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Single Intersection Control For Urban Traffic Using Model-Based Predictive Control

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ABSTRACT

In this paper, urban road traffic control is presented using model-based predictive control, and the modeling of traffic and state-space parameters at an intersection is extracted. Subsequently, a predictive controller is designed to manage the traffic lights based on the queue length and the number of incoming and outgoing vehicles as inputs to the controller. The cost function is calculated using state-space parameters, and given that the output is predicted according to the model at future moments, optimal control efforts to minimize the cost function are obtained. The stability of the system using predictive control is proven. The advantages of this controller, such as the ability to optimize the current state while considering future states and its design simplicity, have resulted in the predictive controller performing significantly better compared to the fixed-time method. The simulation results also indicate the desirable performance of the controller compared to other control methods, leading to a reduction in queue length.

1. INTRODUCTION

With the rapid advancement of urban societies and the swift transformations in urban life, there has been a significant increase in the number of vehicles, particularly in large cities [1-7]. This phenomenon is attributed to factors such as population growth, economic conditions, social and cultural factors, migrations, and others, bringing numerous challenges. In [8], the U.S. Department of Transportation announced in 2006 that the country incurred approximately $200 billion annually in damages due to transportation bottlenecks and freight delays. In [9], traffic lights at intersections are considered one of the primary tools for urban traffic control. To reduce traffic, optimal control methods can be utilized to decrease travel time along a route and the queue length of vehicles. In [10], traffic control is categorized into fixed-time and intelligent methods. According to [9], fixed-time intersection control can be implemented either locally or in a coordinated manner, with settings optimized offline at different times throughout the day.

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The effective parameters in traffic control include flow rate, flow speed, occupancy, density, queue length, traffic volume, delay, offset, sector, vehicle advancement time, and vehicle headway. Various dynamic models have been discussed for traffic control. In [12], a dynamic model for traffic signal control within a model predictive control framework is presented, where the online settings of all free traffic signal parameters, namely cycle times, split times, and offset sets, are simultaneously centralized.

To date, traffic control methods have been based on classical control methods, which employ statistical techniques. However, due to the complex nature of traffic control, these methods do not provide satisfactory responses. Therefore, with the advancement of intelligent methods, which include artificial intelligence, fuzzy logic, neural networks, multi-agent systems, etc., it is possible to address and improve urban control problems. In [13], a neural network was used to conduct a set of training sessions for the system. In [14], a neural network and fuzzy logic were used at an intersection as an intelligent agent to learn how to adjust the green time in each cycle based on the information, thereby improving the controller's accuracy. In [15], a genetic algorithm was presented for optimizing traffic signals under saturation conditions. A wide range of optimization strategies have been evaluated to minimize delay and maximize capacity at various intersections. In [16,17], a model for vehicle queue traffic flow and average vehicle waiting time was provided.

Intelligent methods lack predictive capabilities, but using model predictive control (MPC) not only encompasses all the advantages of intelligent methods but also provides predictive capabilities, making this method superior to the aforementioned methods. MPC is one of the optimal control methods based on the receding horizon theory and is among the intelligent control methods. This controller has also developed rapidly. In [18], MPC was used to control and coordinate urban transportation networks. The optimization in MPC, with nonlinear modeling, requires significant computational time. Considering the nonlinearity of the optimization problem, logical combinatorial programming can reduce the computational time. In [19], MPC focused on the uncertainties related to the flow rate entering the traffic network and can also be successfully used to control urban traffic signal systems. In [20], the use of urban transportation networks with distributed model predictive control can offer more flexibility compared to centralized strategies.

Based on the various studies mentioned regarding predictive control in traffic, this controller has so far been used for traffic lights designed based on the queue length of vehicles and the number of incoming and outgoing cars. In this paper, predictive control is utilized to adjust the traffic light control. The inputs to the controller are the current queue length in the traffic (vehicles), and the number of incoming and outgoing cars at each arm, considering the parameters of the problem. This controller can minimize the difference between future output values and future events. Predictive control has been shown to improve traffic flow compared to fixed-time control. One of the advantages of this intelligent method is the reduction of queue length, which ultimately leads to decreased traffic congestion. Moreover, one of the main reasons for using this controller is the complexity of traffic, as it reduces the impact of uncertainties in the system.

With these preliminaries, the structure of this research is as follows: In the second section, the dynamic model is presented. Then, in the third section, the proposed method is discussed. Finally, the simulation results and conclusions derived from MATLAB are provided.

2. DYNAMIC MODEL OF THE INTERSECTION

To control traffic at an intersection, the state-space equations related to the real model in a traffic network are required.

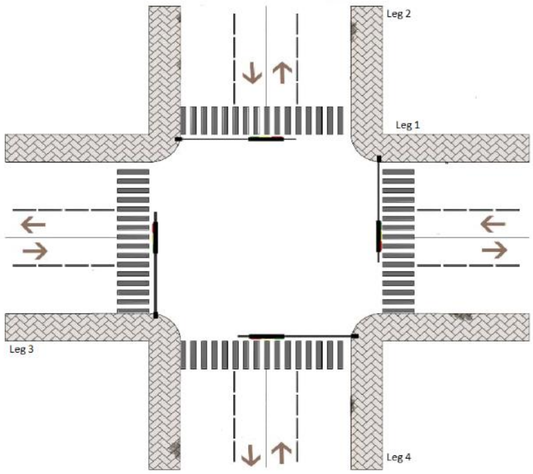

Fig. 1. A two-phase signalized intersection.

In Figure 1, an illustration of a two-phase signalized intersection is presented. In this scenario, queue length is considered one of the critical parameters of traffic flow, representing the state and condition of traffic at an intersection. It is depicted as follows [20].

$$Q_i(n+1) = Q_i(n) + q_i(n) - d_i(n)s_i(n) \tag{1}$$

Regarding (1): The i = 1, 2, 3..., n denotes the input traffic stream arms at an intersection, while n = 0, 1, 2,...., N-1 represents the sampling time index. Qi(n) indicates the queue length formed by the number of vehicles, qi(n) denotes the inflow, di(n) signifies the outflow of vehicles from the queue, and the signal control status at the intersection. Figure 1 illustrates that, in the first phase of a four-way intersection, traffic implies that the second and fourth arms have a green light, while the first and third arms have a red light; the opposite scenario also exists. One of the factors examined in traffic studies is the vehicle delay, which refers to the amount of time public vehicles and cars spend in the queue. The vehicle delay in the i -th queue from the start of the time interval to the beginning of the n -th time interval is obtained as follows [20].

$$W_i(n+1) = w_i(n) + T\,Q_i(n) - 1/2T\,d_i(n)s_i(n) + 1/2T\,q_i(n) \tag{2}$$

The state-space equations are presented as follows:

$$\begin{cases} X(n+1) = AX(n) + B(n)S + C(n) \\ Y(n) = CX(n) \end{cases} \tag{3}$$

where $X(n) = [Q_1(n)Q_2(n).....Q_M(n)W_1(n)W_2(n)...W_M(n)]'$ represents the state variables and $S(n) = [S_1(n)\ S_2(n)....S_M(n)]'$ denotes the control variables. The remaining coefficient matrices and vectors are defined as follows [20]:

$$
\begin{aligned}
C &= \begin{bmatrix} I_M & 0 \\ 0 & I_M \end{bmatrix} \\
A &= \begin{bmatrix} I_M & 0 \\ TI_M & I_M \end{bmatrix} \\
B(n) &= -\begin{bmatrix} d_1(n) & 0 \ldots\ldots\ldots\ldots 0 \\ 0 & d_2(n) \ldots\ldots\ldots\ldots 0 \\ \vdots & \vdots \\ 0 & 0 \ldots\ldots\ldots\ldots d_M(n) \\ 1/2Td_1(n) & 0 \ldots\ldots\ldots 0 \\ 0 & 1/2Td_2(n) \ldots\ldots\ldots 0 \\ \vdots & \vdots \qquad \vdots \\ 0 \ldots\ldots 0 & \ldots\ldots\ldots 1/2Td_M(n) \end{bmatrix} \\
C_n &= [q_1(n)q_2(n)\ldots q_M(n)1/2Tq_1(n)1/2Tq_2(n)\ldots.1/2Tq_M(n)]^T
\end{aligned} \tag{4}
$$

The traffic equations in relation (4) are expressed based on the state-space equations. The equation pertains to the queue and total delay of vehicles approaching the intersection under different traffic light conditions (green and red) [20].

3. CONTROLLER DESIGN

Model Predictive Control (MPC) is a model-based controller where the accuracy of the model is of paramount importance. Some of the capabilities of this controller include the ability to impose constraints, limit the input and output signals, generate control signals, and ease of use in multivariable systems. The general schematic diagram of the Model Predictive Control can be referenced in Figure 2.

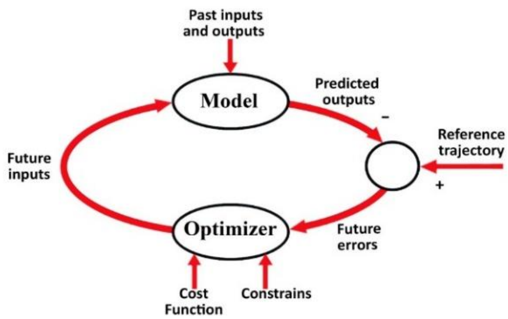

Fig. 2. General schematic diagram of Model Predictive Control (MPC).

The structure of Model Predictive Control (MPC) consists of the process model, the cost function, and the control law. This structure is derived from a set of control rules such as predicting the future output of a system over a specified time horizon using the initial process model, computing control signals over the prediction horizon by minimizing a cost function, applying the first computed control signal to the system, and repeating the entire process in subsequent stages [20]. The primary goal is to predict and reduce the queue length concerning future system inputs at each sampling time, thereby optimizing the system's future behavior.

In this controller, the inputs include the queue length of vehicles and the number of incoming and outgoing vehicles at each arm. The state-space equation is defined in (3). T represents the sampling time and is considered optional. Assuming that the sampling time (T) is sufficiently large, the arrival of vehicles can be observed uniformly at each time interval. The intersection has four arms, each with three lanes, with vehicles being independent in each lane and a normal distribution used for generating inputs. The maximum and minimum green times are also taken into account.

Modeling and the cost function, as per [21], are based on a four-way intersection model. The cost function, considering the model of an intersection, is derived as follows:

$$J = X^T(n+1)QX(\mathrm{n}+1) + \Delta S^T(\mathrm{n})\,\mathrm{W}\,\Delta S(n) \tag{5}$$

The optimization of a single intersection is presented as follows:

$$y' = \begin{bmatrix}1 & 1 & 1 & 1 & 0 & 0 & 0 & 0\end{bmatrix}\begin{bmatrix}\Delta x_1(n) \\ \dots \\ \Delta x8(n)\end{bmatrix} = 1\times\Delta x_1(n) + \dots + \Delta x_4(n) + 0 + 0 + 0 + 0$$

$$\Delta x_m(n) = \begin{bmatrix}Q_1 \\ \dots \\ Q_M \\ W_1 \\ \dots \\ W_M\end{bmatrix} \tag{6}$$

Assuming ξ = [1 1 1 1 0 0 0 0] in equation (6), the Hamiltonian equation will be as follows:

$$H = (\mathrm{A}\Delta\mathrm{X} + \mathrm{B}\Delta\mathrm{S} + \mathrm{C})^T \xi^T \xi(A\Delta X + \Delta S + C) + \Delta S^T R\Delta S \tag{7}$$

Finally, by taking the derivative of the cost function with respect to the control effort and solving the formulated Hamiltonian equation, it is observed that the optimal solution for calculating the desired control effort in the Model Predictive Control is obtained as follows:

$$\Delta S = (-2(\Delta X^T A^T \xi^T B + C^T \xi^T \xi B)(B^T \xi^T \xi B + R^T)^{-1})^T \tag{8}$$

4. SIMULATION RESULTS

The objective of the simulation is to reduce the queue length of vehicles at an intersection. This is achieved under two conditions: fixed-time and using a stable Model Predictive Control (MPC) intelligent controller. The sampling time is set to T = 0.1 seconds. Table 1 presents different traffic scenarios with their respective values.

Table 1. Values of β in different traffic scenarios.

Traffic Status	β
Non-Saturated	$\beta \geq 0.7$
Saturated	$0.4 \leq \beta \leq 0.6$
Over-Saturated	$0.1 \leq \beta \leq 0.3$
Unstable	$\beta = \mathbf{0}$

The number of vehicles that have exited the i-th queue during the n-th time interval is updated by the following equation:

$$d_i(n) = \min(Q_i(n) + q_i(n), d_{si}(n)) \tag{9}$$

Additionally, the saturation flow rate during the time interval T is given by the following equation:

$$d_{si}(n) = d_{cons}(n) + \beta q_i(n) \qquad i = 1,2,3,4 \tag{10}$$

The parameters d_i and q_i can be randomly defined in equation (10). The simulation results are obtained by comparing the fixed-time control with the designed controller.

4.1. Fixed-Time Control

In fixed-time control, the simulation results for the number of vehicles in the queue without applying the controller indicate that the control variables represent the green and red times of the traffic light at an intersection. In this case, the red light corresponds to the traffic signals on the first and third arms, as shown in Figure 3, while the green light corresponds to the traffic signals on the second and fourth arms, as shown in Figure 4.

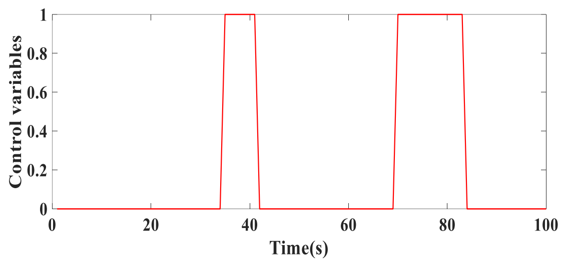

Fig.3. Red light at the first and third arms of the single intersection.

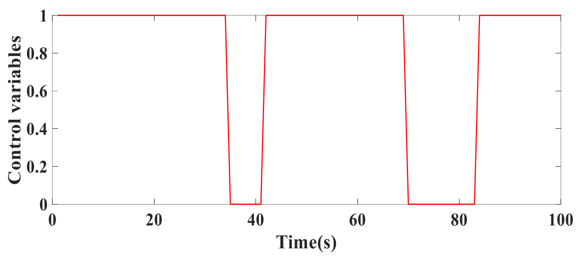

Fig. 4. Green light at the second and fourth arms of the single intersection.

The queue length of vehicles on the first arm of the intersection is shown in Figure 5, and on the second arm in Figure 6. These figures represent the fixed-time control and demonstrate how it improves with the Model Predictive Controller (MPC).

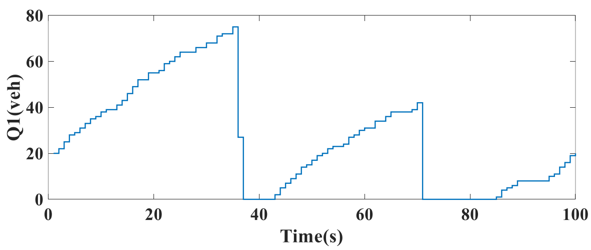

Fig. 5. Queue length of vehicles on the first arm of the single intersection.

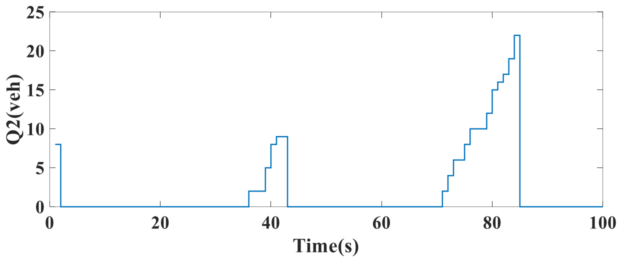

Fig. 6. Queue length of vehicles on the second arm of the single intersection.

Figure 7 shows the number of vehicles on the third arm of a single intersection under fixed-time control, where the initial queue length is short but increases over time. Figure 8 illustrates the traffic volume on the fourth arm, which also increases over time.

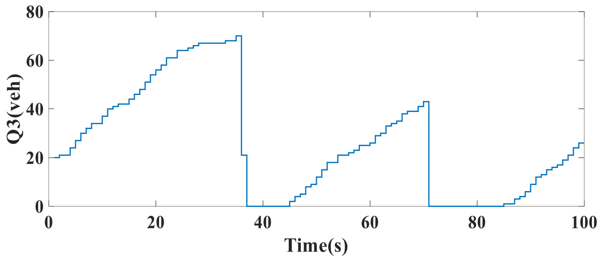

Fig. 7. Queue length of vehicles on the third arm of the single intersection.

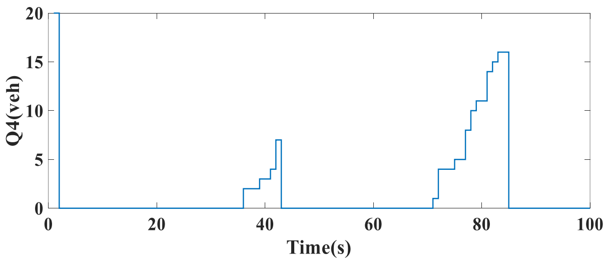

Fig. 8. Queue length of vehicles on the fourth arm of the single intersection.

4.2. Model Predictive Intelligent Controller

In this section, the designed controller in equation (6) is implemented on the dynamic system of an intersection. As shown in Figures 9 and 10, these figures illustrate the control variables indicating the green and red light times of the traffic signal when applying the Model Predictive Controller (MPC) at an intersection.

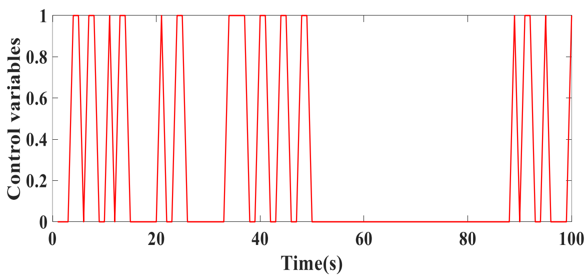

Fig. 9. Green or red light status on the first and third arms of the single intersection.

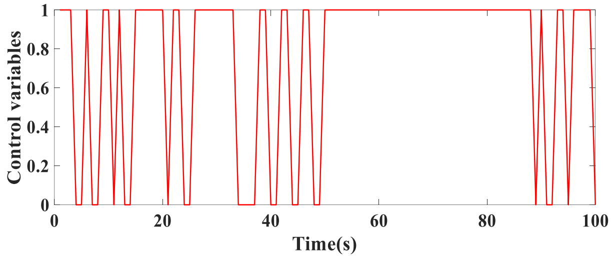

Fig. 10. Green or red light status on the second and fourth arms of the single intersection.

The queue length of vehicles on the first arm of an intersection, when the controller is implemented, has decreased compared to the scenario without the controller. This can be seen in Figure 11.

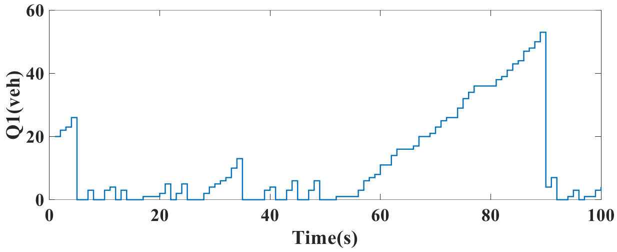

Fig. 11. Queue length of vehicles on the first arm of the single intersection.

The queue length of vehicles on the second arm of the intersection with the controller, compared to the fixed-time control, has significantly decreased. This is shown in Figure 12.

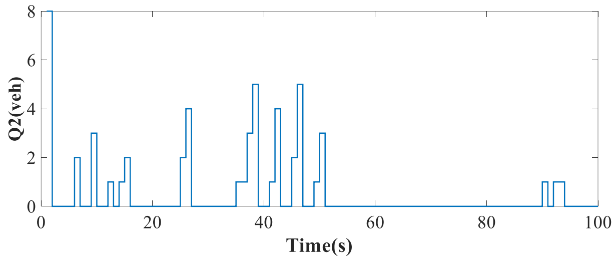

Fig. 12. Queue length of vehicles on the second arm of the single intersection.

The queue length of vehicles on the third arm of an intersection, shown in Figure 13, has been minimized and improved with the application of the controller.

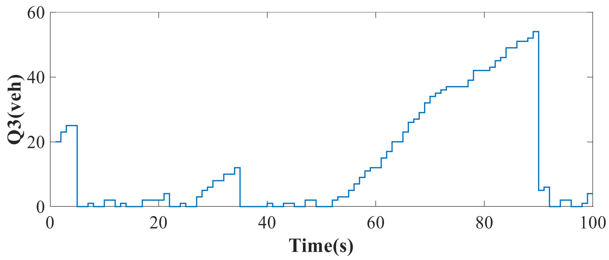

Fig.13. Queue length of vehicles on the third arm of the single intersection.

Figure 14 shows the queue length of vehicles on the fourth arm of the intersection. The number of vehicles in the traffic queue has been minimized with the application of the Model Predictive Controller and has significantly decreased compared to the scenario without the controller.

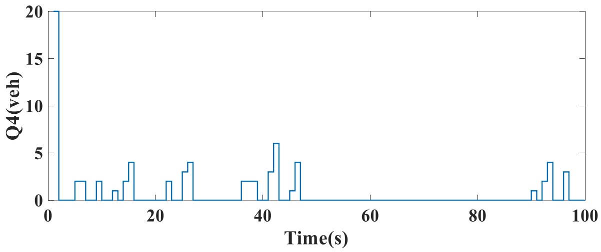

Fig.14. Queue length of vehicles on the fourth arm of the single intersection.

According to the simulation results, it can be concluded that by employing the Model Predictive Controller, the queue length of vehicles at each arm of an intersection is reduced compared to the fixed-time control. Considering the sampling time of every 0.1 seconds, the traffic volume decreases, leading to improved efficiency.

5. CONCLUSION

In this paper, a Model Predictive Control (MPC) for generating and adjusting traffic light signals at an intersection has been designed and presented, and its stability has been examined. The designed MPC model for an intersection is based on two essential parameters: queue length and vehicle delay. By applying the controller, which is based on discrete-time state-space equations, it is observed that the queue length of vehicles at each arm decreases compared to the fixed-time scenario, minimizing the traffic volume at each arm. Additionally, the simulation results demonstrate the effectiveness of the proposed method for an intersection.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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