Green Wave Speed Guidance on Signalized Road Networks

Md.Fuad Hasan
Technische Hochschule Ingolstadt

***Abstract*—This study presents a novel approach to enhancing traffic flow at intersections within bustling urban environments. Traditionally, vehicles experience delays at traffic lights, impeding the smooth progression of traffic. While conventional solutions, such as optimizing signal timings, have been employed, they often fall short of enabling uninterrupted traffic flow.**

The proposed method introduces a paradigm shift by allowing vehicles to maintain momentum through intersections without necessitating a complete stop. By implementing this innovative strategy, vehicles can accelerate more swiftly post-intersection, thus minimizing overall travel time. Moreover, this approach boasts economic and environmental advantages, as it reduces fuel consumption and emissions associated with frequent stops and starts.

The study elucidates the mechanics of this method and evaluates its efficacy using advanced simulation software like VISSIM. Through rigorous testing and analysis, the research aims to demonstrate the tangible benefits of this approach in improving traffic efficiency and mitigating congestion in urban areas. Ultimately, by offering a viable alternative to conventional traffic management techniques, this study seeks to pave the way for more sustainable and streamlined transportation systems in densely populated city streets.

***Keywords*—** traffic efficiency promotion algorithm, speed guidance, IVICS, VISSIM

I. Introduction

The majority of traffic in an urban traffic network moves over arterial roadways. Intersections are a common site of accidents on arterial roadways because they act as a bottleneck[1]. The majority of urban traffic congestion phenomena, according to data, are brought on by inadequate traffic capacity, which is also cited as the cause of delays and disrupted traffic flow. Given these conditions, one solution to the urban traffic problem and traffic security is the intelligent traffic control for the urban arterial route.

The green wave control method is one popular control technique for urban arterial roads. The control theory known as "arterial road cooperative control for green wave" creates a coordinate signal timing scheme by using the coordination of several crossings as the study object[2]. The green wave strategy's primary goal is to maximize the green wave bandwidth [3]. Numerous algebraic methods exist for controlling arterial road coordinates, including the Purdy, Maxband, and Multiband methods [4].

However, the above-mentioned green wave approach necessitates thinking about signal control design. Every traffic signal in the arterials should be programmed to run in unison, and if the control strategy is made for a bidirectional green wave, then some linkages must be symmetrical in space. Because of these drawbacks, certain districts are unable to implement the green wave technique, which necessitates the adoption of a different control method. One method that has the assembled results of the previous ones and can manage every single vehicle based on real-time information.

All vehicles on the road now have access to real-time traffic flow information thanks to the development of Intelligent Vehicle Infrastructure Cooperation Systems (IVICS), which is already being used by a few research groups to improve service. A few initiatives have already created their own IVICS, including eSafety in the European Union, Smartway in Japan, and IntellidriveSM in the United States[5]. Drivers receive safety services as well as specific situational information about the vehicle[6]. An algorithm for speed guiding can be proposed using such data.

The variable speed limit (VSL) control system for highways is the source of inspiration for this innovative program. VSL could be represented as the intended speed choices of small traffic simulators.

vehicles or as speed directives conveyed directly to cars.[7] VSL makes an effort to regulate the average vehicle speed (or driving style) of mainline traffic [8].[/9]. It is possible to obtain speed recommendations for urban traffic flow by utilizing the data obtained from the IVICS. This method is aimed to optimize road capacity and reduce travel time based on the previously provided data.

II. Related work

Several researchers have worked on variable speed algorithms for urban roads. Marchau and Jiménez focused on advising drivers on optimal speeds, considering factors like weather and road conditions, to enhance safety. Abu-Lebdeh used dynamic speed control to help drivers choose the best speed, improving traffic flow and preventing congestion. Yang and Mandava developed algorithms to advise drivers on speeds that increase the chances of catching green lights and avoiding stops at intersections. Barth designed an algorithm to minimize fuel consumption and emissions by adjusting speeds dynamically. Rakha compared fuel efficiency of different speed profiles at signalized intersections. Sun developed a speed guidance strategy to reduce fuel consumption and emissions, considering road conditions. These strategies can be displayed through signs or in-vehicle devices, which are needed for personalized guidance.

A. Algorithms

In here two separate strategies for advising vehicle speeds on highways with traffic signals: the Green Wave-based Speed Guidance Strategy (GWSGS) and the Emission-driven Speed Guidance Strategy (EDSGS). Vehicles on these highways receive speed advice regularly, considering factors like signal timings, vehicle location, speed, and road conditions. Using optimal speed algorithms, we determine the best speed guidance for each vehicle based on these inputs.

1) GWSGS: The goal of GWSGS is to help as many vehicles as possible pass through intersections without stopping. Due to the unpredictable arrival of vehicles, some inevitably stop at intersections. To avoid this, we release guided speeds to vehicles before they reach the intersection. Some vehicles (shown in red) accelerate and pass before the green light ends, while others (shown in blue) decelerate and pass after the green light starts.

The system calculates four types of guidance modes for each vehicle based on its trajectory: passing with high speed, passing with acceleration, passing with deceleration, and passing without guidance. Vehicles compare the guidance speed with their current speed, and a decision is made whether to follow the guidance or not during the renewal interval.

2) EDSGS: The EDSGS consists of two main modules: an optimization module and an ecological index calculation module. The guided velocity is adjusted dynamically based on the vehicle's trajectory. The optimization module uses a rolling horizon and dynamic programming to minimize fuel consumption and CO2 emissions while maintaining preset speed levels. In the optimization process, fuel consumption along the segment is calculated for various guided velocities over a specified distance. The velocity with the lowest fuel consumption is selected as the optimal guided velocity. The speed advice provided at guided positions is real-time, considering the vehicle's current speed, signal phase, timing information, and distance to the next intersection. If the driver doesn't follow the advice, they receive a new speed recommendation at the next guided position.
In summary, the EDSGS leverages advanced optimization techniques and real-time data analysis to provide dynamic speed guidance. This system enhances fuel efficiency, reduces emissions, and promotes eco-friendly driving habits by continuously adjusting speed recommendations based on current driving conditions and traffic signals.

3) DQN based speed guidance algorithm: Reinforcement Learning (RL) has shown promise in driving decision-making, where agents learn to interact with the environment to maximize rewards. The RL framework includes an agent (the controlled vehicle) and an environment (a multi-intersection road network). The environment's state space includes traffic light signals and surrounding vehicles, and the available actions include acceleration, deceleration, and maintaining speed. Rewards are based on the opposite of travel time. In the DQN-based speed guidance algorithm, simulations are conducted in the SUMO traffic simulator, and traffic data from SUMO is used to train the agent to optimize actions based on rewards. Initially, the agent has no experience and explores different states until it completes the specified route, called an episode. Each decision epoch involves the agent entering the speed guidance area and leaving the stop line at the downstream intersection. During training, multiple episodes are executed, with several decision epochs in each. Data from each epoch, including the state, action, and reward, are stored in memory. When enough data is collected, a DQN model, constructed using a deep neural network, is trained using this data.

III. Methodology

Imagine a city street system with a main road and many crossroads. Our study looks at when cars have to go through this system on the main roads. The goal of the plan is to reduce how long it takes to travel. Instead of adjusting when the traffic lights change, this plan focuses on controlling the cars themselves. Each car that enters the main road gets instructions on how to drive, and here's how it works:

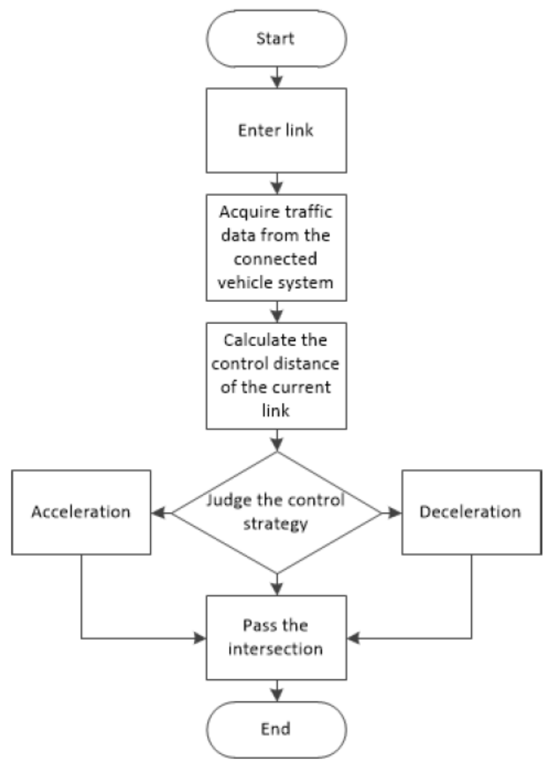

Fig:Flow chart of the distributed control strategy

Using the algorithm mentioned earlier can significantly reduce travel time. Here's how it's mainly done:

- Obtain the data of the current vehicle. As for the vehicle No. j which is in the link i, the data including the vehicle's real time distance from the current point to the intersection x_i, j, the real time velocity v_j , the signal timing model of the current link, red light time R_i and green light time G_i, the operation time t of the vehicle ever since it enters the link and the time point in the timing model phase t_i, j

- Figure out where to take control on the current road using the optimization method mentioned earlier. Keep track of the distance from this point to the intersection as Li, j
- Determine the control strategy by the value of the ti_j when the vehicle passing the $L_{i,j}$ point.

- While, $\frac{-Li,j}{V_{max}} < t_{i,j} < R_i - \frac{L_{i,j}}{V_{max}}$ the vehicle is not able to passing the intersection during the current timing period, which means this certain vehicle needs to slow down to avoid the red light. The controlled vehicle velocity should not be faster than the minimal velocity V_{min} calculated as follow:
$V_{min} = \frac{L_{i,j}}{R_i - T_{i,j}} - [(0)$
As the velocity is calculated under the situation of the constant deceleration[$\triangle V$, is a required compensatory velocity to the calculation.
  - While, R_i- $\frac{-Li,j}{V_{max}} < t_{i,j} < R_i + G_i - \frac{L_{i,j}}{V_{max}}$ the vehicle could pass the signal without any deceleration.A faster velocity approximating the V_{max} can be provided to the driver to save their time.
  - Move to the next vehicle enter the current link, and present the controlling algorithm to all the vehicles on the current link.

A. CONTROL DISTANCE MODEL

By coordinating the constraints related to vehicle speed, timing models, and road length, an optimization model can be developed. In this model, the aim is to maximize the vehicle speed when passing intersections. Vehicles that can pass intersections without needing control don't have to worry about control distance. The optimization model focuses more on vehicles that need to slow down. Consequently, the constraints mainly address situations requiring deceleration, which is sufficient for control purposes. The optimization model and parameter explanations are as follows:

$$\text{Max } v_{\min}$$

$$s.t.$$

$$\begin{cases} x \ge \dfrac{(v^2 - v_{min}^2)v_{max}}{2a(v_{max} - v_{min})} + \dfrac{v_{min}v_{max}}{v_{max} - v_{min}}(R - \dfrac{v - v_{min}}{a}) & (1) \\ x \le L & (2) \\ x \le \dfrac{v_{\max}v}{v_{\max} - v}R & (3) \\ v \ge v_{\min} & (4) \\ G \ge \dfrac{x}{v_{\max}} & (5) \\ x, v, v_{max}, v_{min}, R, G, a \ge 0 \end{cases}$$

TABLE I. DEFINITION OF THE VARIABLES

Variable	Definition
v_{min}	the minimal velocity that the vehicle is required to decelerate, which is also the optimize goal;
x	the length from the control point to the intersection;

TABLE II. DEFINITION OF THE PARAMETERS

Parameter	Definition
v_{max}	the maximal velocity that a vehicle can attain under the legal speed limits;
v	the desire velocity the vehicle is willing to attain without control;
R	the red light time of the timing model of current link;
G	the green light time of the timing model of current link;
a	the equivalent deceleration of the vehicle.

Among these variables, V_{min} and x are not fixed. The optimization solution can be easily found using software like LINGO or other operations research tools. The constraints are influenced by various factors, including the velocity-distance relationship and the length of the road segments. Control needs are also considered in the constraints to prevent exceeding the duration of red lights. The controlled time should not exceed one phase either.

Let's break down the constraints for better understanding:

Constraint (1) follows Newton's laws of motion, stating that a vehicle must slow down to a certain speed before reaching a traffic signal, or else it will encounter a red light.

Constraint (2) is a crucial geographical limitation. It ensures that the control distance doesn't exceed the road length between two intersections. Ignoring this constraint might lead to unrealistic demands for control distance. Short distances between intersections might not allow enough control distance.

Constraints (3) and (4) are logical: cars need to slow down to avoid red lights, and controlled vehicles should be slower than before.

Lastly, controlled time shouldn't surpass a signal cycle's duration; otherwise, the control won't be effective. All other constraints are about ensuring non-negative values. Considering all these factors, we've listed the constraints above.

IV. SIMULATION AND OUTPUT

VISSIM is a tool used to simulate urban traffic and public transit operations. It has a feature that lets it interact with other programming languages using COM functionality, and parts of the simulation are written in C++.

The simulation network used in this study is from Tianjin, China, and includes four intersections. These intersections are connected by four-lane urban roads with traffic lights. Distances between intersections vary, ranging from 200 to

900 meters, to accommodate different simulation scenarios.

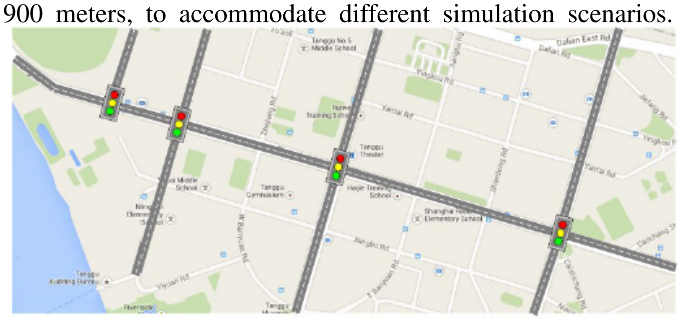

Fig:Map of the simulation network

The selected network uses static timing plan and the timing plan is designed as follows.

TABLE III: SIGNAL TIME MODEL OF THE INTERSECTIONS

Intersection No.	Red-time (sec)	Green-light (sec)	Yellow-light (sec)
1	30	27	3
2	40	22	3
3	65	22	3
4	20	42	3

To test the algorithm's effectiveness, we need different hourly traffic flow rates. We'll compare it with uncontrolled traffic to see how well the algorithm works. Traffic flow rates range from 1000 to 3600 vehicles per hour. We'll simulate the first 150 vehicles entering the network from the same entrance. Data recording starts when the first vehicle leaves the network to minimize errors. All vehicles entering the network will be subject to the control strategy, and data from the last 100 vehicles will be analyzed. We'll plot vehicle paths and the reduction in travel time caused by the control

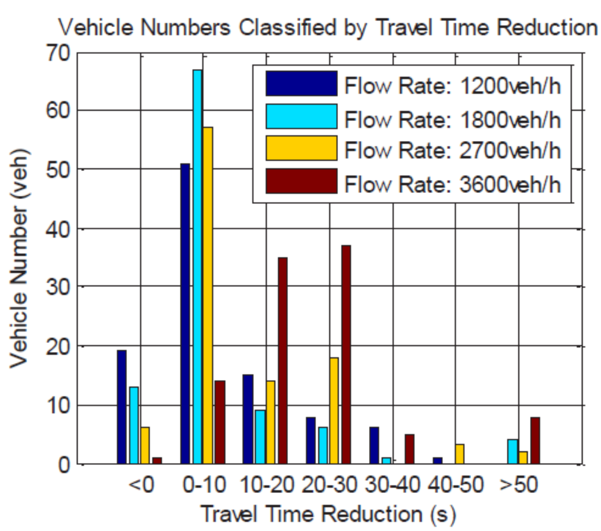

Fig:Distribution of TTR under different flow rates

These flow rates represent different levels of traffic: light, moderate, and heavy. In all cases, vehicles experience reduced travel times. As traffic volume increases, so does the amount of time saved. This suggests that controlling all vehicles from the start can maximize time savings. At lower traffic volumes, the algorithm prevents queues at signals. Even at higher volumes near road capacity, the control strategy prevents queues. Overall, the algorithm is highly effective at preventing traffic backups. The amount of time saved in these situations is documented.

Traffic flow rate (vehicles/h)	Average TTR (sec)
1000	7.310
1200	6.778
1800	5.506
2700	10.216
3000	10.194
3600	18.942

Fig: The TTR different traffic flow rate

The findings from different flow rates confirm what we thought before. With more vehicles entering, congestion is probable without control, meaning vehicles stay longer in the link. But if speed guidance is provided before congestion, vehicles won't stop at red lights, preventing queues and saving time.

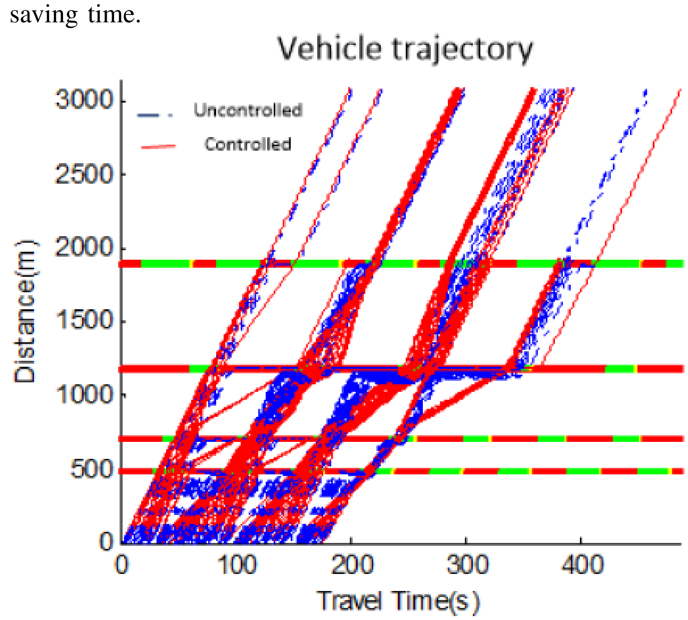

Fig:Vehicle trajectories under flow rate of 3600 vehicles per hour

Through the figure above, we can have a proper idea how this algorithmic works. The signal time plan is plotted, as well as the first 150 vehicles' trajectories. Compared with those uncontrolled ones, the controlled vehicles slow down or speed up to avoid all the red light time.

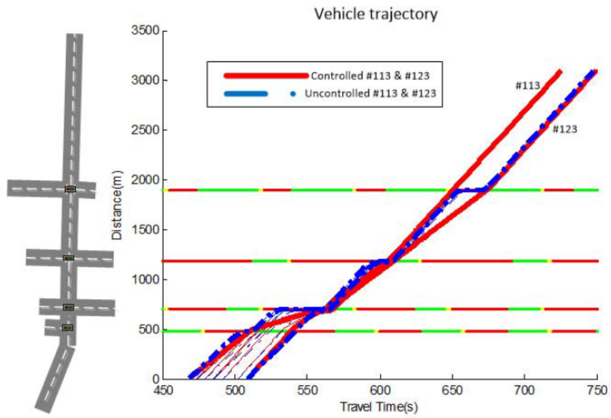

Fig:Trajectories of two specified vehicles

V. Comparison

The DQN-based speed guidance algorithm, EDSGS, and GWSGS are three different approaches used in Green Wave Speed Guidance on Signalized Road Networks.

A. DQN-based speed guidance algorithm

- This approach utilizes Reinforcement Learning (RL) techniques, specifically Deep Q-Networks (DQN), to optimize the mapping between the current state of the environment (e.g., traffic conditions, signal states) and the optimal action (e.g., acceleration, deceleration) to maximize rewards (e.g., minimizing travel time).
- It involves training an agent (controlled vehicle) to learn from interactions with the environment and make decisions based on learned policies.
- The algorithm learns over time through exploration and exploitation of different state-action pairs to achieve the best outcomes.

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B. EDSGS (Emission-driven Speed Guidance Strategy)

- EDSGS focuses on minimizing fuel consumption and CO_2 emissions by dynamically adjusting vehicle speeds based on real-time information such as signal timings, vehicle location, and road conditions.
- It includes an optimization module that calculates optimal control plans to minimize fuel consumption and emissions while satisfying predefined speed constraints.
- The guidance provided by EDSGS is based on ecological considerations, aiming to achieve environmentally friendly driving behaviors.

C. GWSGS (Green Wave-based Speed Guidance Strategy):

- GWSGS aims to guide vehicles through signalized intersections without stopping by coordinating their speeds to match the green wave.
- It involves releasing guided speeds to vehicles upstream of intersections to allow them to pass through without stopping.
- The strategy optimizes the timing of speed guidance to ensure that vehicles can maintain a continuous flow through the network, minimizing delays and congestion.

In summary, while all three approaches aim to optimize vehicle movements on signalized road networks, they differ in their underlying principles and objectives. The DQN-based algorithm focuses on learning optimal speed actions through RL, while EDSGS emphasizes emission reduction, and GWSGS targets uninterrupted traffic flow through signalized intersections. Each approach offers unique advantages and may be suitable in different contexts depending on the specific goals and requirements of the transportation system.

VI. Conclusion

Based on the simulation results, it's evident that this particular algorithm greatly reduces travel time. Additionally, by minimizing braking and acceleration, it can extend the lifespan of vehicles and benefit the environment. Since it doesn't require significant investment in new infrastructure, it presents a cost-effective option for road maintenance. This algorithm shows promise in reducing queues and congestion, especially during periods of high traffic flow. It can serve as an alternative to traditional green wave strategies. Furthermore, when used in conjunction with actuated controllers, it can create a feedback loop to optimize signal timing plans based on real-time conditions.

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