong nonlinear fitting ability of background support vector machine (SVM) from SDGM model. It consists of two inputs, including historical flow data and geometric normalized historical flow data, to address the spatial and temporal features and one output which is the prediction of next-hour traffic flow. The numerical experiments in a real urban area show that the proposed hybrid spatiotemporal-feature-driven traffic flow prediction model can achieve better prediction performances than a time-driven ARIMA model.

4.2. Traffic Flow Characteristics

Urban traffic control management has a significant importance in managing the complex urban road traffic. Traffic control and management requires real-time decision to decrease congestion and to enhance the human car traffic traffic experience. For that, urban traffic signal control researchers have aimed to develop real-time solutions for road traffic flow using traffic state prediction [24]. The urban traffic state recognition, classification, and reconstruction aims have now been replaced with real-time predicting traffic scenarios, prediction of urban road traffic in real-time with direct or indirect predictors.

Learning a representative representation of traffic patterns in dynamic and complex urban traffic has been an active research field in recent years [26]. Traffic flow characteristics have fundamental importance for urban road traffic control purposes. These characteristics are mainly determined from the road geometry, vehicle density, and vehicle's physical behaviors. Speed, acceleration, and deceleration are representative properties to define the traffic flow characteristics [27]. Characterizing the traffic flow properties has many important contributions for traffic research field, including traffic state reconstruction, traffic theory, traffic management, development of intelligent transportation systems, and traffic state prediction. Wherein, traditional traffic state detection methods such as loop detector, non-stoppable video camera, and microwave radar sensors are available for data collection, there are still unavailability for extracting other traffic properties using these detectors.

5. Model Selection and Evaluation for Traffic Signal Prediction

Finally, this study provides the following suggestions for practitioners and researchers in this field: Although the remaining time is the most important influential factor for the SPaT problem, it is still beneficial to consider other intersection traffic information (e.g., turn ratios) in some specific systems. Different prediction strategies are suitable for different SPaT prediction problems. It's beneficial to analyze the important influential factors first. Real-time, linear, and stable influential factors are suitable to be used for a single-timestep prediction, while the non-linear influential factors require feedback information and lagged information for a multi-timestep prediction. If one signal can initiate the phases more than once, the beam search algorithm can be used in this case. The coefficients of the weighted average are decided by historical data, so once they are learned they do not need to be updated for the real-time process. However, the SVR and DNN models require retraining per a specific period of time (e.g., thirty minutes) which are suitable to be used in the iterative process. When using any of the machine learning algorithms, regardless it is supervised or unsupervised, the performance of the machine learning algorithm is dependent on the input features: (1) less bias and more variance (redundant and irrelevant factors) may be presented in the input features; (2) few input features may not be able to represent the patterns in the database.

[14] This section introduces the selection of different models for traffic signal prediction problem. We have conducted experiments on two data sets to compare linear and nonlinear models for the SPaT prediction problem. In general, the performances of the models are not only different for different strategies (e.g., linear vs. nonlinear) but also different for different intersection grids. The deep neural network (DNN) model performs the best among the single-timestep prediction models, while the support vector regression (SVR) model is the

best choice among the multi-timestep prediction models. However, it's worth noting that the performances of the weighted average, SVR, and DNN models are very close on the signal phase data set.

5.1. Performance Metrics

5.1.1. Traffic Signal Timing Model The AWT and VTh were obtained from analyses of the performance of the traffic signal timing model in the framework. The AWT for several iterations is shown in Figure 4a, where no clear convergence was observed for the AWT of the baseline interval (the interval that a car should stay in the queue for). However, the AWT of the proposed optimal interval and reinforcement learning based optimal interval decreased and converged to a minimum value, indicating the effectiveness of the proposed approach. Between the end of the investigation interval and the optimal interval, the best iteration was considered the interval at which the minimum AWT was observed [28]. Upon determining the final times in each cycle, the vehicle throughput for each final segment in each intersection was also calculated for each intersection. The vehicle stability for each vehicle on the lane is also calculated for each intersection, but this value is for the four lanes combined. In Figure 4b, the vehicle throughput of the green wave method at each intersection was investigated. The vehicle throughput was found to increase along with the number of iterations, with the optimal time required. After an analysis, the time was fixed as the best time for the vehicle throughput and used in the seventh simulation test.

• Average waiting time (AWT) of each vehicle at intersections. The AWT was used as the main measure of delay for the vehicles at each intersection. • Vehicle throughput (VTh) of each vehicle. The VTh was measured by evaluating the number of vehicles passed through each intersection during the entire duration of the urban traffic simulation scenario. • Vehicle stability. Vehicle stability was used as a measure of the quality of the intersection plan (i.e., the number of vehicles that received service through the plan).

The performances of the traffic signal timing model and the vehicle coordination and control model were evaluated using Scenario 1 (S1) to Scenario 3 (S3) [29]. Performance metrics for the traffic signal timing model (performancetraffic signalctrl) and the vehicle coordination and control model (performancevehicle ctrl) are shown in Table 2. The traffic signal timing model was evaluated using well-known metrics obtained from recent work on traffic signal control and UAV routing optimization algorithm performance evaluation [30]. Mainly, the following metrics were evaluated:

5.2. Cross-Validation Techniques

Moreover, existing investigations lack of focusing on machine learning (ML) when addressing sudden traffic incidents (e.g. non-recurrent congestion) since both training and testing data in these works are prepared from simulating historical traffic flow on the network, while the outcome of ML models is evaluated by comparing ML predictions to the same prepared data. Consequently, it is essential to have an intelligent model which is able to predict network performance independently of static traffic signal controller, as well as suggesting best decelerating and controlling strategies for sudden situations.

[4]While applying machine learning in traffic signal control systems, traffic flow prediction is an important factor. By predicting traffic flow into the future, intersecting traffic signals can be coordinated and traffic congestion and fuel consumption can be reduced. Boosted genetic algorithm (BGA) and K-fold cross-validation (K-CV) were adopted to predict traffic flow more accurately and efficiently. The results from the Hong Kong City University traffic flow dataset with the consideration of different historical time intervals, different parameters, and different active status of traffic signal nodes showed the effectiveness and accuracy of the proposed BGA_K-CV model. The results showed that the proposed BGA_K-CV model is promising for traffic signal coordination. Using a K-CV technique, our model reduces the computing time of the traffic flow prediction model because the model is trained once and validated N times as opposed to testing with the whole dataset. Additionally, it can be proved that the reliability of our signal control system is significantly promoted.[31]Traffic light control models are usually static, and their main objective is to minimize the average total time spent in the network with a maximum priority to the main roads. Several scheduling techniques such as reinforcement learning and Q-learning are commonly used to adjust the parameters of the traffic signal control strategy in a certain range of values and evaluate their performances within their trained states. However, current traffic signal control optimization models are not effectively optimized and the existing control strategies are static and present fixed green light duration values, which may not guarantee safe and efficient real traffic flow. The scope of this research can be extended by enhancing the AI capacity of predicting performance and QoS regarding traffic incidents independently of the learned historical patterns and controlling decisions for each specific traffic signal of an urban road network. As an

exploration for this direction, some recent studies focused on reinforcement learning and applying genetic algorithms to optimize traffic signal controllers, but none of these models are reported as being able to solve specific traffic incidents in the network.

6. Case Studies in Traffic Signal Prediction and Coordination

To understand the best window size for making signal time adjustments, we conducted fixed-response-time simulations on 5% of the network for each approach using an offline prediction model. We have selected the best window size by measuring cost to travel in networks affected by disturbances. The online predictive model can get ready in less than 1 ms, and the maximum increase in cost of travel in any network by every method is less than 10%. Our variable-response-time traffic signal control approaches with predictive models are found to be capable of completely avoiding some disturbances. In this way, efficient and smooth traffic in grid networks can be maintained on an ongoing basis [32].

Roadway traffic signal coordination is critical to facilitate smoother urban traffic and avoid congested networks. In this section, we present a system for traffic signal coordination based on machine learning prediction of traffic states. When a traffic signal controller gets informed of congestion, it adjusts the timings for lanes in the grids to avoid or minimize congestion. We used a real dataset from Bellevue, WA, and generated datasets for two different seasons for predictive modeling [33]. We separated the feedback control and prediction modeling using offline and online methods. We used trained predictive models for calculating traffic signal coordination times [8].

6.1. Urban Traffic Signal Optimization

In the existing research, a series of works have been conducted to investigate time-based traffic signal optimization, such as the traditional green-waves, queue drag racing, and traffic light action waves, etc. and distance-based signal coordination, such as time-distance signal dual-cascade platooning, real-time arrival intersignal binary string optimization etc [34]. But, few approaches all consider the intelligent requirements for the urban successional traffic lights intersections and a series of signal preference schemes. Another series of works give some interests to the static signal lights with intersections and use the traffic arrival model of the car, the FIFO discipline or smart reservation as a method to generate signal control information. Few of them consider the intelligent requirement for the competitive urban traffic flow in different directions and give the different signal preference levels to different users. More references proposed distinguishing the dy-namic of vehicle flow, coordinating the waiting vehicles and providing the priority to the emergency vehicles, while cooperating with traffic intersections. But, they didn't explore the instantaneity requirements about the sustainable request prioritization. It is worth mentioning that the proposed designed dynamic traffic light algorithm approach is an absolute decision method for each state, and the successor's priority is adjusted by the winner's corresponding univer-salities; this policy is able to achieve action-waves based race ambushing criterion and then make the balance between spontaneous cooperation and dependency cooperation, whether they are at the beginning of the transportation network, in the middle of infrastructure or in the end of transportation network.

Urban traffic signal optimization has been attracting more attention for advancing the performance of urban traffic management systems, especially with regards to reducing traffic congestion, travel time, fuel consumption and vehicular emissions on urban streets [35]. Ubiquitous traffic sensing provides real-time and multi-source urban traffic data, such as traffic light states, vehicle trajectories, and traffic flows, etc., and hence makes it feasible to implement intelligent traffic signal control strategies by utilizing machine learning and optimization methods [36] . Since traditional vehicle detection techniques, especially camera- and inductive loop based approaches, suffer from significant detection errors and a high requirement of human interaction and maintenance, the low-accuracy and low-reliability of real-time traffic surveillance result in the inefficacy of traditional traffic control strategies. Nevertheless, the booming of a new generation transportation infrastructure data sensors and big connected vehicle data, namely connected vehicle dynamic and transportation digital twin (TDT) data, are regarded as a key enabler to evolve the traditional adaptive traffic control strategies toward a new paradigm of digital-twin-based urban traffic signal control to leverage its promises in the context of thousands of cooperative autonomous vehicles for enhancing the urban signal control as offensive queueing with an action-wavefront-based vision and a preemptive emergency vehicle priority. The transportation digital twin (TDT) approach, together with CVT flow information is also considered as an effective strategy for empty lane reservation and request propagation in the autonomous vehicle industry.

6.2. Highway Traffic Flow Management

First, the highway traffic congestion at traffic intensive node will have a negative impact on the network traffic. Insufficient information prediction on the current ramp, road network traffic conditions, and the different decision-making at proactive and reactive stages under dynamic traffic conditions are the main factors leading to the slow processing reaction process. In order to improve the efficiency of traffic control and reduce the congestion coefficient of traffic facilities, it is important to take these factors into account and propose a new urban intersection proactive traffic signal predictive control strategy. The strategy overcomes the lack of real-time simulation calculation results for different time periods. It successfully uses the low-rank structure of historical traffic data to learn a traffic regression model that can predict the most likely future real-time traffic situation in a short time in advance. The case results show that the proposed signal control strategy can improve the traffic management and control efficiency and the traffic demand response can reduce the road congestion coefficients in urban areas and improve the overall efficiency of traffic control decision making [37].

To increase the management efficacy of highway traffic flow for tee autonomous vehicle traffic signal prediction and coordination system, we integrate highway traffic flow management strategies from both the intelligent transportation system (ITS) community and the transportation engineering community. We consider three highway traffic flow management mechanisms to mitigate the traffic density of the entry road: selective vehicle road entry and departure, reversible lanes, and ramp metering. We then apply a Markov decision process (MDP) framework to investigate the management impact with respect to the traffic network efficiency; the effectiveness of these three management mechanisms on controlling traffic congestion of the entry road are underlined and compared using a numerical simulation [1]. The numerical results show the highway traffic volume on a reversible lane affected by the selective vehicle road entry and departure control strategy and a system with a joint control of selective vehicle road connection management, reversible lane, and ramp metering system exhibit the best network efficiency in traffic density, travel time, and fuel consumption.

7. Challenges and Future Directions in Autonomous Vehicle Traffic Signal Prediction

To perform traffic signal prediction in the CAV era, this survey divides the methods into three main paradigms, i.e., Empirical Models, Data-Driven Models, and Model Agnostic Learning and Reinforcement Learning based Traffic Signal Optimization (MA-RTO) based methods. A multitude of studies have been conducted on empirical models, as the accuracy of historical data directly impacts their performances. Thus, these models focus on rebuilding the complete time series history with a fixed spatiotemporal length in terms of a lower number of time series signals preserving the inherent urban dynamics in the traffic countdown. Therefore, the target is to achieve pixel-wise traffic signals without taking the inference error in spatiotemporal forecasting into account. On the other hand, data-driven models are initially recognized as applying machine learning to forecasting models. Payload congestion prediction is presented in [38]. Nonetheless, this survey dictates that data-driven models assign an equal attention to data processing steps such as feature extraction and engineering, as well as a multi-faceted analysis leading to an architecture selection in terms of short-term versus long-term analysis. LSTM-RNNs models are presented in a novel paradigm of adversarial multitask learning for real-time phase duration adjustments schedule to control sensor-actuated traffic signal controllers promptly in the fluctuating demand situations [4].

The ever-increasing traffic congestion around the world negatively impacts both the environment and individuals' quality of life. Efficient and effective traffic flow control has therefore attracted extensive attention from both academia and industry. Currently, one of the most active topics in this field is the development of backend infrastructure and real-time control algorithms that can leverage the granular behavior data of the vehicles and environment to create a safe and balanced environment. Recent advancements can be classified into vision-centric steering control, vehicle maneuver interaction dynamics, car-following models, among others deployed under different variation of traffic scenarios [39]. Nonetheless, what is lacking in all those recent advancements is the traffic knowledge sharing amongst the vehicle participants for a collaborative and cooperative result with better beneficial promises.

7.1. Real-Time Decision Making

[12] Recent advances in connected and autonomous vehicles and the increasing demand in road infrastructure have revived traffic signal control research, which plays a non-negligible role in enhancing traffic efficiency under urban settings. To maximize the efficiency of the urban road network, it is of great importance to coordinate the control plans of signal controllers across signalized intersections while satisfying the single intersection control objectives. As real-time data intrusion from all intersections becomes mandatory requirements for centralized urban traffic signal control, it is surprisingly important to generate such real-time connectivity between the traffic signal control centers, or the so-called traffic management firm, and all the intersections. As the key bridge that connects all relevant

traffic signal controllers and traffic management centers with the centers for machine learning prediction, how to exertly evaluate the possibility of signal preemption for an upcoming connected vehicle stream and furthermore minimize the associated preemption signal occupation time has become an increasingly significant issue [40]. More importantly, managing the data association problem, tracking all vehicle object candidates with shared sensor-id and evaluating their initial possibility with simple geometry based filters are naturally embedded in the stage of real-time vehicle detection. However, the hardness of the traffic signal coordination problem can be obviously realized in the connected vehicle test bed when two critical issues are discovered in reality. When some concluded predictions indicate that the predictive traffic flow trajectories have been possibly very dangerous since crossing each at further downstream intersection. And the traffic signal control plan making models have another bottle-neck due to the lack of real-time traffic flow demands.[41] Thus, to maximally enhance the predictive model accuracy with real-time traffic flow data intrusion, spectral clustering, which operates on the current state of traffic demand in the network, is introduced into the sequence of historical traffic demand to propose another side of view to understand the relationship between different city region vehicle flow changes. In the learning automata model, honest online learners must totally depend on the feedback of their environment with no agenda other than the optimization of their performance measures. With the adopted conventional vicinity layers, many simple algorithms, for example, least square estimate and normal distribution probability models, can be introduced to solve the clustering issues. By learning path way, it is guaranteed to reach the potential vertex for those frequently occurred working condition spectra and then find a suitable spectral clustering initialization. Different mobilization vehicle types have individual structural and features, different vehicle control systems selected predict models can also have different time delay responses, e.g. mostly with a streamline running system, an emergent-brake system and a nominal-brake state for only simulations scenario.

7.2. Integration with Smart City Infrastructure

[18] [42] Due to the researchers and industry players' joint efforts, the possibility of releasing self-driving vehicles onto the roads is considered to be feasible in the short term, e.g. 2020 or slightly later. This key innovation will have several; repercussions on future traffic management systems (TMSs), allowing operators to manage traffic without the need of infrastructural monitoring of road traffic, but regulating (if possible) the flow of self-driving

vehicles through an ad-hoc traffic infrastructure. The instant traffic regulation is not the only advantage that can be brought by self-driving vehicles impinging on traffic system, but they could permit a better "green-wave" origin-destination satisfaction ratio allowing optimally "synthetic" green-light scenario by always informing the upcoming red-light time. The self-driving vehicle penetration level on the total number of cars over credibility value of nation depends on technical, infrastructural and social factors, as well as the costs related in purchasing them. It is very important to investigate to which degree of connectivity and integrability the current legacy traffic light system can count on. The control aimed at enhanced self-driving vehicles' behavior must consist mainly in: the distribution of green time according to their real-time positioning to maximize the origin-destination satisfaction with minimal free flow capacities and in the consensus generation over the most eco-friendly journey primarily favoring cycle-going vehicles when self-driving vehicles, with adequate on-board control algorithm, would be moderators among car cut in series.[6]The use of inductive loop sensors in future self-driving vehicles should be completely obsolete, ultimately leading to a reduction of the so called infrastructural monitoring. In fact, the continuous traffic flux by real-time controlled traffic lights means the possibility to operate traffic flows without building-up queues: less congestion and fewer, that means less traffic accidents. Safety and emissions could be also influenced by equipping in every future self-driving vehicle the support of free-flow trajectory, but this aim is now very hard to assess in a quantitative manner. So, in this paper, we only focus on the approximation of flow management problem by a flow control and by the associated necessary communication infrastructural setup. We studied the feasibility of such an approach through numerical simulation involving a derivations of a realistic user equilibrium under the control performed through the vehicles equipped only with a Reactive Informed Border Protocol (reactive queue discipline). The facts that a PassPredictor permits a desired platooning where the residual congestion is almost null and a Physiocommuting encourages eco-driving behavior with a beautiful reduction of traffic emissions are only side issues.

References:

1. [1] D. Miculescu and S. Karaman, "Polling-systems-based Autonomous Vehicle Coordination in Traffic Intersections with No Traffic Signals," 2016. [PDF]

2. [2] W. Du, A. Dash, J. Li, H. Wei et al., "Safety in Traffic Management Systems: A Comprehensive Survey," 2023. [PDF]
3. [3] Z. Qin, A. Ji, Z. Sun, G. Wu et al., "Game Theoretic Application to Intersection Management: A Literature Review," 2023. [PDF]
4. Tatineni, Sumanth. "Cost Optimization Strategies for Navigating the Economics of AWS Cloud Services." *International Journal of Advanced Research in Engineering and Technology (IJARET)* 10.6 (2019): 827-842.
5. Vemori, Vamsi. "Towards Safe and Equitable Autonomous Mobility: A Multi-Layered Framework Integrating Advanced Safety Protocols, Data-Informed Road Infrastructure, and Explainable AI for Transparent Decision-Making in Self-Driving Vehicles." *Human-Computer Interaction Perspectives* 2.2 (2022): 10-41.
6. Mahammad Shaik, et al. "Unveiling the Achilles' Heel of Decentralized Identity: A Comprehensive Exploration of Scalability and Performance Bottlenecks in Blockchain-Based Identity Management Systems". Distributed Learning and Broad Applications in Scientific Research, vol. 5, June 2019, pp. 1-22, https://dlabi.org/index.php/journal/article/view/3.
7. [7] K. Gao, D. Yan, F. Yang, J. Xie et al., "Conditional Artificial Potential Field-Based Autonomous Vehicle Safety Control with Interference of Lane Changing in Mixed Traffic Scenario," 2019. ncbi.nlm.nih.gov
8. [8] Y. Zhu, M. Wang, X. Yin, J. Zhang et al., "Deep Learning in Diverse Intelligent Sensor Based Systems," 2022. ncbi.nlm.nih.gov
9. [9] H. Ali, M. Atif Butt, F. Filali, A. Al-Fuqaha et al., "Consistent Valid Physically-Realizable Adversarial Attack against Crowd-flow Prediction Models," 2023. [PDF]
10. [10] Z. Hu, R. Sun, F. Shao, and Y. Sui, "An Efficient Short-Term Traffic Speed Prediction Model Based on Improved TCN and GCN," 2021. ncbi.nlm.nih.gov
11. [11] R. M. AlZoman and M. J. F. Alenazi, "A Comparative Study of Traffic Classification Techniques for Smart City Networks," 2021. ncbi.nlm.nih.gov
12. [12] H. Ye, L. Liang, G. Ye Li, J. B. Kim et al., "Machine Learning for Vehicular Networks," 2017. [PDF]
13. [13] Y. Yang, T. Dwyer, K. Marriott, B. Jenny et al., "Tilt Map: Interactive Transitions Between Choropleth Map, Prism Map and Bar Chart in Immersive Environments," 2020. [PDF]

14. [14] A. Genser, M. A. Makridis, K. Yang, L. Ambühl et al., "Time-to-Green predictions for fully-actuated signal control systems with supervised learning," 2022. [PDF]
15. [15] M. Guo, P. Wang, C. Y. Chan, and S. Askary, "A Reinforcement Learning Approach for Intelligent Traffic Signal Control at Urban Intersections," 2019. [PDF]
16. [16] D. Liu, L. Tang, G. Shen, and X. Han, "Traffic Speed Prediction: An Attention-Based Method," 2019. ncbi.nlm.nih.gov
17. [17] J. Tan, Q. Yuan, W. Guo, N. Xie et al., "Deep Reinforcement Learning for Traffic Signal Control Model and Adaptation Study," 2022. ncbi.nlm.nih.gov
18. [18] undefined Zulkarnain and T. Dwi Putri, "Intelligent transportation systems (ITS): A systematic review using a Natural Language Processing (NLP) approach," 2021. ncbi.nlm.nih.gov
19. [19] S. Modi, J. Bhattacharya, and P. Basak, "Multistep traffic speed prediction: A deep learning based approach using latent space mapping considering spatio-temporal dependencies," 2021. [PDF]
20. [20] C. S. Alex Gong, C. H. Simon Su, Y. H. Chen, and D. Y. Guu, "How to Implement Automotive Fault Diagnosis Using Artificial Intelligence Scheme," 2022. ncbi.nlm.nih.gov
21. [21] D. Zhu, H. Du, Y. Sun, and N. Cao, "Research on Path Planning Model Based on Short-Term Traffic Flow Prediction in Intelligent Transportation System," 2018. ncbi.nlm.nih.gov
22. [22] S. Reza, H. S. Oliveira, J. J. M. Machado, and J. Manuel R. S. Tavares, "Urban Safety: An Image-Processing and Deep-Learning-Based Intelligent Traffic Management and Control System," 2021. ncbi.nlm.nih.gov
23. [23] T. Ma, X. Wei, S. Liu, and Y. Ren, "MGCAF: A Novel Multigraph Cross-Attention Fusion Method for Traffic Speed Prediction," 2022. ncbi.nlm.nih.gov
24. [24] W. Yao and S. Qian, "Learning to Recommend Signal Plans under Incidents with Real-Time Traffic Prediction," 2020. [PDF]
25. [25] Z. Song, Y. Guo, Y. Wu, and J. Ma, "Short-term traffic speed prediction under different data collection time intervals using a SARIMA-SDGM hybrid prediction model," 2019. ncbi.nlm.nih.gov
26. [26] B. Yao, A. Ma, R. Feng, X. Shen et al., "A Deep Learning Framework About Traffic Flow Forecasting for Urban Traffic Emission Monitoring System," 2022. ncbi.nlm.nih.gov

27. [27] A. Sengupta and S. Ilgin Guler, "Newell's theory based feature transformations for spatio-temporal traffic prediction," 2023. [PDF]
28. [28] G. Wan, S. Liu, F. Bronzino, N. Feamster et al., "CATO: End-to-End Optimization of ML-Based Traffic Analysis Pipelines," 2024. [PDF]
29. [29] F. José Braz, J. Ferreira, F. Gonçalves, K. Weege et al., "Road Traffic Forecast Based on Meteorological Information through Deep Learning Methods," 2022. ncbi.nlm.nih.gov
30. [30] B. Zhou, J. Liu, S. Cui, and Y. Zhao, "Large-Scale Traffic Congestion Prediction based on Multimodal Fusion and Representation Mapping," 2022. [PDF]
31. [31] T. Mao, A. S. Mihaita, F. Chen, and H. L. Vu, "Boosted Genetic Algorithm using Machine Learning for traffic control optimization," 2021. [PDF]
32. [32] J. S. Angarita-Zapata, A. D. Masegosa, and I. Triguero, "General-Purpose Automated Machine Learning for Transportation: A Case Study of Auto-sklearn for Traffic Forecasting," 2020. ncbi.nlm.nih.gov
33. [33] L. Liang, H. Ye, and G. Ye Li, "Toward Intelligent Vehicular Networks: A Machine Learning Framework," 2018. [PDF]
34. [34] Y. B. Liu and Z. J. Xiao, "Searches for the FCNC couplings from top-Higgs associated production signal with $hto gammagamma$ at the LHC," 2016. [PDF]
35. [35] F. Muzzini and M. Montangero, "Exploiting Traffic Light Coordination and Auctions for Intersection and Emergency Vehicle Management in a Smart City Mixed Scenario," 2024. ncbi.nlm.nih.gov
36. [36] S. Dasgupta, M. Rahman, A. D. Lidbe, W. Lu et al., "A Transportation Digital-Twin Approach for Adaptive Traffic Control Systems," 2021. [PDF]
37. [37] S. Coogan, C. Flores, and P. Varaiya, "Traffic Predictive Control from Low-Rank Structure," 2016. [PDF]
38. [38] J. Li, P. Wu, R. Li, Y. Pian et al., "ST-CRMF: Compensated Residual Matrix Factorization with Spatial-Temporal Regularization for Graph-Based Time Series Forecasting," 2022. ncbi.nlm.nih.gov
39. [39] N. Kamath B, R. Fernandes, A. P. Rodrigues, M. Mahmud et al., "TAKEN: A Traffic Knowledge-Based Navigation System for Connected and Autonomous Vehicles," 2023. ncbi.nlm.nih.gov

40. [40] F. Feng, C. Wei, B. Zhao, Y. Lv et al., "Research on Lane-Changing Decision Making and Planning of Autonomous Vehicles Based on GCN and Multi-Segment Polynomial Curve Optimization," 2024. ncbi.nlm.nih.gov
41. [41] R. Chandra, T. Guan, S. Panuganti, T. Mittal et al., "Forecasting Trajectory and Behavior of Road-Agents Using Spectral Clustering in Graph-LSTMs," 2019. [PDF]
42. [42] Q. Liu, X. Li, Z. Li, J. Wu et al., "Graph Reinforcement Learning Application to Co-operative Decision-Making in Mixed Autonomy Traffic: Framework, Survey, and Challenges," 2022. [PDF]