Urban Traffic Network Control in Smart Cities; a Distributed Model-based Control Approach

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Abstract—This paper proposes a distributed model predictive control (DMPC) approach for an urban traffic network (UTN) system. The control objective is to minimize the traffic congestion and the total travel time spent (TTS) in each link. The proposed DMPC algorithm considers traffic demand and disturbance predictions. The CasADi optimization tool is used to solve the constrained optimization problem. The proposed distributed control approach achieved 60% less computation time, 14.3% less TTS, and 15.1% less queue length compared to the centralized approach. Moreover, while the centralized algorithm neglected the input and state constraints, the distributed approach resulted in the satisfaction of all the constraints over the whole horizon.

Keywords: Distributed model predictive control; Traffic management and optimization; Intelligent transport systems and control; Smart city.

I. INTRODUCTION

Traffic congestion is a critical problem with multiple effects on humans lives, environment, and society. Several traffic control approaches have been used recently to address the traffic management and optimization problem. Model predictive control (MPC) approaches have been widely employed to manage urban traffic networks. The success of MPC in intelligent transport systems, which is a key component in a smart city, arises from its ability to take the predictions about the systems environmental conditions into account. UTN systems are usually subject to various changes in their structure such as the vehicles flow, turning rate, timing, incidents, climatic conditions, and road structure conditions. Recently, several studies have been conducted on using model-based predictive control on UTN systems. However, most of the MPC research on traffic networks are based on the centralized control structure which is impractical in real UTN applications [1-8]. Since UTN systems are associated with large-scale optimization problems, using a centralized strategy demands an extensive computation overhead as well as complex communications. Real-life UTN networks are innately networked systems as they are composed of several lanes with different structures, ramps, slopes, and capacities. Therefore, applying distributed control methodologies to UTN networks is considered a more suitable approach.

In a distributed control approach, the UTN network is decomposed into several subsystems with their local controllers and local objectives. The subsystems interact with each other, and the local controllers exchange their variables through the whole network. Using a distributed control reduces the systems computational demand and eliminates the need for the systems global information. In addition, distributed controls are usually more accurate and tolerant to model inaccuracies and system failures.

To the best of our knowledge, a limited amount of literature has addressed the UTN system control problem using distributed MPC approach [9-13]. In [9], a distributed two-layer MPC is developed on a linear traffic model. A distributed MPC based control strategy is proposed in [10] such that the travel time and traffic congestion are reduced. In [11], a distributed MPC approach is implemented on a linear traffic model without taking the system’s constraints into account. A hierarchical MPC is developed for a UTN system in [12]. In [13], a distributed MPC scheme is proposed to control a multi-vehicle platoon. The noted literature applied distributed MPC method either on a nonlinear UTN system without constraints or on a linear UTN system, and some literature (e.g. [12]) did not include the controllers’ coordination in the distributed algorithm. The work in [13] also did not consider the external disturbances in the traffic network. Furthermore, none of the related studies considered the traffic inflow demand and the disturbance predictions in the control algorithm.

This paper introduces a distributed control approach for a nonlinear urban traffic network. The proposed approach is demonstrated on a system with eight junctions and 17 links. The aim is to reduce traffic congestion and total travel time by controlling the signal split time. The main innovation in the proposed approach is utilizing the disturbance and traffic demand predictions. A space-time autoregressive integrated moving average (STARIMA) prediction model is used in the prediction process, and the coordination mechanism is based on the duality Lagrangian functions. The CasADi optimization tool is used to solve the optimization problem, considering the system constraints. The results of the proposed distributed MPC strategy is compared with the results of a centralized MPC on the model. The proposed DMPC strategy improved the system performance significantly. Moreover, the proposed distributed MPC scheme can be implemented in any urban traffic network of this kind.

The rest of the paper is organized as follows. Section II describes the UTN model. Section III introduces the centralized and distributed model predictive control approaches. The next section presents the simulation results. Finally, section V provides the conclusions and discusses future research.

II. SYSTEM DEFINITION

A benchmark problem of the nonlinear urban traffic network (Fig. [1]) is considered in this work [3]. The UTN is composed

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of 8 intersections and 17 links. The road links, the intersections, and their associated states are numbered. Inputs are the links green time, and the states are the number of vehicles in the links. Fig. 2 illustrates the coupling graph of the network. In this graph, we assume link $z$ is connecting junctions $j$ and $i$, and there are sets of upstream links $u$ and downstream links $d$ associated with link $z$.

The state space model of the network is defined as (II).

$$x_z(k+1) = x_z(k) + [f_{z,in}(k) - f_{z,out}(k) + e(k)] \ast c_j$$

where $e(k)$ is the disturbance of link $z$, i.e. the number of vehicles entering and exiting link $z$. The system parameters are defined in Table I. Hence, the inflow rate and outflow rate of link $z$ are defined as (2) and (3), respectively.

$$f_{z,in}(k) = \sum_{d \in D_z} f_{z,d}(k)$$

$$f_{z,out}(k) = \sum_{u \in U(z)} f_{z,u}(k)$$

The outflow rate, $f_{z,out}$, is updated through (II) in each step.

$$f_{z,out}(k+1) = f_{z,out}(k) + [f_{z,d,arrive}(k) - f_{z,d,out}(k)] \ast c_j$$

Moreover, the arrival flow rate, $f_{z,d,arrive}$, is defined as (II).

$$f_{z,d,arrive}(k) = f_{z,arrive}(k) \ast \beta_{z,d}(k)$$

where the delayed flow rate, $f_{z,arrive}$, arriving the tail of the queue is attained through (II).

$$f_{z,arrive}(k) = \left(\frac{c_j - \gamma(k)}{c_j}\right) \ast f_{z,in}(k - \delta(k)) + \frac{\gamma(k)}{c_j} \ast f_{z,in}(k - \delta(k) - 1)$$

where $\delta(k)$ and $\gamma(k)$ are attained from the time delay equations in (II).

$$\delta(k) = \left\lfloor \frac{\tau(k)}{C_z} \right\rfloor$$

$$\gamma(k) = \text{rem}(\tau(k), \tau_d)$$

$$\tau(k) = \frac{(C_z - q_{z}(k)) \ast l_{veh}}{N_{z,lane} \ast v_{z,free} \ast c_j}$$

The number of vehicles waiting in queue for turning to downstream links $d$ is updated through (II).

$$q_{z,d}(k+1) = q_{z,d}(k) + [f_{z,d,arrive}(k) - f_{z,d,out}(k)] \ast c_j$$

Having (II) and (II), (II) can be converted to (II). Three different scenarios are considered in (II): unsaturated, saturated, and over-saturated traffic flows.
\[ f_{z}^{in}(k) = \min\left\{ \frac{q_{z,d}(k)}{c_{j}} + f_{z,\text{arrive}}(k), \left( \frac{\beta_{z,d}(k) * u_{c,z,d}(k)}{c_{j}} \right) \right\} \]

\[ \left( \frac{\beta_{z,d}(k)}{\sum_{u \in U(z)} \beta_{z,d}(k)} \right)^{*} (C_{a,d} - n_{a,d}(k)) \right) \right] \}

(9)

Note that the cycle times \( c_j \) and \( c_i \) can be different from each other, and the offset time \( \Delta c_{j,i} \) can be defined for junctions \( i \) and \( j \). So the simulation steps for intersections \( j \) and \( i \) are denoted as \( k_j \) and \( k_i \), respectively, which are not necessarily equal. Therefore, to synchronize the inflow and outflow rates, the discrete-time outflow rate of upstream links is transformed into its continuous-time form by sampling counts of \( k_i \). Then, it is converted to its discrete-time form by sampling counts of \( k_j \) as (II).

\[ f_{u,z}^{out}(t) = f_{u,z}^{out}(k_j), \quad k_j + c_j \leq t < (k_j + 1) * c_j \]

\[ f_{u,z}^{out}(k_i) = \int_{t \in c_{m} + \Delta c_{j,i}} f_{u,z}^{out}(t) dt \]

(10)

It is required to define a common control time interval for all the subnetworks so that they can communicate synchronously. \( T_c \) is defined as an integer \( N \) times the least common multiple, \( T_{lc,m} \), of all the intersections’ time intervals.

\[ T_c = N \times T_{lc,m} \]

\[ k_e(k_j) = \left\lfloor \frac{k_j}{N \times N_j} \right\rfloor, \quad j \in \mathcal{J}, \quad N_j \text{ and } N \text{ are integers} \]

(11)

### III. THE MODEL PREDICTIVE CONTROL APPROACH

This section introduces the control approach for the traffic system discussed in the previous section. We first introduce the centralized approach and then extend this structure to a distributed control in which a set of local controllers are coordinating toward a given global objective.

#### A. Centralized MPC

The centralized cost function is defined as (III-A), containing the states (number of vehicles in links) and control signal (total green time).

\[ J(k) = \min\left\{ \sum_{p=1}^{K_p} \sum_{z \in \mathcal{Z}} \| \hat{x}_c(k + p | k) \|_Q^2 + \sum_{p=1}^{K_c} \sum_{z \in \mathcal{Z}} \| \hat{u}_c(k + p | k) \|_R^2 \right\} \]

(12)

\( Q \) and \( R \) are the weighting matrices associated with the system states and the control signals, respectively [14], [15]. \( \hat{u} \) and \( \hat{x} \) are the predicted control signal and the predicted state up to the control horizon \( K_c \) and prediction horizon \( K_p \), respectively. The constraints are the model constraints (III-A), the inflow traffic demand constraints (III-A), and the control signal constraints (III-A). Note that the input constraints implicitly include the disturbance (\( e \)) constraints.

\[ \hat{x}_c(k + p + 1) = f(\hat{x}_c(k + p), u_c(k + p), d_c(k + p)) \]

\[ f_{u,z}^{out}(k_j) = f_{u,z}^{out}(k_j) \]

(13)

\[ \sum_{z \in \mathcal{J}(j)} u_z + L_z = C \]

(14)

\[ u_z^{min} \leq u_z \leq u_z^{max} \]

(15)

In above, \( f_{u,z}^{out} \), \( C \), and \( L_z \) denote the predicted traffic inflow demand, whole cycle time, and the total lost time of link \( z \), respectively. The control signal constraints (the minimum and maximum green time) are to maintain the safety and the total cycle time. Furthermore, the last term of (III-A) associated with over-saturated condition can be omitted by adding the state constraints (III-A) to the optimization problem. In result, the number of vehicles in a link would not exceed the link capacity, and over-saturated condition will not happen.

\[ 0 \leq x_c(k) \leq C_z \]

(16)

The STARIMA prediction model (III-A) is applied to predict the disturbances and traffic demand. STARIMA is an extension of autoregressive integrated moving average (ARIMA) model in which the spatial dimension of the UTN is taken into account. It is proved that prediction results will be significantly improved by including the spatial dimension in the prediction model [16].

\[ \nabla \hat{x}(t) = \sum_{i=1}^{p} \sum_{k=0}^{m_i} \theta_{ik} W_k \nabla \hat{x}(t - i) - \sum_{i=1}^{q} \sum_{k=0}^{n_i} \theta_{ik} W_k \hat{e}(t - i) + \hat{e}(t) \]

(17)

The \( N \) by \( N \) dimension weight matrix \( W_k \) indicates spatial dimension factor of the network. \( \phi_k \) and \( \theta_k \) denote the auto-regression parameter and the moving average parameter, respectively. \( p \) and \( q \) are the time lags, and \( d \) is the degree of differencing. \( \hat{x}(t) \) is the detected signal at time \( t \), \( m_i \) is the spatial order of the \( i \)th autoregressive term, and \( n_i \) is the spatial order of the moving average term.

Hence, the cost function in the centralized framework is subject to the model constraints (III-A), demand constraints (III-A), input constraints (III-A), and state constraints (III-A). Fig. 3 shows the block diagram of the system and the centralized MPC controller. The centralized MPC algorithm for UTN system is as follows.

- At step \( k = 0 \), determine the state value \( x(0) \), and get the input value \( u(0) \) by solving the optimization problem.
- At step \( k > 0 \), get the state, input, traffic demand, and disturbance predictions from (III-A) (with \( K_c \) as the disturbance and input horizon, and \( K_p \) as the state horizon).
- At step \( k > 0 \), solve the optimization problem (III-A) to get the optimum input signal through the control horizon.
- Apply the optimum control signal at step \( k \) to the system, and get the updated state values.
k = k + 1, and go to the second step.

The disturbance, traffic demand, output, and input predictions are attained in each step of the algorithm. However, the centralized algorithm requires excessive computation since, in each step, a large optimization problem with many variables is being solved.

B. Distributed MPC

In the proposed distributed approach, one local MPC controller is assigned to each subsystem. The goal is to achieve a specific global system objective. Fig. 4 shows a diagram of a distributed MPC for a system with m subsystems [17], [18].

To apply distributed MPC on the traffic network, the system is decomposed into M subsystems, m is regarded as a subsystem if and only if it contains a center junction j with connecting links. Hence, the dynamic equation of subsystem m is stated as (III-B). Note that only the neighboring subsystems interactions are considered in each subsystems model. In (III-B), \( i, m \in M \) are the neighboring subsystems with interaction equations \( D_{im} \).

\[
\begin{aligned}
x_m(k + 1) &= x_m(k) + \sum_{i \in N(j)} D_{im}(k) - f_{out,m}(x_m(k), u_m(k))
\end{aligned}
\]

\[ (18) \]

Above, \( x_m \) and \( u_m \) are the state and input vectors of subsystem \( m \). \( f_{out,m} \) is the outflow of subsystem \( m \). Moreover, the cost function is decomposed into sub cost functions \( \phi_m \) for each subsystem \( m \). Therefore, the general cost function and each sub cost function is stated as (III-B).

\[
\begin{aligned}
J(k) &= \min \{ \sum_{m \in \mathcal{M}} \phi_m(k) \} \\
\phi_m(k) &= \left\{ \sum_{p=1}^{K_p} \| \dot{x}_m(k+p) \|_{Q_m}^2 + \sum_{p=1}^{K_u} \| \dot{u}_m(k+p) \|_{R_m}^2 \right\} \quad (19)
\end{aligned}
\]

In (III-B), \( Q_m \) and \( R_m \) are the weighting matrices associated with the state and input vectors of subsystem \( m \), respectively. Also, the distributed problem constraints are the model constraints (III-A), the demand constraints (III-A), the input constraints (III-A), and the state constraints (III-A). The control objective is to minimize the cost function containing the system’s inputs and states.

The coordination mechanism of the proposed distributed MPC approach is based on the dual decomposition method [19]. The Lagrangian multipliers are used to impose the system model, the input signal and the state constraints into the optimization cost function. In result, there is only one optimization problem without constraints, and the solution to this problem is approximately equal to the solution to the original problem subject to constraints. Thus, the augmented function for subsystem \( m \) is stated as (III-B).

\[
\begin{aligned}
L_{im}(k) &= \phi_{im}(k) + \sum_{i,m \in N(m)} [\lambda_{im}(k)^T (D_{im}(k) - \hat{D}_{im}(k)) \\
&+ \frac{\rho}{2} \| D_{im}(k) - \hat{D}_{im}(k) \|_2^2]
\end{aligned}
\]

\[ (20) \]

where \( \hat{D}_{im} \) is the predicted interaction between neighboring subsystems \( i \) and \( m \), and \( \lambda_{im} \) is the duality function coefficient.

At each time step, each subsystem only communicates with its neighbors in \( N(m) \) to get the interconnecting information from them, and send its last updated state and input variables to them. Therefore, the optimization problem for each local controller would be the minimization of (III-B), subject to constraints (III-A). It is worth mentioning that the duality function coefficients \( \lambda_{im} \) should be optimized as well as the input signal in each iteration, through (III-B).

\[
\lambda_{im}^{s+1}(k) = \lambda_{im}^s(k) + \alpha^s \left( D_{im}^s(k) - \hat{D}_{ij}(k) \right)
\]

\[ (21) \]

The local cost functions are modified in the coordination procedure such that they include the global cost function of the whole system. In fact, the impact of input signal \( u_m \) on the global objective function \( J(k) \) is considered through the interaction term \( D_{im} \). By defining \( \mu_{im} \) parameter as (III-B), the global cost function changes can be added to the local cost of each subsystem as (III-B).

\[
\begin{aligned}
\mu_{im}(k) &= \frac{d \phi(t)}{d u_m} \\
\phi_i(k) &= \left\{ \sum_{p=1}^{K_p} \| \hat{\xi}_i(k_1+p) \|_{Q_i}^2 + \sum_{p=1}^{K_u} \| \hat{u}_i(k_1+p) \|_{R_i}^2 \right\}
\end{aligned}
\]

\[ (22) \]
\[ \phi_m^{updated}(k) = \phi_m(k) + \sum_{i \in N \cap m} \mu_m(k)(u_m - u_m^{opt}) \] (23)

Thus, the following distributed MPC algorithm is proposed for the nonlinear traffic network problem.

Step 1:
- Send \( u_m(k-1|k-1) \) and \( \hat{x}_m(k|k-1) \) to its neighboring controller \( C_i \) (coordination mechanism).
- Estimate the future state trajectories \( \hat{x}_i(k|k-1) \) \( i \neq m \) and control inputs \( u_i(k-1|k-1) \) \( i \neq m \) from its neighboring controller through information exchange [III-B].
- Observe the values of \( x_m(k) \).
- Build \( \hat{x}_i(k|k-1) \) and \( u(k|k) \) by adding the subsystem's state estimations \( \hat{x}_m(k|k-1) \), control inputs \( u_m(k|k) \), and subsystem's neighbor information \( \hat{x}_i(k|k-1) \), and \( u_i(k-1|k-1) \) to attain the predictions of \( \hat{D}_m(k|k-1) \).

Step 2:
- Calculate the optimal control law \( u_m(k|k) \) by solving the optimization problem [III-B] through CasADi optimization tool.
- Apply the first element of the optimal control \( u_m(k|k) \) to the system, and update the local cost function through [III-B].
- Update \( \lambda \) from [III-B].

Step 3:
- Compute the estimation of the future state, disturbance, and traffic demand trajectory of \( m \)th subsystem over the horizon \( K_p \) from the prediction model [III-A].

Step 4:
- replace \( k \) by \( k+1 \), and go to step 1 to repeat the algorithm.

The coordination strategy in the proposed distributed algorithm based on duality function avoids global communication in the whole network [19]. Moreover, the distributed approach requires less computation, demonstrates improved overall performance, and considers all the constraints.

IV. SIMULATION RESULTS

The control horizon, \( K_c \), and prediction horizon, \( K_p \), are chosen as 4 and 7, respectively. Moreover, the weight matrices \( Q \) and \( R \) are chosen as [IV]. In the distributed approach, the weighting matrices are defined for each local controller.

\[ Q = 0.1 \times I_{17K_p \times 17K_p}, \quad R = 0.3 \times I_{17K_c \times 17K_c} \] (24)

At each time instant, the optimization problem is solved using CasADi tool in MATLAB, then the optimum input is considered as the current input for the next step. Minimizing the total time spent (TTS) criterion is the control objective which corresponds to the accumulated amount of time spent by the vehicles. The simulations are performed for 4 hours, with the sampling rate of 10 seconds. The simulation assumptions are as follows.
- The cycle time for all the junctions is 120 s.
- The vehicles’ speed in the free flow rate is 40 km/h.
- The traffic supply flow rate (demand) is a balanced Gaussian distribution function between 300 and 800.

- The maximum and minimum values for the green time are 10 and 520 seconds respectively.
- The capacity of each link is 1000.

For the centralized MPC case, the cost function is a global function as [III-A], and the control law is calculated at each time step through the centralized algorithm.

Based on the UTN graph in Fig. 2, 8 subsystems corresponding to 8 intersections are considered in the distributed control case. Moreover, each subsystem has one objective function \( \phi_m(k) \) as [III-B]. The interactions of subsystem \( m \) with its neighboring subsystem \( i \) (\( D_m(k|k) \)) is stated using the turning rate and the outflows. For instance, subsystem 5 has two interactions \( D_5(k|k) \) and \( D_5(k|k) \) with subsystem 1 and 4 respectively. Thus, the dynamic interaction equations are stated as [25].

\[
\begin{align*}
D_{15}(k) &= \left[ \begin{array}{c} \tau_{1,10} q_{out,1} \ 0 \\
0 & \tau_{2,11} q_{out,2} \end{array} \right] + \left[ \begin{array}{c} \tau_{3,10} q_{out,3} \ 0 \\
0 & \tau_{3,11} q_{out,3} \end{array} \right] \\
D_{45}(k) &= \left[ \begin{array}{c} 0 \ 0 \\
0 & 0 \end{array} \right] \\
f_{out,5} &= \left[ \begin{array}{c} q_{out,1}(x(k),u(k)) \\
0 \end{array} \right]
\end{align*}
\] (25)

Without loss of generality, the interaction parameter (\( \mu_{mi} \)) for subsystem 5 is calculated in [26]. \( \phi_S \) corresponding to subsystem 5 cost function is composed of the input signal \( \hat{u}_i \), \( k = 1, \ldots, K_p \). The control vector of subsystem 1 (subsystem 5 neighbor) is \([u_1, u_2, u_3]^T\).

\[
\mu_{Si} = \sum_{s=k}^{K_p} \left[ \begin{array}{c} \frac{d \phi_S}{d \hat{x}_i(t)} \\
\frac{d \phi_S}{d \hat{x}_j(t)} \end{array} \right] \left[ \begin{array}{c} d \hat{x}_i(t) \\
\tau_{ij}(t) d \hat{x}_j(t) \end{array} \right] + \sum_{s=k}^{K_p} 2Q_S \| \hat{s}_i(s) \| d \hat{x}_i(t) \end{array} \right] \left[ \begin{array}{c} d \hat{x}_i(t) \\
\tau_{ij}(t) d \hat{x}_j(t) \end{array} \right] + \sum_{s=k}^{K_p} 2Q_S \| \hat{s}_i(s) \| d \hat{x}_i(t) \end{array} \right] \] (26)

The derivatives of the interaction equations \( D_{im} \) versus the input signals can be behaved as [IV].

\[
\frac{dD_{15}^i}{dt_i} = \begin{cases} 0 & \text{if } x_i < u_i(S_i/C_i), \ i = 1, \ldots, 3 \\
\tau_{10}(S_i/C_i) & \text{if } x_i > u_i(S_i/C_i), \ i = 1, \ldots, 3 \end{cases}
\] (27)

Subsystem \( m \) cost function is derived from [III-B] as [IV].

\[
\phi_m(k) = \left\{ \sum_{p=1}^{K_p} \| \hat{x}_m(k+p|k) - x_m^d(k+p|k) \|^2_\Omega \right\} + \sum_{p=1}^{K_p} \| \hat{u}_m(k+p|k) \|^2_{R_u}
\] (28)

Having \( D_{im} \) and \( \phi_m \) values, augmented function \( L_m \) is defined as [III-B]. Based on the proposed distributed
algorithm, optimum input is calculated, and applied to the system. The output/input, disturbance, and demand predictions, $\mu_{mi}$, $D_{im}$, and $L_{im}$ are updated up to the horizons and then, the next optimum input is calculated.

Figs. 5 and 6 show the simulation results using the centralized and distributed MPC on the traffic network, respectively. Furthermore, Table II compares the numerical values of TTS, maximum number of vehicles, maximum queue length, and computation time using the two controllers. As shown in state (output) graphs, the distributed MPC shows slightly less number of vehicles in each link compared to the centralized MPC strategy. Moreover, using the centralized approach, the number of vehicles in links 5 and 11 exceeds the state constraint (1000 vehicles), whereas the distributed method resulted the satisfaction of all the constraints throughout the simulation time. From the first two row values of Table II, the maximum queue length and the maximum number of vehicles are reduced by 15.1% and 45.5%, respectively, using the distributed MPC. Besides, the TTS value decreased by 14.3% using the proposed distributed approach (third row of Table II). Also, comparing the control trajectories of Fig. 5 and 6, the distributed approach performs slightly better in minimizing the control signal than the centralized method. Worth mentioning that, the distributed structure performance is slightly better compared to the centralized MPC, since it is more accurate and responds faster due to the lower computational demand.

Furthermore, the maximum optimization time, in a corei7 3.2GHz computer, for distributed MPC controllers is 60% lower than that of a centralized MPC (last row of Table II). Using the proposed scheme for the traffic network, not all the agents need to be connected; therefore the communication effort is significantly lower compared to the centralized scheme. CasADi optimization tool is also perfectly appropriate for the distributed plant with less complication and computation. The critical feature of the proposed DMPC algorithm is that it considers the traffic demand and disturbance predictions based on the history of traffic flow, and it distributes the traffic congestion in the links evenly (noticeable in the state graphs of 17 links).

V. CONCLUSIONS

In this paper, distributed model predictive control strategy was implemented on a nonlinear urban traffic network. The UTN consists of 8 intersections and 17 links. The objective was to reduce the total time spent, the number of vehicles traveling, and the queue length in each road/link.

In this approach, the algorithm considered disturbance and traffic inflow demand predictions. A STARIMA prediction method was used to attain the predictions. The constrained optimization problem was solved using the CasADi tool.

The maximum computation overhead of controllers in the proposed distributed strategy was 60% lower compared to the classical centralized MPC. Besides, the TTS and the maximum queue length were reduced by 14.3% and 15.1%, respectively, and the state and input constraints were totally satisfied throughout the simulation time. For the future, the UTN response to some unpredicted failures, such as actuator failures, can be surveyed practically; e.g., the physical intelligent transportation system testbed of [18].

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