Research Article

Signal Traffic Optimization Using Control Algorithm in Urban Traffic Framework

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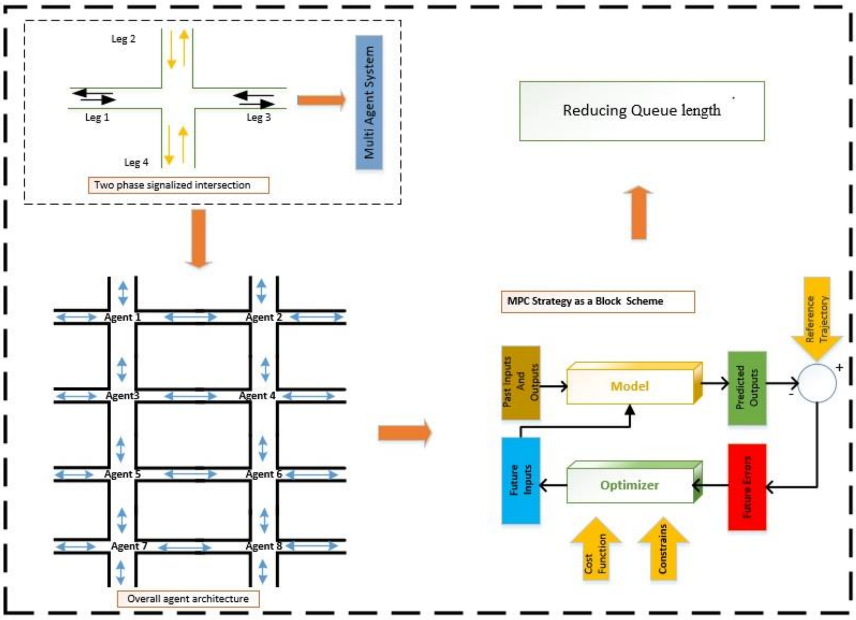
Abstract: Increasing urbanization, rapid urban population growth and economic development are signs of society's rapid development. There are increasing traffic problems in the city, which affect the city's normal function. This paper aims to create a computational model to study vehicle queues on urban roads to control vehicle crashes, traffic volumes and average vehicle delays. This model offers analysis at multiple intersections with traffic lights controlling vehicle queues based on fixed time intervals. We defined our objective function as minimizing the queue length. We used the Matlab program to simulate the proposed method. MPC-based traffic control can be implemented in any urban transportation network, but a modern traffic controller and a proper measurement system are needed for that goal. Furthermore, we address this issue explicitly by employing a sampled multi-agent system at the intersection. The intersections are considered independent agents, which share information, and their stability is established independently. The simulations show the model predictive control in the simulation results prove the effectiveness of the designed model predictive control based traffic control strategy and show that the system can improve the network efficiency and cause reduces the lengths of cars.

Keywords: Traffic lights, multi-agent systems, urban traffic signal control,fixed time controller, model predictive control.

1. Introduction

The congestion of traffic on roads is a well-known problem across the globe. On freeways, just as in urban transportation networks, people face traffic jams every day. As rush hour approaches, the roads become saturated. However, the traditional methods of controlling traffic flow are becoming less effective. Traffic in areas and cities, particularly at intersections and roads connection, cause the formation of long queues of cars, leading to expecting cars in line. However, metropolises have different programs to reduce traffic congestion, effective in some cities. For example, bicycle can cause create traffic in an intersection, in urban areas where bicycle traffic is increasing, the allocation of space for additional transportation methods is reevaluated. The goal is to quantify and assess the potential impacts of developing an urban bicycle highway. This process presented bicycle highway traffic quality thresholds that could be achieved by implementing bicycle traffic control measures, such as bicycle coordination and passing time extension, described in official bicycle approaches **(Grigoropoulos, G.et al.,2021**).The problem we consider here is the emergence of long queues behind traffic lights at intersections and immoderate waiting for drivers to cross the intersections, leading to reduced safety, security health of people, increased air pollution, society, and road accidents**(Yen, C. C.et al. &Du, Y.2021**) Modern transportation is leading to increasing numbers of vehicles on the road. Although the number of cars is rising, the road capacity cannot improve. Therefore, they have a limited capacity. For this reason, models need to be developed in which a traffic control system is implemented and performing at the highest possible level while requiring the least calculation time **(Guilliard, I.et al.,2020 &Kuboth, S. et al.,2019**).Indeed, an inappropriate control of traffic lights which does not take into account the ongoing traffic situation surrounding the road intersection results in a very poor traffic flow performance.The urban transportation system requires adequate solution methodologies. The most exciting features of agents from a transportation point of view are cooperation, freedom, and accountability. These features help in the implementation of intelligent traffic management and control systems (**Sankhyadhar, S.et al., (2020) &Zakharov, M.,et al (2020))**.The expansion of urbanization, the increasing use of private cars, and the lack of urban transportation infrastructure have increased urban travel time. This topic causes people to be on the streets for a long time. Urban life has reduced clean air, noise pollution, and wasted time these days. Queue length and fuel consumption increase are reasons for the weather becoming polluted. In research related to traffic control, there has to be a correct understanding and realization of the traffic system.Traffic control methods are primarily based on traditional control methods obtained by statistical and experimental methods. The required parameters converted to a more specific control level in these studies. The transmission system responsible for this high complexity of the structure includes parts that involve a large amount of control, communication, computer, and operation and maintenance costs. Traffic control studies should have a proper and complete understanding of the transmission system.Models and control methods are essential for controlling dynamical systems to produce a preferred or optimal output while simultaneously demanding minimal computing time. This work aims to develop an effective control modeling method to optimize traffic network intersections. Research studies operating model predictive controllers have been conducted in many fields (**Ye, B. L.et al.,2019)**.The first study on the model predictive control (MPC) approached urban traffic control and demonstrated that model predictive control was more effective in reducing the number of vehicles at intersections.The model is dynamic and nonlinear, introducing an unconstrained model predictive control. Additionally, model predictive control allows us to personalize parameters. A further benefit of predictive model control is limiting green time and turning speeds for vehicles, providing secure intersection control (**Jamshidnejad, A.et al.,2016)**.To achieve the desired output, it is necessary to model the intersection traffic system in more detail and design powerful controllers that allow the desired response, which reduces the number of vehicles in the intersections. It has led to a lot of research on intersection traffic systems.As shown, Figure. 1 presents the proposed overview of the method. This multi-agent model has been used for eight intersections in traffic control and reduces the queue length using predictive control. We used a dynamic model from a single intersection in the first step in this figure. After that, we have proved stability with attention to the dynamic model intersection. In the second step, to expand an intersection to 8 intersections, we proposed a multi-agent approach in which intersections are connected. Ultimately, we want to reduce the queue length created at the intersections by the offered model.

Figure.1 The suggested approach architecture.



This study suggests an urban traffic control method based on model predictive control. We aimed to optimize vehicles traffic and reduce traffic jams at traffic lights. We introduce a computational model to study urban traffic by model predictive control. The new system realizing control for traffic lights was designed for the test, depending on the traffic condition and operating urban traffic control techniques to predict the green time. The offered system is linear equations; first, we used a dynamic model linear an intersection, and condition evolution equations for the system are linear. Thus, we offer a model predictive model for proofing stability. The MPC-based strategy optimizes the traffic network by minimizing the number of vehicles. We consider a multi-agent model in the combined multi intersection; then, we got a new equation with attention to a multi intersection.We operate only linear dynamics as part of the presented model predictive control framework to achieve this result.A model has been developed to predict queuing dynamics through links while maintaining the linearity of the state evolution equations.The proposed MPC framework smartly provides a description and an efficient simulation of traffic behavior using only linear dynamics.

2. Problem Statement

Developing an effective control system and simulating a physical process requires modelling a system. According to the study, the following is its objective: the study proposes two-phase models of vehicle behaviour at eight intersections during urban traffic, the intersection model is tested and simulated in traffic conditions, in addition to reducing the number of cars waiting behind a red light, a predictive controller is designed to reduce waiting times. The structure of the paper is organized as follows. First, discuss the related work in Section (i). The details of the proposed method are presented in Section (ii). Then the stability analysis is mentioned in

Section (iii); we verify the effectiveness of our proposed method via simulations in Section (iv). We conclude the paper and point out some future work remarks in Section (v).

3.Literature Review

The application of model predictive methods has recently become increasingly popular in traffic signal optimization and control. Traffic situations are unexpected, so the method needs to model and adapt to the environment. As a result, the traffic signal control model should enhance with predictive. Traffic signal management with model predictive control is adjustable and dynamic and can be applied in unexpected environments.

3.1. Model predictive control of urban traffic

Urban road networks with large traffic magnitudes stay a challenge to control. Aggregate dynamical simulations of city-scale traffic allow the evolution of model-based perimeter control methods based on the macroscopically fundamental diagram (MFD). A nonlinear model predictive perimeter control system has been presented in this article to control and optimize economics using closed-loop stability by structure **Sirmatel, I. I., &Geroliminis, N (2021)**.Control traffic signal coordination and control in urban traffic networks using stochastic model predictive control (MPC); this essay presented a model predictive control framework. One of the proposed stochastic model predictive control elements is that stochastic disturbances are considered and uncertain traffic demands. The scheme aims to model uncertainty and avoid queue spillback in traffic networks. As described above, this aims to minimize the queue length and the fluctuation of green time between any two successive control steps **Ye,Wu, Gao,Lu,Cao., &Zhu (2017)&Jafari, S., Shahbazi, Z., & Byun, Y. C. (2021)**.The most effective way to use the available network capacity is to control traffic according to the traffic conditions, including model-predictive control. They have demonstrated their computationally and performance-wise efficiency in finding optimal solutions to optimization problems. A model-predictive control system presented for an urban traffic network that solves the control optimization problem by utilizing a gradient-based optimization approach **Jamshidnejad, Papamichail, Papageorgiou., & De Schutter (2017)**.Traffic signals are updated at regular intervals in most optimization-based traffic control systems. Based on the trade-off between the control performance and the analysis efficiency, the length of the fixed update interval is decided. This article suggested a distributed threshold-based event-triggered control strategy; due to independent triggers, traffic signals are updated asynchronously by using model predictive control **Wu, Li, Xi., & De Schutter (2020)**. In **Ye, Wu, Ruan, Li, Chen, Gao., & Chen (2019)**has been presented a survey of predictive model control in urban traffic. Over the past 20 years, model predictive control has been studied widely in traffic signal control since it has a lot of benefits when modeling dynamic systems. The control of traffic signals by model predictive control-based methods requires to be understood in depth. The presented article provides the rationale for using predictive model control to control traffic signals. In addition, this article has been summarized recent developments in model-predictive control-based traffic signal control systems for traffic coordination and control within traffic networks. An application of coalitional model predictive control to freeway networks is discussed in **Chanfreut, P., Maestre, J. M., & Camacho, E. F. (2020)**. Using model predictive, a dynamic setting of speed limits and ramp metering decreases the number of times drivers spend on the road. As a result of the continued improvement of clustering techniques, their usefulness in controlling large-scale and spatially dispersed systems discussed.

3.2. Urban traffic by Machine learning and other work

As a society, we face a growing problem of urban traffic congestion. This issue was resolved by building a software-defined Internet of things with a proper traffic control scheme. Also, as a result, current traffic control schemes fail to leverage the advances found in deep reinforcement learning with multi-agents. In **Yang, J., Zhang, J., & Wang, H. (2020).**proposed a software-defined internet of things via a multi-agent Deep reinforcement learning approach algorithm for optimization, which has been presented traffic lights and vehicles are controlled globally to enhance urban traffic control. In**Mao, Malaita., & Vu (2021)** has been aimed to identify the optimal traffic signal timing in signalized urban intersections under conditions with non-recurrent traffic happenings. The challenge of optimizing control plans for severe experiences remains available. Control plans are still not optimized when trying incidents happen; the problem is particularly acute when several lanes or entire intersections are affected. The problem is particularly critical when several roads or complete intersections are affected. A deep learning model presented to develop a traffic jam control system operating data fusion for intelligent cities. Intelligent traffic flow predictions in smart cities have been created using the hybrid model of convolutional neural networks and extended short-term memory architectures**Khan, S., Nazir, S., García-Magariño, I., & Hussain, A. (2021)**.Intersection security and efficiency depend on traffic signal control. A novel adaptive multi-input and multi-output traffic signal control method has been proposed in this analysis. Not only can this method decrease traffic delays and energy consumption, but it can also improve network-wide traffic procedures **Wang, Zhu, Hong, Wang, Tao., & Wang (2020).**By utilizing cultured models, urban traffic prediction can determine invisible patterns of traffic based on crucial historical mobility data and then predict traffic situations in the future employing that knowledge. Deep learning emerges as a promising alternative to traffic modelling due to its powerful representation learning and feature extraction abilities. This article presented various traffic indicators predicted using deep learning **Liu, Li, Wu., & Li (2018)&Shahbazi, Z., & Byun, Y. C. (2022)**. For solving the urban traffic control, a deep reinforcement learning offered, which combines several tricks to get a suitable control strategy within a reasonable amount of time utilizing the Deep reinforcement learning algorithm. The subject has been fixed the traffic request design assumption**Lin, Dai, Li., & Wang (2018)&Jafari, S., Shahbazi, Z., Byun, Y. C., & Lee, S. J. (2022)**. The application of modern technologies makes it possible for a transportation system to gather real-time data of specific traffic scenes, allowing traffic control centres to enhance traffic efficiency. Based on such considerations, a variation of deep reinforcement learning agents have been analysed, showing their performance in traffic conditions **Zeng, J., Hu, J., & Zhang, Y. (2018)&Khan, P. W., & Byun, Y. C. (2020)**. A set of variables from traffic characteristics has been used to model traffic noise at intersections, traffic management, geometry, and pavement conditions. Regression models were used to identify which factors contributed to modelling traffic noise at the urban traffic**Khajehvand, M., Rassafi, A. A., &Mirbaha, B. (2021).**This research used traffic signal scheduling and phase sequence control; the algorithm techniques have been combined with general type-2 fuzzy logic sets at the urban traffic network. The aim has been to minimize wait times and average queue lengths to enable smooth traffic flow. Furthermore, state charts and object diagrams have shown the urban traffic network model **Khooban, Vafamand, Liaghat, &Dragicevic(2017)**.There has not been enough exploration of its potential application to advanced artificial transportation systems. A traffic optimization system based on agent technology and fuzzy logic to manage road traffic, prioritize emergency vehicles, and promote coordinated transportation methods in smart cities **Ikidid, A., El Fazziki, A., &Sadgal, M. (2021).**In **Ramirez-Polo, Jimenez-Barros,Narvaez., &Daza(2022)**signals and traffic lights considered due to the number of vehicles in the streets and population in cities which increased and directly has been impacted traffic on the roads. Thus to improve mobility in the intersections, are used an optimization model that causes developed traffic lights for vehicles in high traffic areas. This technique has been used to calculate the appropriate time of the traffic lights on one of the busiest and most congested roads to reduce the time spent.Traffic models are applied to analyse historical and real-time traffic data to predict the situation of urban traffic in the future. Traffic signal control has been a primary tool for urban traffic management. This article is based on an urban traffic control system founded on traffic flow; the primary goal is to minimize the number of vehicles for signalizing intersections in the road network**Jiang, C. Y., Hu, X. M., & Chen, W. N. (2021)**.

3.3.Urban traffic by multi agent

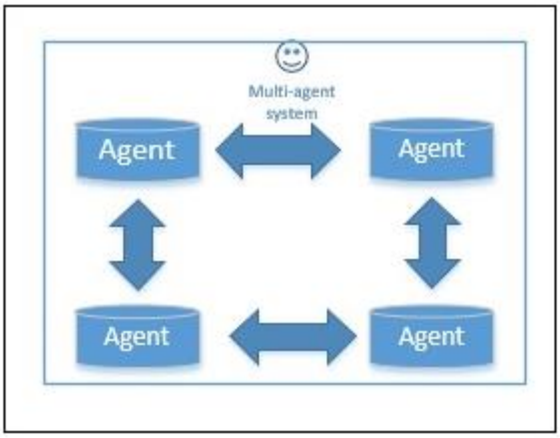
Urban traffic congestion, which has negatively affected the economy and environment for many decades, is a global issue. The signal control system is a well-established but challenging engineering solution that decreases traffic congestion by coordinating vehicle movements at intersections. Agent-based deep reinforcement learning for large-scale traffic signal control checked the performance of congestion time and network delay presented **Wu, Wu, Shen, Telikani, Fahmideh& Liang (2022)**. A multi-agent system for optimizing urban traffic has been presented, which; a hierarchical multi-agent system is used in managing an urban traffic system. However, members are local agents representing intersections within the system. Attention to traffic accidents and morning rush hour has been checked**France, J., &Ghorbani, A. A. (2003)&Shahbazi, Z., & Byun, Y. C. (2022)**. Recent developments in multi-agent systems in the areas of consensus problems, formation control, flocking control, among others which are based on the interaction level, find it challenging to perform intelligent collaboration due to double rules of limited interaction abilities and systems **Shi, P., & Yan, B. (2020)**.An interaction of dynamic multi-agent systems at a macroscopic level presented. In a hybrid and scalable system, the agents can create continuous-time networks, Petri Nets (PN) can create discrete-time networks, resulting in complex networks. Several real-world streets and intersections have been used to evaluate the approach's performance **Geronimo, Martinez, Vazquez, Godoy., & Anaya (2021).**

4. Traffic signal control based on multi-agent and model predictive control architecture

4.1.Multi-agent system (MAS) control

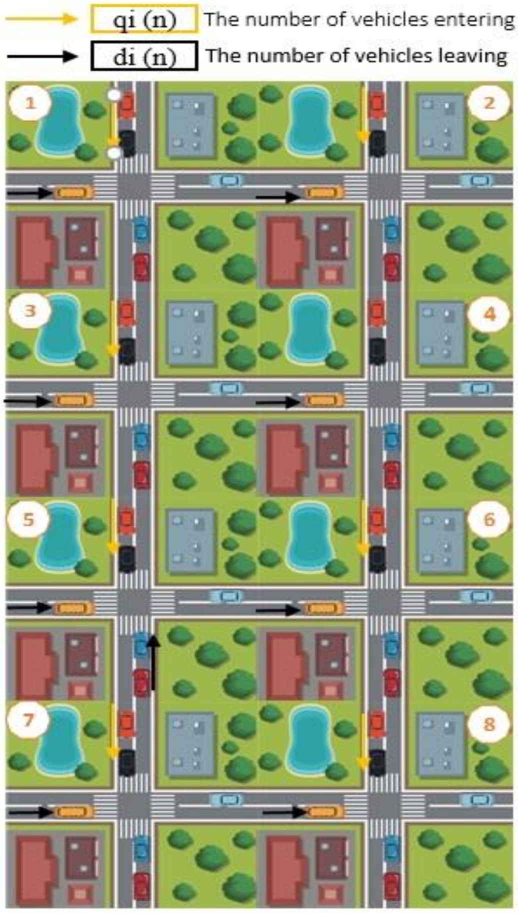
Multiple agents are coordinated to control complex systems through the multiple agent control system. The term agent refers to an autonomous, cooperative, and initiative-oriented physical or abstract entity. Distributed intelligent systems include multi-agent systems. Agents of the Multi-Agent Model can share information and coordinate themselves to complete tasks. A Multi-Agent Model utilizes several agents with different functions that coordinate and share information to accomplish a task.Multi-agent control system structure, see Figure. 2exhibit interactions between agents, in contrast to simple combinations of agents.

Figure.2 Structure of multi-agent model.



A modern city's traffic system is composed of hundreds of intersections, some of which are distant. Traffic conditions in different network areas may significantly differ due to the huge urban network. The control of traffic network signals uses multi-agent technology. According to the two frameworks of multi-agent systems, there are two ways to construct the signal control system of a multi-agent urban traffic network **Choy, M. C., Srinivasan, D., & Cheu, R. L. (2003)**. As shown in Figure. 3, an agent-controlled intersection described. At this intersection of a road network, per agent chooses its actions autonomously or via another supervisory agent system. The general goal of such distributed multi-agent architecture is to ensure that network-wide congestion is reduced through coordinating signal control to predict traffic patterns in the future. When such agents constantly control signals, the situation reaches an unlimited horizon. A distributed architecture that tries to approximate the infinite horizon of traffic would be impossible due to the need to record every state of traffic going back in time **Recker, Ramanathan, Yu, & McNally (1995)**.

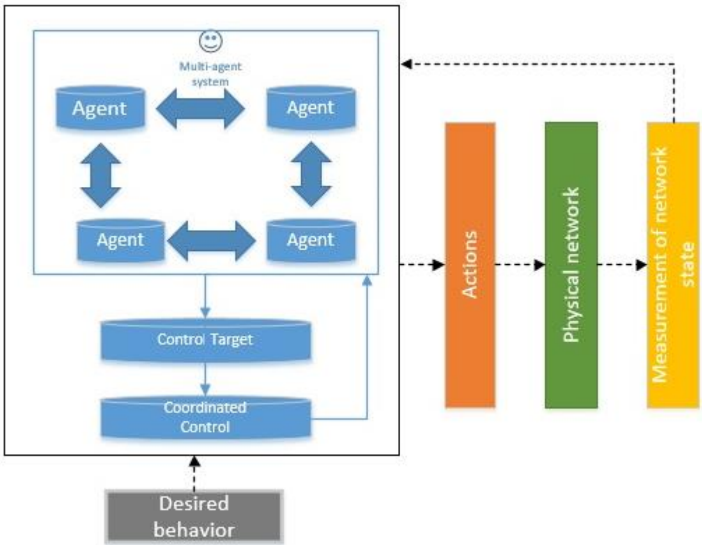
Figure.3 The model of multi intersections based on multi-agent system.



4.2.Multi-agent system (MAS) control

Multi-agent by model predictive control system structure, see Figure. 4 exhibit interactions between agents, in contrast to simple combinations of agents. The server agent gathers and analyses data from client agents and provides assistance to them. Information is exchanged with client agents, stored, and retrieved from databases. It gives the server agent with data processing operations different system parameters as soon as possible and then uses the waitperson agent's knowledge to do the related management. Also, in collaboration, one or more agents create the state they need. Competition and cooperation are the two fundamental modes of cooperation. A cooperative event occurs when several agents work together and share their knowledge and skills to accomplish a common goal. The first demonstrates spatial, material, and functional allocation, and the latter indicates that the method is extensive and complex to be resolved with a single centralized approach. Large-scale, dynamic, available, heterogeneous multi-agent systems enable unique strategies for managing and analysing distributed computing and information systems. We managed multiagent-based control and model predictive control together, as shown in Figure. 4. The design behaviour and method input and output in this methodology are limited, which process instrument based on the benefit of design behavior and activities. Signal light timings are optimized by the intersection agents independently. Similarly, the intersection agents notify the regional agents with traffic flow and signal light timing information. This physical network has been controlled with several control layers to control the network; the agent system model has been used model predictive control to predict the strategy's behavior to obtain the most suitable performance. It is primarily used to improve technical performance and signify that costs in minimum level**Zhou, DeSchutter, Lin, & Xi (2015)**.

Figure.4 Multi agent system based on model predictive control structure in urban traffic.



5. Methodology

Model predictive control automates complex systems by using multivariable control and explicitly viewing limitations. Traffic light cycles, we suppose time moves in discrete steps $n = 0, 1, 2, \dots.$which based on a discrete-time prediction model, the next state is defined as a function of the current state can be at time $n = n_0$, current requests, and the current control vector are at time $n = n_0$Each time model consists of a measured current state to solve the optimal control issue and the predicted demand over a finite time horizon considered at time $n = n_0, \dots, N-1$. Involving the system as a first control state can consider in the time $n = n_0$. Furthermore, for the next control state, the time can be $n = n = n_0 + 1$. The optimization generates a sequence of control vectors, though simply the first is used to the system. Following this, the optimal control issue is solved similarly for the time horizons. The control vector is utilized as the only control vector to be applied to the system information, as seen in Table. 1.

Table.1. Describe of discrete model.

Describe	
Current state	$X(k), time\colon n = n_0$
Control vector	$S(k), time\colon n = n_0 + 1$
Prediction horizon	$N_P, time\colon n = n_0 + 1$

$X(k)$represents the network state vector, and $S(n)$ represents the control vector. According to the state of the network, the number of vehicles is determined at different abstractions of locations based on two kinds of cars: queue (Q) and signal traffic (S). Which each queue has the capacity $K \epsilon K_Q$, the highest number of cars in queue k, generally based on physical limitations.At first, we considered a single intersection that includes four roads. (phase 1: legs 1 and 3, phase 2: legs 2 and 4). which the intersection dynamic system with attention an intersection can be written as an Equation. 1 as input.

$$X(k+1) = AX(k) + B(k)S(n) + C(k) \tag{1}$$

which $X(k) = [Q_1, Q_2, Q_3, \dots, Q_M, (n)]'$ is the vector of variables of model. As an output of dynamic system signal intersection can be written as an Equation. 2:

$$Y(k) = CX(k) \tag{2}$$

There are matrices$A$, B, and C coefficients and vectors, which as inputs in the single intersection. One of the primary parameters in the flow traffic at an intersection is the length of cars in the queue, which is estimated with Equation. 3:

$$Q_i(k+1) = Q_i(k) + q_i(n) - d_i(n)S_i(n) \tag{3}$$

Regarding enters of cars in the intersection, if the leg index is$i = 1, 2, 3, \dots, n$. Additionally, the discrete intervals are indexed by$n = 0, 1 \dots, N-1$. There is some information which we mentioned in the below Table.2.

Table.1. Explanation of signal intersection.

Explanation	
$q_i(n)$	The number of vehicles entering the queue.
$d_i(n)$	The number of vehicles the queue.
S_i	Control signal: If $S = 1$ refers to green. If $S = 0$ refers to red light.

With attention to a single intersection $S(n) = [S_1(n), S_2(n), \dots, S_m(n)]^t$ a control variables , the red light $S1, S3$ refers to in the first phase, and $S2, S3$ refers to green light in the second phase, as the states of signal traffic (0,1,0,1). It also refers to the red light $S2, S4$ in the first phase, and $S1, S3$ refers to green light in the second phase, as the states of signal traffic (1,0,1,0). The car's arrivals at every time interval can be assumed to be consistent if T is considered the discretized time interval and is short enough Azimirad, E.,et al.,(2010).

5.1.Modelization based on multi-agent intersections

This study assessed a regular traffic network with eight intersections, each signalized, to estimate the evolutionary strategy. In the intersection, all approaches are two-way, and per link consists of three lanes. Figure.3 shows a network diagram showing the entire network. As a link is built, the highest queue originated is utilized as input data. Each intersection consists of the same parameters. The coefficient matrix is the same as the intersection; the sole contrast is between the state-space equations, which contain the Kronecker effect. For the further details about matrices of coefficients and vectors are equal $A = (I_M \otimes A_i)\, X(k)$ and $B = (I_M \otimes B_i)\, S(n)\, X(k)$ at the intersection. With using a multi-agent for linking multi-intersection, as input, a new state-space equation can be written in the below Equation 4:

$$X(k+1) = (I_M \otimes A_i)\, X(k) + B = (I_M \otimes B_i)\, S(n) + 1 \tag{4}$$

The output of dynamic system multi intersection is given by Equation5:

$$y(k) = CX(k) \tag{5}$$

Kronecker is displayed as $\otimes$. This multiplication factor is on two matrices of optional size. Kronecker multiplication can be expressed by multiplying matrix A in all B matrices. This multiplication has no displacement property and is widely used in proving relationships in multi-factor systems. Kronecker multiplication is defined as Equation 6:

$$A \otimes B = [\, a_{i,j} \quad B] \tag{6}$$

If the matrix A is assumed to have dimensions $m \times n$ and the matrix B is assumed to have dimensions $p \times q$ then the Kronecker $A \otimes B$ multiplication produces a matrix with dimensions $m_p \times n_p$ in Equation 7 :

$$A \otimes B = \begin{bmatrix} a_{11}B & a_{1n} \\ a_{m1}B & a_{mm}B \end{bmatrix} \tag{7}$$

Suppose which define A in Equation 8:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{bmatrix} \tag{8}$$

Thus with attention to Equation 7, 8 we mentioned as an example in the below in Equation 9:

$$A \otimes B = \begin{bmatrix} a_{11} \times B & a_{12} \times B & a_{13} \times B \\ a_{21} \times B & a_{22} \times B & a_{23} \times B \end{bmatrix} \tag{9}$$

6. Control algorithm

As a mature technology, model predictive control proposes a comprehensive explanation for operating techniques and can handle complex dynamics, interacting variables, and constraints. The main goal of predictive model control is to ensure that an optimal control scheme is enforced and applied over the prediction horizon $N_p$in a rolling horizon N_uModel predictive control is thus widely used in manufacturing as a developed control approach. Due to its advantages over classical optimal control methods, MPC is considered the most innovative approach in current research, especially when it comes to closed-loop systems \cite{sirmatel2017economic}. Based on a prediction horizon of N_p time steps, the system is anticipated to act in a certain way. The method behavior is predicted, the controller's objective function is considered, and the constraints are considered for a discrete-time system. The MPC method is described in detail in this Section. A discrete-time horizon $N > 0$ is used to parameters the controller. As a function of the current state $X(k)$ and the controls $S(n)$, a future state prediction is generated and appears in the objective. Then we can define a cost function J based on a multi-agent system is utilized in an intersection model in Equation 10:

$$J = min \sum_{i=n}^{N-1} X^t\,(k+1)AX(k+1) + \triangle S^t(n)B \triangle S(n) \tag{10}$$

A minimum cost function results in vehicles queuing at intersections waiting to cross. As a result, the green time for the control signal compares to the state of the intersection.

Theorem:

A dynamic equation that fits the hypotheses presented in the preceding section. The main goal is to minimize the cost function when the control input. With attention to Equation 1 and Equation 2 supply at the system's dynamical makes all signals, including those formed in the closed-loop, uniformly bounded.

Proof:

On urban intersections, traffic lights are red. On green phases, the vehicles can enter or exit the intersection, which state dynamic equation with matrices A and B are defined as follows in Equation 11:

$$\begin{bmatrix} \Delta X_{g,r}(k+1) \\ y_{g,r}(k+1) \end{bmatrix} = \begin{bmatrix} q_i \otimes A_i \\ C \end{bmatrix} \Delta X_{g,r}(k+1) + \begin{bmatrix} q_i \otimes B_i \\ 0 \end{bmatrix} S_{g,r}(n) + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \tag{11}$$

The state feedback controller $S(n)$ is assumed to be a function of $X(k)$ with complete observations. With attention to $X(k)$, the control needs to satisfy when in each time be n as follow in the Equation 12 :

$$\begin{bmatrix} Q_i(k) \\ S_{g,r}(n) \end{bmatrix} \leq 0 \tag{12}$$

Now to prove optimal and stability introduced in this theorem that $S(n)$ to minimizes J is found from the solution of in Equation 13:

$$\frac{\partial J}{\partial \Delta S} = 0 \tag{13}$$

Expand J as in Equation 14:

$$J_{min} = \big(\lambda \Delta X(k+1)\big)^t \big(\lambda \Delta X(k+1)\big) + \triangle S(n) R \triangle S(n) = 0 \tag{14}$$

To give in Equation 15:

$$\frac{\partial J_{min}}{\partial \Delta S} = \sum \Delta X^T \mathrm{A}^T \lambda^T \lambda B + \Delta S^T \mathrm{B}^T \lambda^T B + \Delta S^T R \Delta S = 0 \quad (15)$$

To obtain Equation 15 we substitute the above into Equation 16:

$$\Delta S^T = \frac{1}{2(\Delta X^T \Delta X^T (I_M \otimes A_i)^T \lambda^T \lambda (I_M \otimes B_i) + C_i^T \lambda^T \lambda \\ ((I_M \otimes B_i))((I_M \otimes B_i)^T \lambda^T \lambda (I_M \otimes B_i) + R + R^T} \quad (16)$$

It completes the proof.

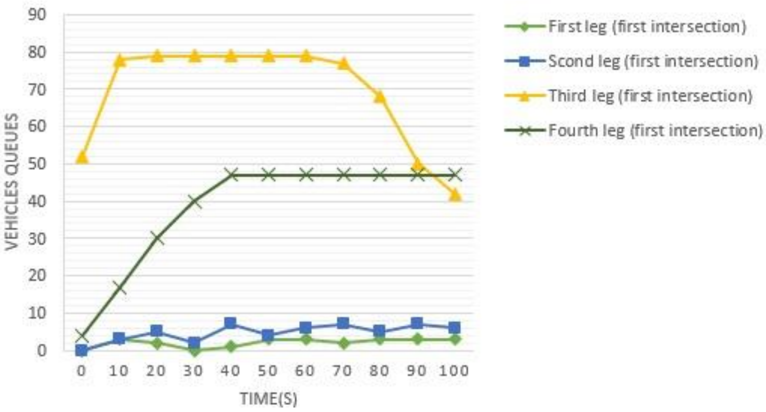
6. Simulation Results and Evaluation

The proposed traffic light control system was evaluated utilizing two traffic parameters in two different traffic scenarios. MATLAB code was used to simulate the suggested model of predictive traffic control.A quadruple length decrease standard is operated in simulation both in a fixed time frame and in a model predictive control scenario as well as a sampling time of $T = 0.1\ s$ is used. The following assumptions each intersection with four legs and three lanes per leg, on the per road, vehicles reach unaided. Standard distribution is used to generate arrivals based on the inter-arrival of cars. The values reflected traffic situations with additional times. With attention to different traffic conditions, considered the position of traffic, non-saturation, saturation, supersaturation, and in a stable. This predictive model uses random and distributed parameters q_i and d_i and the value of λ is between 0 and 1. The below model is explained without a controller.

6.1.Constant time based on multi intersection

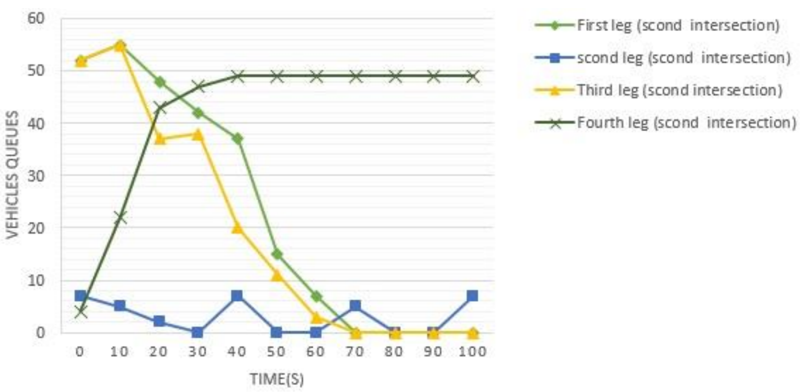
In this part, the model predictive control is compared to the fixed time control. The simulation results for the number of vehicles in the queue without controller actions in fixed time control are followed. Figure. 5 shows that car numbers have remained relatively constant during the initial phase. Compared to the adjacent second and fourth legs, the number of vehicles in the third leg sees a higher traffic volume.

Figure.5 Performance evaluation of the number of vehicles in the first intersection without controller.



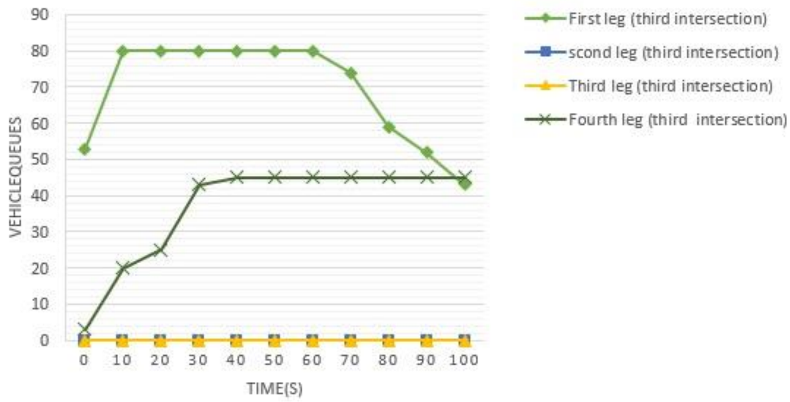
As shown in the Figure.6, the length of the queue of vehicles in the first leg raised, then the number of cars in the second leg utilized to fixed time control increased; in the third leg of the intersection, the number of vehicles increased. As a result, in Figure. 6the length of the queue of vehicles in the fourth leg is more than with comparing other legs in the intersection.

Figure.6 Evaluating the number of cars without a controller at the second intersection.



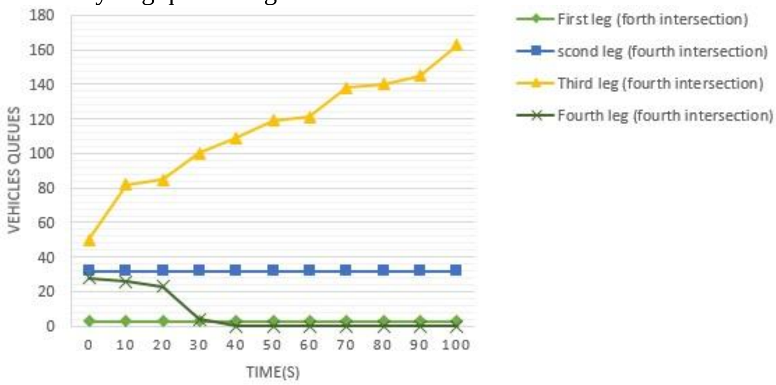
This Figure. 7shows the number of vehicles in the third intersection without model predictive control; the number of cars on the first leg is that the queue of cars is increasing. However, the queue of cars in the second and third leg has been fixed after a while. The traffic magnitude in the fourth leg is more than that of other legs in the intersection.

Figure.7 Analyze the number of cars without the controller in the third intersection.



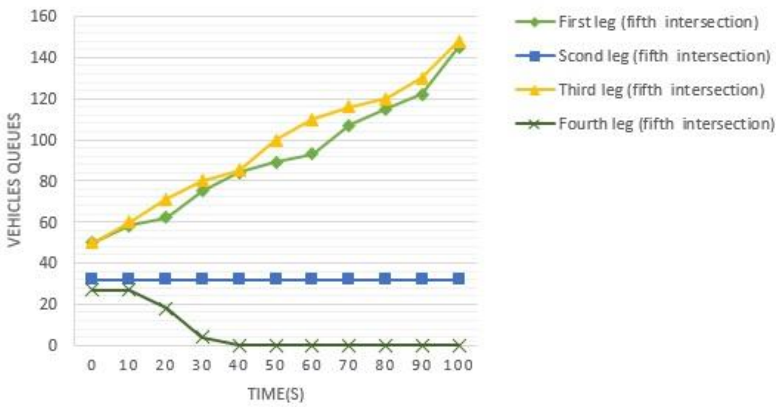
The fourth intersection without controller shows in Figure. 8, as a result, at first, the queue numbers of cars at the first leg in the fourth intersection is fixed and does not also fluctuate the second leg of the fourth intersection is fixed and does not fluctuate. Then due to a decrease over time, the number of vehicles in the third leg will stabilize. In the fourth leg of the fourth intersection, the traffic volume has been increased as shown in Figure. 8.

Figure.8 Analyzing queue lengths with fixed-time controllers at the fourth intersection.



Here, the simulation showed that the fifth intersection that the number of vehicles has increased in the first leg without using a predictive model controller; in the second leg, the queue of cars is fixed. Still, the queue of many vehicles will be proved in the third leg after a while. The traffic volume on the fourth leg raised at the fifth intersection is more increased than the other legs, as shown in Figure.9.

Figure.9 The fixed-time controller performs the number of queue lengths at the fifth intersection.



The number of vehicles under traffic light in the sixth intersection without a predictive model controller at the first line increased the number of cars under the traffic light. Still, as you see, the number of vehicles under traffic light on the second leg and the third is fixed and does not fluctuate. The outcome showed that the number of cars under traffic lights on the fourth line traffic dimensions reduced as shown in Figure. 10.

Figure.10 The performance number of vehicles in the sixth intersection based on fix time controller.

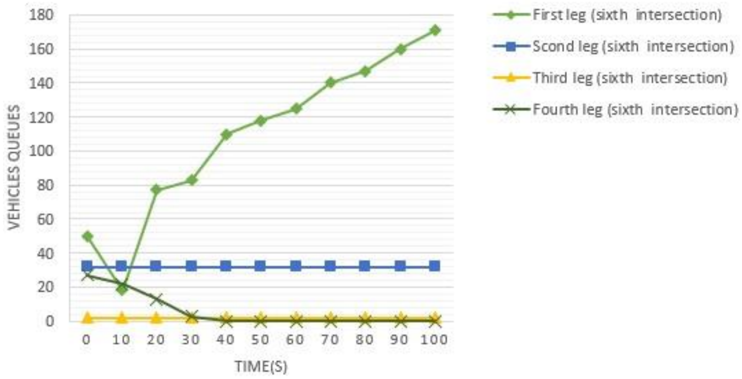
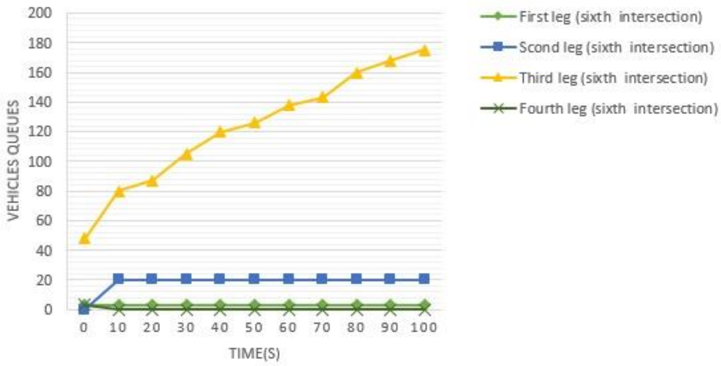


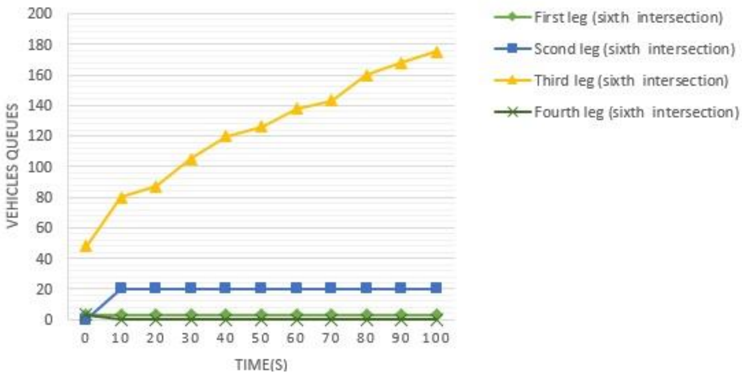
Figure. 11shows the queue length in the seventh intersection without the predictive controller. During the constant time, the number of vehicles is depicted. The simulation shows the queue length of cars fixed in the first leg has been proven after a while. Furthermore, the number of cars in the second line has been established after a period. While the volume of traffic in the fourth leg first increases and then decreases. Indeed, the fixed time controller has been demonstrated a significant performance loss compared to model predictive control.

Figure.11 The number of cars at the seventh intersection evaluate by using a fixed-time controller.



The eighth intersection in Figure. 12 has been shown. As seen in the first leg in the eighth intersection, there is an increasing traffic trend. Which this trend of traffic is in the third leg too. As a result of using predictive model control, we expect a decrease. Furthermore, the second and fourth legs still have traffic, but the number of legs drops after a while.

Figure.12 Utilizing a fixed-time controller, the analyze the performance of queue lengths at the eighth intersection.



Control of variables is the output of a controller. The variables that determine whether traffic lights are green or red. Variables controlled for intersections are shown in Figure. 13. A model predictive control has even been used to enhance the length of vehicles' queues at additional intersections. A demonstration of the predictive controller's output is S_i as the traffic system's control variable.

Figure.13 The control of variables of intersection.

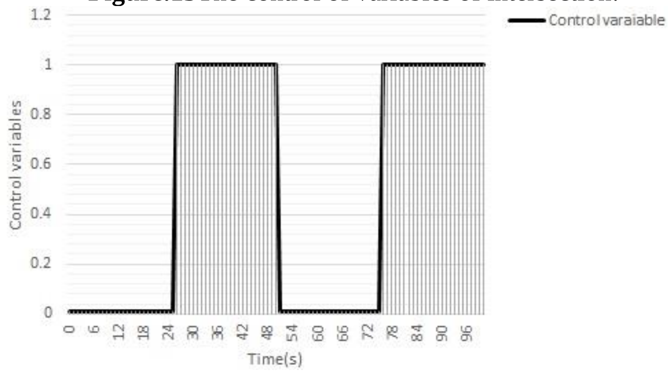
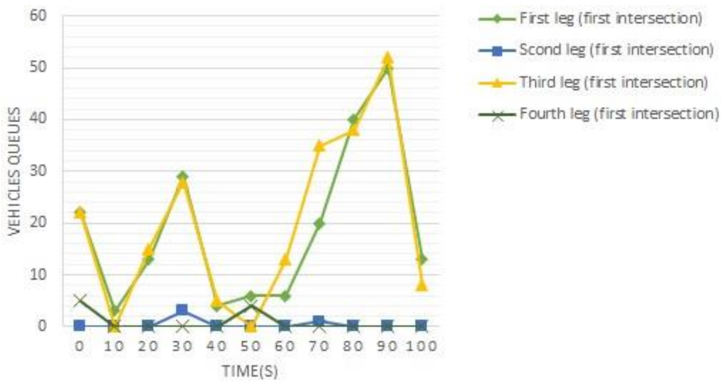


Figure.13shows control variables indicating green or red traffic lights. Similarly, the vehicle's queue length has been shown at other intersections, which has improved by using a predictive controller. The proposed controller is designed based on equations. The output of the predictive controller as the control variable$S_i$of the traffic system was demonstrated as follows. The proposed model we explained with using model predictive control in the below figures:

6.2.Stable Model Predictive Control Design on Multi intersection

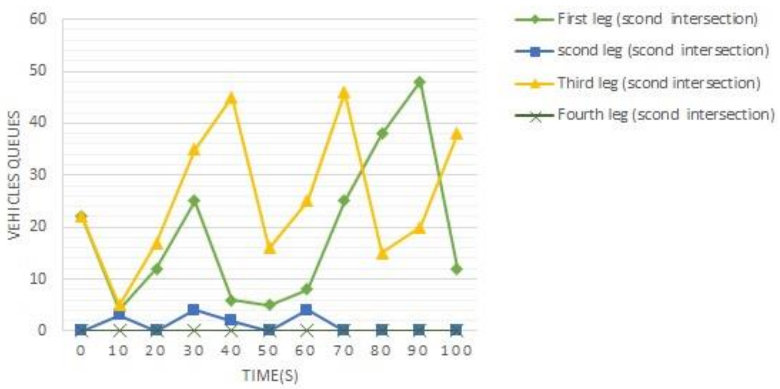
Here we explained with using predictive model control and the variable controller output $S_i$is as follows:

Figure.14 Analysis of the number of cars in the first intersection using model predictive control.



As shown in Figure. 14, we used model predictive control for designing a multi intersection. The number of vehicles standing in a line exhibited in the first line in the first intersection compared to the case without a controller, the first stop queue did not change. On the second leg from the first intersection, the number of vehicles in traffic a reduced. There was a significant decrease in the number of vehicles in the third line compared to without control. However, as predicted from the results, the queue length has been drastically reduced on the fourth leg. The MPC controller (model predictive control) predicts that the behavior of the waiting vehicles would improve compared to the previous example without a controller. As a result, by using model predictive control in the second leg from the second intersection, as seen in Figure. 15 the queue length trend traffic has decreased compared to other legs.

Figure.15 Model predictive control to analyze the queue lengths at the second intersection.



As predicted from the results in Figure.16, the number of cars line in the first leg has not changed from the previous one without a controller. In the second leg of this intersection queue, cars have been able to move faster as the length of the queue has been reduced. The length of the queue increased then decreased in the fourth leg for the cars at this intersection. Compared without a controller, the number of vehicles at the third intersection is now fixed; with comparison, the other legs have improved.

Figure.16 Model predictive control to examine queue lengths at the third intersection.

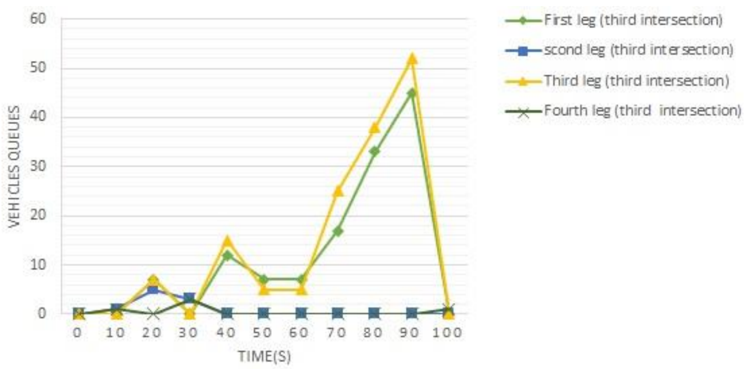
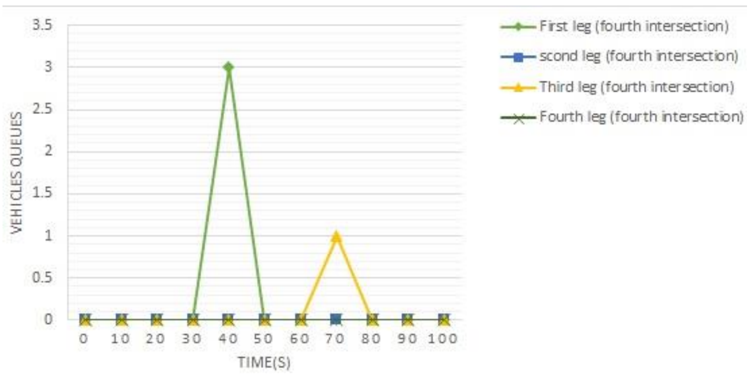


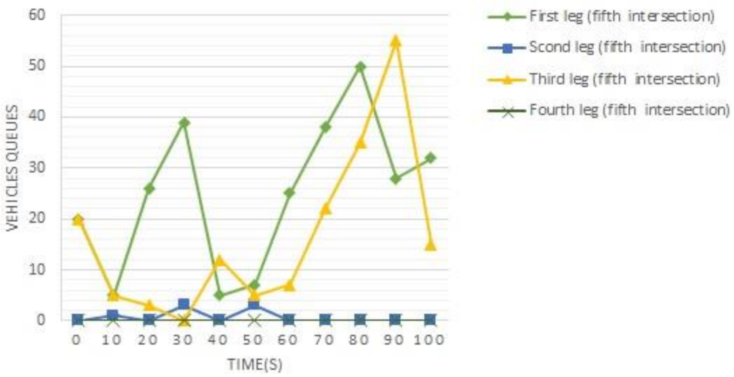
Figure.17 shows the fourth intersection which as vehicles queued in the first leg, their length was initially constant and then it increased, eventually decreasing. The number of vehicles from the second leg reduced, while there was a significant reduction in the number of cars in the third and fourth legs. Therefore, the predictive model controller has been performing well at intersections.

Figure.17 The performance of queue lengths at the fourth intersection with model predictive control.



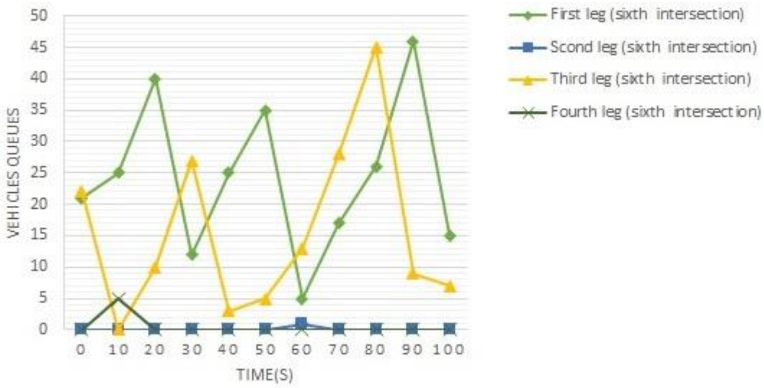
The number of vehicles standing in line is represented in the line at traffic lights using predictive model control. However, the number of cars on the first and third roads the proposed method decreased significantly in the second and fourth roads dropped to zero in the fifth intersection, as shown in Figure.18.

Figure.18 Analysis the number of vehicles in the fifth intersection based on the model predictive control.



The sixth intersection is shown in Figure.19 at the start, the number of vehicles as a result in the simulation the queue length of cars has increased then have been decreased. However, the length of the queue for the third leg did not change significantly. In the second leg, the number of cars has been decreased. As seen, the fourth leg has been reduced too. While third-leg in the sixth intersection experienced increased traffic, the number of vehicles increased.

Figure.19 Result of performance by using model predictive control at the sixth intersection with queue lengths.



The number of standing vehicles at traffic lights is represented with predictive model control. This Figure.20 illustrates the number of vehicles at the seventh intersection. The length of the car queue has reduced in the second leg; furthermore, in the third leg, trend traffic encounters a decrease in the length of the car queue. Attention to simulation result of traffic trend in the fourth legs queue has reduced. We have noticed a considerably more satisfactory effect.

Figure.20 Model predictive control performance at the seventh intersection with considering the number of cars queue lengths.

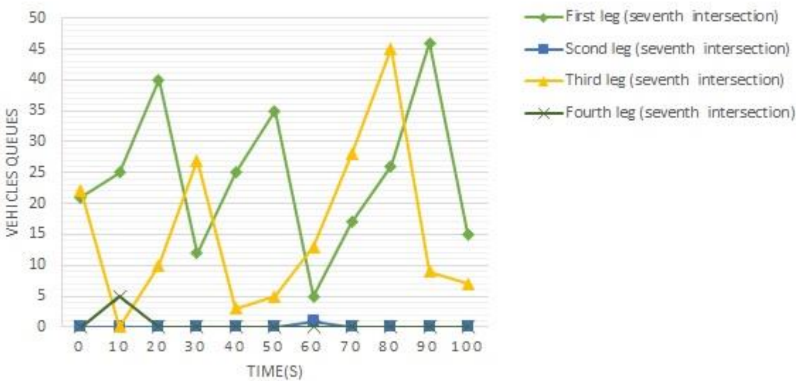
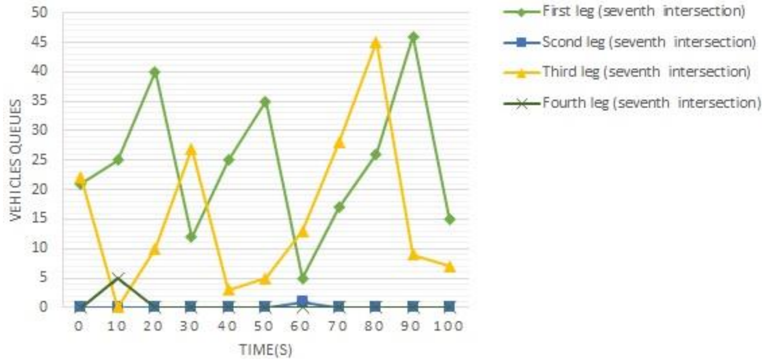


Figure.21 shows the number of vehicles entering the eighth intersection. After using predictive model control, reduced queue length in the first leg and the third leg also as you have seen traffic trend reduced queue length more the second and fourth legs.

Figure.21 Using model predictive control, an evaluation of queue lengths at the eighth crossroad.



To summarize, in this work, we examine several intersections in this chapter to construct a multi-factor system. We demonstrated the dynamic stability of several intersections in diagrams demonstrating the relationship between characteristics. Based on the simulation results, we can also state that compared with fixed-time control, the queue length of cars in each leg was reduced utilizing a predictive controller.

7. Discussion

After traffic models became available, advanced model-based controllers were developed to conform to urban networks. In optimal control, the cost function is optimized based on the network model for a specific future time horizon to find the optimal control measures for the whole urban network in the future. An urban traffic network can be coordinated centrally utilizing optimal control methods. In this part, we discussed the comparison of the proposed method with a fuzzy and predictive model for a single intersection as a discussion. The fuzzy controller is first applied in a single intersection in the fuzzy method. In fuzzy systems, the input information can be inaccurate, which is inaccurate using a fuzzy rule database. There is no specific method in designing fuzzy control, the performance of the fuzzy system is highly dependent on the experience of the expert. In Azimirad, E., et al., 2010it has been used a fuzzy logic control for traffic flows under both normal and exceptional traffic conditions, and the dynamic model is not stable. But in the model predictive control, in addition to having all the advantages of all intelligent methods, the superiority of the model-based predictive control over the rest of the fuzzy control is its inherent predictive property. It does not depend on anything. Model predictive control also has the intrinsic ability to compensate for dead time. But in fuzzy, it depends on the expert. Here Jafari, S.,et al., 2021 considered only one intersection; in the proposed model, we added several intersections to one intersection. Additionally, the results show the excellent performance of the proposed model.

8.Conclusion and Future Work

An algorithm suggested determining the order of green signals at multiple intersections. There is a signal control system to determine the order of green signals at multiple intersections. Model predictive control has been first developed for developing and controlling traffic signals at multi-agent intersections. The model predictive control is designed based on the theory of multi-functional systems, and the effect of adjacent intersections on their behavior is considered. There are two primary parameters in each phase: the length of the queue and traffic signal traffic to reduce the number of queues at intersections, with the use of the state space equations to design the model predictive control, the queue of vehicles per phase reduced in comparison via the constant time model. Traffic trend in the intersections based on model predictive control has been maximized. Results showed that the intersections method is efficient according to simulations. Research reported herein is multidisciplinary, encompassing multiple fields such as multi-agent technology, optimization, and urban traffic control. We proposed a method for traffic signal control at multiple intersections, which calls for large-scale studies, including those in urban areas, by extending the range of traffic signal control. Also, as for future work, further improvements will be pursued along with the following directions:

I. Multi-agent model predictive control framework test numerically and simulate on extensive networks.
II. The integration of constraints on state variables in the multi-agent framework.
III. Estimating the uncertainty of the current traffic prediction system for determining the predicted.
IV. Impose traffic restrictions on pedestrians, weather situations, etc.

V. A kind of future work can check the controller with attention to conditions the level of congestion in urban traffic such as infrastructure, travel speed, parking, intersections in the model have side roads, etc.

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