Network-Level Coordinated Speed Optimization and Traffic Light Control for Connected and Automated Vehicles

Mehrdad Tajalli, Mehrzad Mehrabipour, and Ali Hajbabaie

***Abstract*— This study develops a methodology for coordinated speed optimization and traffic light control in urban street networks. We assume that all vehicles are connected and automated. The signal controllers collect vehicle data through vehicle to infrastructure communications and find optimal signal timing parameters and vehicle speeds to maximize network throughput while harmonizing speeds. Connected and automated vehicles receive these dynamically assigned speeds, accept them, and implement them. The problem is formulated as a mixed-integer non-linear program and accounts for the trade-offs between maximizing the network throughput and minimizing speed variations in the network to improve the network operational performance and at the same time smoothen the traffic flow by harmonizing the speed and reducing the number of stops at signalized intersections. A distributed optimization scheme is developed to reduce the computational complexity of the proposed program, and effective coordination ensures near-optimality of the solutions. The case study results show that the proposed algorithm works in real-time and provides near-optimal solutions with a maximum optimality gap of 5.4%. The proposed algorithm is implemented in Vissim. The results show that coordinated signal timing and speed optimization improved network performance in comparison with cases that either signal timing parameters or average speed of vehicles are optimized. The coordinated approach reduced the travel time, average delay, average number of stops, and average delay at stops by 1.9%, 5.3%, 28.5%, and 5.4%, respectively compared to the case that only signal timing parameters are optimized.**

***Index Terms*— Connected and automated vehicles, distributed coordination, signal timing optimization, speed harmonization.**

I. Introduction

THE connected vehicle technology provides a great opportunity for traffic control methods not only to collect real-time vehicle information and make online decisions, but also to coordinate their action and make decision cooperatively. Traffic signals play an important role in controlling traffic in urban street networks and have significant effects on network performance [1]–[5]. Signalized intersections cause about 5-10% of the total vehicular delay on major roads [6]. Receiving online information from approaching connected and automated vehicles (e.g. vehicles' speed and position) helps signal controllers to estimate vehicle arrivals more accurately and find more efficient signal plans. In addition, exchanging information between signal controllers yields network-wide optimal operations.

Advisory speed systems can adjust automated vehicles speeds and consequently their arrival time to signalized intersections to reduce the number of stops and unnecessary acceleration/deceleration. Preventing stop-and-go conditions reduces travel delay, fuel consumption, and yields a more efficient network performance [7]. Traffic operations can be further improved by coordinated signal timing and speed optimization. In other words, signal timing parameters and vehicle speeds can be optimized jointly to plan the arrival of vehicles to signalized intersections more accurately to utilize green durations more efficiently. It should be noted that the intersection signals may not be required in a fully connected and automated environment (i.e., level 5 automation) in the absence of other system users such as pedestrians or bicyclists. However, signals are still required to communicate the right of way to other system users even though all vehicles are automated.

This paper develops a mathematical program for Coordinated Signal timing and Speed Optimization (CSSO) in urban-street networks assuming that all vehicles are connected and automated, and intersection controllers can communicate to each other. It is assumed that connected and automated vehicles receive the assigned speeds through communication with intersection controllers and accept them. The mathematical program is based on the Cell Transmission Model (CTM) [8], [9] network loading concept. We develop a Distributed Optimization and Coordination Algorithm (DOCA) to find near-optimal solutions to the coordinated signal timing and speed optimization problem in real-time in networks of various sizes. To reduce the computational complexity, the proposed methodology decomposes the network-level CSSO problem into several intersection-level sub-problems by relaxing the constraints that represent interrelationship between intersections. Effective coordination among sub-problems pushes their solutions towards global optimality [10]–[15]. The coordination is achieved by exchanging information among sub-problems, re-enforcing the re-introduced relaxed constraints and incorporating the information in them. The complexity of the problem is further reduced by using Model Predictive

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Control (MPC) and solving the problem over a planning horizon rather than the entire study period. Moreover, the proposed objective function in this study takes into account the trade-off between maximizing the intersection throughput and minimizing the spatial and temporal speed variations over the entire network. In particular, we minimize the absolute value of speed differences between two subsequent cells and two successive time steps to provide smoother traffic flow and reduce the number of stops at signalized intersections [16]. However, smoothening the speed of vehicles excessively might lead to lower network throughput, while the highest network throughput may cause frequent changes in speeds. Hence, a suitable balance between improving the network performance and speed variations could be achieved through evaluating a trade-off between the two terms of the objective function (i.e., throughput maximization vs. speed difference minimization). For that purpose, a Posteriori scalarization approach [17] is used to find the Pareto optimal solutions of CSSO problem.

In the remainder of this paper, a review of the relevant literature is presented. Then, the problem formulation and solution technique are detailed. The case study and the results of applying DOCA to solve the CSSO problem will be discussed next, and finally, concluding remarks are presented.

II. Background

A. Speed Optimization at Signalized Networks

Speed optimization can help reduce the number of stops and energy consumption in urban street networks. Tajalli and Hajbabaie [16] showed that dynamic speed harmonization based on predetermined signal timing parameters in an oversaturated urban-street network reduced the travel time, speed variance, and number of stops by 5.4%, 20.2%, and 16.8%, respectively. Moreover, the average speed and the total number of completed trips were increased by 5.9% and 4.0%, respectively. Speed optimization can also reduce fuel consumption by mitigating the stop-and-go conditions. He *et al.* [18] showed that advisory speeds calculated based on fixed-time signal timing information successfully reduced fuel consumption by 29%. Moreover, Kamalanathsharma *et al.* [19] considered additional constraints (e.g., safe distance to the following vehicle, maximum acceleration and deceleration of a vehicle) and showed that fuel consumption was reduced by up to 25% as a result of an advisory speed strategy in arterial streets with fixed time signal parameters. Hao *et al.* [20] proposed an eco-driving algorithm for an actuated signalized intersection by providing an upper-bound and lower-bound of the remaining actual green time to approaching vehicles. The simulation results showed significant energy savings and fuel consumption reductions by 12%. Applying this strategy in the field showed a 2% energy saving [21]. Jiang *et al.* [22] proposed an eco-driving system for an isolated signalized intersection with fixed signal parameters and showed that optimal advisory speed can reduce the fuel consumption of connected and automated vehicles by 2.02% - 58.01%. However, the proposed approach was tested on a simple intersection with two approaches and its performance is not clear for a network of multiple intersections.

B. Coordinated Signal Timing and Speed Optimization

There are many studies in the literature that proposed methodologies for optimizing the timing of signalized intersections in arterial street or urban street networks, and showed significant improvement in traffic operations [23], [24]. It has been also shown that optimizing the speed and trajectory of vehicles in conjunction with signal control yields a more efficient utilization of intersection capacity. Erdmann [25] considered the speed and location of vehicles in the vicinity of an isolated intersection and solved the signal timing and trajectory optimization problem in two levels with a dynamic programming procedure. Simulating the proposed algorithm based on Green-Light-Optimal-Speed-Advisory (GLOSA) assistance system [26] in SUMO [27] showed that the delay was decreased between 33% and 72% in comparison with fixed time and adaptive signal timings, respectively. Li *et al.* [28] optimized signal timing parameters and vehicle trajectories in a single intersection with two phases assuming all vehicles were connected. The optimal signal timing was found by enumerating the feasible timing plans. Then, the optimal vehicle trajectories were found based on minimum average travel delay for each timing plan. As a result of this strategy, the average travel delay was reduced by 16.2% - 36.9% and throughput was increased by 2.7% - 20.2% in comparison with an actuated signal timing. Jung *et al.* [29] developed an Eco-Traffic Signal System (Eco-TSS) in an isolated intersection by optimizing the signal timing parameters and vehicle desired speeds and acceleration rates using a bi-level programming approach. They used genetic algorithms to solve the problem and found that Eco-TSS reduced fuel consumption by 5% - 10% and travel time by up to 12% compared to other exiting signal control methods (i.e. fixed time signal timing, actuated signals, and eco-driving with fixed time signals). Yang *et al.* [30] proposed an algorithm to find the optimal signal timing and vehicle arrival time to an isolated intersection based on the position of connected and autonomous vehicles and provided the optimal trajectory for autonomous vehicles. A bi-level program with branch and bound algorithm was used to solve this problem. In comparison with the actuated signal timing, the proposed approach reduced the total delay and number of stops significantly when the penetration rate of equipped vehicles was above 50%. Xu *et al.* [31] optimized traffic signal timing and vehicle trajectories cooperatively at an isolated intersection using a bi-level problem. Receding horizon control with an enumeration technique was used to solve the signal optimization problem in the upper level. In addition, the pseudospectral control method [32] was used to find the vehicle trajectories in the lower level. The pseudospectral approach approximates the state and control variables using an interpolating polynomial function. The proposed approach was tested in Vissim and the results showed that the proposed approach reduced fuel consumption, travel time, and stop rate more than actuated signal timing, and independent vehicle speed control.

Li *et al.* [33] considered the effect of adding signal timing optimization to eco-driving of electric vehicles. This study formulated a bi-objective optimization that considered delay minimization at an intersection and the energy saving of approaching electric vehicles. A hybrid algorithm including genetic algorithms and particle swarm optimization was developed to solve the problem iteratively in a central unit. The result of the algorithm in a four-intersection arterial showed a trade-off between delay minimization and energy saving. For instance, changing the emphasis from only signal optimization to both signal and energy optimization increased delay by 14% and reduced energy consumption by 11% in the over-congested conditions. Kaths [34] also used GLOSA to optimize the signal timing parameters and vehicle speeds cooperatively. This study formulated the signal and speed problem in a single-level mathematical program and used a model predictive control strategy to reduce the problem complexity. To find a more stable signal timing, a penalty function in the objective function was considered to push the speed solutions toward the predicted values from the previous horizon optimization. Simulating the algorithm in SUMO with one intersection showed that cooperative signal and speed optimization reduced the number of stops and waiting time by 36.3% and 56.2%, respectively in comparison with optimizing signal timing alone. Yu *et al.* [35] optimized signal timing parameters and the arrival time of connected and automated vehicles at an isolated intersection. To reduce the complexity of MILP problem, they only optimized the trajectory of leading vehicles in platoons and assumed that other vehicles follow the leader through a car-following model. This study assumed that the platoon leader can always be controlled. The result of this study showed that joint optimization of signal and trajectory of automated vehicles increases intersection throughput by 0.55% - 19.80% for various demand levels. However, the effect of proposed formulation was not evaluated under over-saturated traffic condition and a network of multiple intersections.

C. Summary of the Literature and Contribution of the Paper

The existing studies show the effectiveness of cooperative signal timing and speed optimization in managing traffic congestion in either an isolated intersection or at most four intersections due to the computational complexities that were associated with the cooperative problem. The existing algorithms are complex due to their microscopic nature, where the trajectory of each connected and automated vehicle is controlled. The existing approaches are enumerative or centralized heuristic/metaheuristic techniques that limit their scalability, real-time application, and optimality.

This paper addresses the knowledge gap and enables studying the effects of cooperative signal timing and speed optimization in large transportation networks. We formulate the problem using macroscopic network loading concept and develop a scalable solution technique that can find near-optimal solutions in real-time. The solution technique distributes the complex network-level signal timing and speed optimization problem into several intersection-level sub-problems and implements them in a model predictive controller. As such, it significantly reduces computational complexity and finds solutions in real-time. We have created distributed coordination between sub-problems that pushes their solutions towards global optimality. We implement the proposed algorithm in Vissim and to show that cooperative traffic signal and speed optimization can significantly improve traffic operations (increase throughput, reduce travel time and number of stops) compared to independent speed optimization and independent signal timing optimization in a more realistic simulated environment.

III. Problem Formulation

The problem formulation utilizes the CTM network loading concept that is introduced by Daganzo [9], [36] and used in other traffic control studies [37]–[39]. CTM divides a network link into homogeneous segments and discretizes the study period to short time steps. The cell length is the distance that a vehicle can travel with the free flow speed during a time step. Let C, C_O and C_S respectively denote the sets of all cells, source cells, and sink cells in the network. In addition, we define C_S^N and C_S^I as the sets of network sink cells and internal intersection sink cells, respectively. The sets of predecessors $P(i)$ and successors $S(i)$ cells are defined for each cell $i \in C$. Moreover, we defined T as the set of discrete time steps. Table I summarizes the notations used in this study.

The decision variables are (a) the status of traffic signal g_i^t (one if green, zero otherwise) on intersection cell $i \in C_I$ at time step $t \in T$, (b) space mean speed v_i^t on cell $i \in C$ at time step $t \in T$, and (c) the number of vehicles y_{ij}^t flowing from cell $i \in C$ to successor cell $j \in S(i)$ at time step $t \in T$. The state variable of the system is the number of vehicles x_i^t in cell $i \in C$ at time step $t \in T$, which is equivalent to cell occupancy assuming that each cell is one length unit long. The space mean speed is defined as the ratio of the outgoing flow y_{ij}^t from a cell to its occupancy x_i^t as shown in equation (1) [16]. Note that the space mean speed is equal to the free flow speed when a cell is empty.

$$v_i^t = \begin{cases} \dfrac{\sum_{j\in\Gamma_i} y_{ij}^t}{x_i^t} v_f & x_i^t > 0 \\ v_f & x_i^t = 0 \end{cases} \quad \forall i \in C,\ t \in T \tag{1}$$

The objective function of the CSSO problem has two terms that aim at maximizing the cumulative throughput and minimizing speed variations. Past research has shown the effectiveness of throughput maximization in congestion management especially when the demand level is high [40]–[42]. The cumulative throughput maximization accounts for both network and intersection throughputs: a larger weight (M) is assigned to the network sink cells $i \in C_S^N$ to prioritize the number of completed trips, while a smaller weight (m) is assigned to the number of vehicles exiting each intersection through the internal sink cells $i \in C_S^I$. In addition, the difference of space mean speeds between two adjacent cells at two consecutive time steps as well as the space mean speed differences in one cell at two consecutive time steps are minimized in the second term of the objective function. This term prioritizes the smooth movement of vehicles in the network. There is a trade-off between these two terms, as smooth vehicle speed does not necessarily yield a higher throughput value. Therefore, we defined γ (vehicle/mph) as a weight factor to define the desired emphasis on each term of

TABLE I
DEFINITION OF SETS, DECISION VARIABLES, AND PARAMETERS

Sets:	
T	set of all time steps
C	set of all network cells
C_O	set of all source cells
C_S	set of all sink cells
C_S^N	set of all network sink cells
C_S^I	set of internal intersection sink cells
C_I	set of all intersection cells
C_{OD}	set of all dummy source cells
C_{SD}	set of all dummy sink cells
C_R	set of all right turn movement cells
C_T	set of all through movement cells
C_L	set of all left turn movement cells
C_F	set of all conflicting movement pairs at an intersection
C_{RT}	set of all concurrent adjacent right and through movements
$P(i)$	set of all cells predecessors
$S(i)$	sets of all cells successors
State Variable:	
x_i^t	number of vehicles in cell $i \in C$ at time step $t \in T$
Decision Variables:	
g_i^t	a binary variable for signal status at cell $i \in C_I$ at $t \in T$
y_{ij}^t	number of vehicles flowing from cell $i \in C$ to downstream cell $j \in S(i)$ at time step $t \in T$
v_i^t	space mean speed in cell $i \in C$ at time step $t \in T$
Other Variables:	
f_i^t	variable saturation flow rate in cell $i \in C_I$ at $t \in T$
z_{ij}^t	auxiliary variable
u_{ij}^t	auxiliary variable
Parameters:	
d_i^t	entry demand on source cell $i \in C_O$ at time step $t \in T$
F_i	saturation flow rate of cell $i \in C$
N_j	capacity of cell $j \in C$
r_i^t	turning proportion at intersection cell $i \in C_I$ at $t \in T$
f'	the star-up lost time reduction factor
$G_{\max}$	maximum green time
$G_{\min}$	minimum green time
$\hat{x}_j^t$	predicted occupancy of cell $j \in C$ at $t \in T$ from CTM
v_f	free flow speed

the objective function and convert the units of the two terms, see objective function (2).

$$\text{Max}\left[\sum_{t\in T}\sum_{i\in C_S^N} Mx_i^t + \sum_{t\in T}\sum_{i\in C_S^I} mx_i^t - \gamma \sum_{t\in T}\sum_{i\in C\setminus\{C_s\}}\sum_{j\in\{\text{i},S(i)\}}\left|v_i^t - v_j^{t+1}\right|\right] \quad (2)$$

The defined objective function is nonlinear due to the inherent nonlinearity of the space mean speed. Tajalli and Hajbabaie [16] showed that the speed harmonization term in the objective function is equivalent to the difference of occupancy and flow between two subsequent cells and two subsequent time steps, see objective function (3). This term is linear as such, significantly reduces problem complexity. Since all terms of the objective function have a unit of vehicles, we use a unit-less factor α to assign priority to each term.

$$\text{Max}\left[\alpha\left(\sum_{t\in T}\sum_{i\in C_S^N} Mx_i^t + \sum_{t\in T}\sum_{i\in C_S^I} mx_i^t\right) - (1-\alpha)\sum_{t\in T}\sum_{i\in C\setminus C_s}\sum_{j\in\{\text{i},S(i)\}}\left|\left(x_i^t - \sum_p y_{ip}^t\right) - \left(x_j^{t+1} - \sum_k y_{jk}^{t+1}\right)\right|\right] \quad (3)$$

Equations (4) to (6) represent the state transition of the system. Let D_i^t denote the entry demand level on source cell $i \in C_O$ at time step $t \in T$. Constraints (4) to (6) ensure the flow conservation in source cells $i \in C_O$, sink cells $i \in C_S$, and ordinary cells $i \in C\setminus\{C_S, C_O\}$, respectively. The number of vehicles in a cell in the next time step is equal to the number of vehicles that are in that cell in the current time step, minus those who are leaving, plus those who are entering during the current time step.

$$x_o^{t+1} = D_o^t + x_o^t - \sum_{j\in S_o} y_{oj}^t, \quad \forall o \in C_O,\ t\in T \quad (4)$$

$$x_s^{t+1} = x_s^t + \sum_{i\in P_s} y_{is}^t, \quad \forall s \in C_S,\ t\in T \quad (5)$$

$$x_i^{t+1} = x_i^t + \sum_{u\in P_i} y_{ui}^t - \sum_{j\in S(i)} y_{ij}^t, \quad \forall i \in C\setminus\{C_S \cup C_O\},\ t\in T \quad (6)$$

The number of vehicles $\sum_{j\in S(i)} y_{ij}^t$ moving between cell $i \in C\setminus C_s$ and all successor cells $j \in S(i)$ at time step $t \in T$ must be less than or equal to the number of vehiclesx_i^t that exists in cell $i \in C$ at time $t \in T$, as follows:

$$\sum_{j\in S(i)} y_{ij}^t \le x_i^t, \quad \forall i \in C,\ t\in T \quad (7)$$

Let us define F_i as the saturation flow rate of cell $i \in C$. Constraints (8) and (9) limit the number of vehicles flowing from a cell to its successor to the saturation flow rates of the sending and receiving cells, respectively.

$$\sum_{j\in S(i)} y_{ij}^t \le F_i, \quad \forall i \in C\setminus C_S,\ t\in T \quad (8)$$

$$\sum_{i\in P(j)} y_{ij}^t \le F_j, \quad \forall j \in C\setminus C_O,\ t\in T \quad (9)$$

Let N_j denote the maximum number of vehicles that cell $j \in C$ can accommodate. Constraint (10) ensures that the number of vehicles flowing between two cells is less than the available capacity of the receiving cell.

$$\sum_{i\in P(j)} y_{ij}^t \le N_j - x_j^t, \quad \forall j \in C\setminus C_O,\ t\in T \quad (10)$$

Constraint (11) ensures that turning percentages are equal to the pre-defined turning proportions (r_j^t). Let C_I be the set of intersection cells from which, right turning, through, and left turning movements are completed. The number of vehicles traveling to each intersection cell $j\in C_I$from cell $i \in P(j)$ should be equal to the product of corresponding turning proportion r_j^t and the total number of vehicles $\sum_{k\in S(i)} y_{ik}^t$ leaving cell $i \in P(j)$ to all immediately downstream intersection cells at time step $t \in T$.

$$y_{ij}^t = r_j \sum_{k\in S(i)} y_{ik}^t, \quad \forall j \in C_I,\ i\in P(j),\ t\in T \quad (11)$$

Signal controllers at each intersection find the optimal signal timing parameters (i.e. green time duration and phase sequences) in cooperation with vehicles' average speed. Optimizing the sequence of phases yields a more efficient network performance. To optimize signal timing parameters, let the binary variable g_i^t take on the value of one when the signal is green, otherwise zero. Constraint (12) adjusts the saturation flow rate (f_i^t) of an intersection cell based on its signal status, and Constraint (13) ensures that the flow of vehicles leaving intersections cells cannot exceed the adjusted saturation flow rate (f_i^t).

$$f_i^t = g_i^t F_i, \quad \forall i \in C_I, \ t \in T \tag{12}$$

$$\sum\nolimits_{j \in S(i)} y_{ij}^t \leq f_i^t, \quad \forall i \in C_I, t \in T \tag{13}$$

Constraint (14) reduces the saturation flow rate of the intersection when a green signal is initiated. Parameter f' is defined as the saturation flow rate reduction factor due to start-up lost time. A proper joint optimization of signal timing parameters and speeds should regulate the arrival of vehicles at intersections such that the signal has already turned green and the queue is cleared. Therefore, speed optimization reduces the impacts of start-up lost time on traffic operations.

$$\sum\nolimits_{j \in S(i)} y_{ij}^{t+1} \leq F_i - F_i f' \left(g_i^{t+1} - g_i^t\right) \quad \forall i \in C_I, \ t \in T \tag{14}$$

We define C_F as the set of all conflicting movements at an intersection. Constraint (15) ensures that only one of the two non-conflicting movements $(i, j) \in C_F$ receives the green time at time step $t \in T$. It should be noted that all turning movements are assumed to be protected.

$$g_i^t + g_j^t \leq 1, \quad \forall (i, j) \in C_F, \ t \in T \tag{15}$$

Constraints (16) limits the green duration at intersection cell $i \in C_I$ to a maximum green duration G_{max}^i. Constraint (17) ensures a minimum green duration G_{min}^i for each signal.

$$\sum\nolimits_{j=t}^{t+G_{max}^i+1} g_j^t \leq G_{max}^i, \quad \forall i \in C_I, \ t < T - G_{max}^i \tag{16}$$

$$\sum\nolimits_{j=t+1}^{t+G_{min}^i} g_j^t \geq \left(g_i^{t+1} - g_i^t\right) G_{min}^i, \quad \forall i \in C_I, \ t \leq T - G_{min}^i \tag{17}$$

We define C_{RT} as the set of concurrent adjacent right and through movements. Constraint (18) ensures that the adjacent right turn and through movements have the same signal timing, either red or green.

$$g_i^t = g_j^t, \quad \forall (i, j) \in C_{RT}, \ t \in T \tag{18}$$

The objective function (3) is nonlinear due to the presence of the absolute value function. Therefore, a linear equivalent objective function is represented in (19) and constraints (20)-(22) are added to the problem. It should be noted that z_{ij}^t and u_{ij}^t are nonnegative auxiliary variables.

$$f = Max \left[\alpha \left(\sum\nolimits_{t \in T} \sum\nolimits_{i \in C_S^N} M x_i^t + \sum\nolimits_{t \in T} \sum\nolimits_{i \in C_S^I} m x_i^t \right) - (1-\alpha) \sum\nolimits_{t \in T} \sum\nolimits_{i \in C \setminus C_s} \sum\nolimits_{j \in \{i, S(i)\}} \left(z_{ij}^t + u_{ij}^{t+1} \right) \right] \tag{19}$$

$$z_{ij}^t - u_{ij}^{t+1} = \left(x_i^t - \sum\nolimits_{p \in S(i)} y_{ip}^t\right) - \left(x_j^{t+1} - \sum\nolimits_{k \in S(j)} y_{jk}^{t+1}\right), \quad \forall i \in C \setminus C_S, \quad j \in \{i, S(i)\}, \ t \in T \tag{20}$$

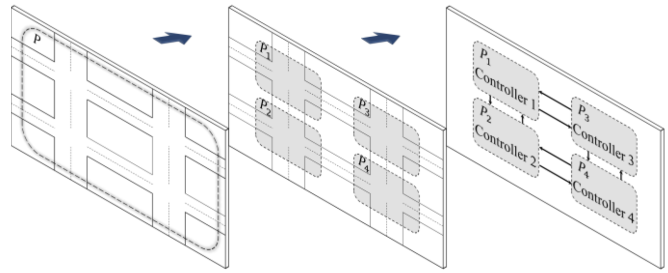


Fig. 1. The intersection-level decomposition.

$$z_{ij}^t \geq 0, \quad \forall i \in C \setminus C_S, \ j \in \{i, S(i)\}, \ t \in T \tag{21}$$

$$u_{ij}^t \geq 0, \quad \forall i \in C \setminus C_S, \ j \in \{i, S(i)\}, \ t \in T \tag{22}$$

Constraints (23) and (24) ensure that the number of vehicles in each cell and the flow of vehicles are always non-negative.

$$x_i^t \geq 0, \quad \forall i \in C, \ t \in T \tag{23}$$

$$y_{ij}^t \geq 0, \quad \forall i \in C \setminus C_s, \ \forall j \in P(i), \ t \in T \tag{24}$$

IV. Methodology

The presented formulation has mixed-integer decision variables and will not scale well with the size of the network when a centralized algorithm is utilized to solve it. We present a distributed optimization and coordination algorithm that can handle the computational complexity of the problem and find near-optimal solutions in real-time. Fig. 1 shows a conceptual representation of the proposed methodology. The distributed optimization decomposes the network-level problem into several stand-alone intersection-level sub-problems and solves them in parallel. The decomposition is achieved by identifying the constraints that represent interrelationships between sub-problems and relaxing them. Distributed coordination pushes solutions towards global optimality by exchanging information among sub-problems that share a relaxed constraint, and re-enforcing the relaxed constraints in sub-problems by incorporating the information that is received from other sub-problems in them. This method is incorporated in MPC to account the dynamic nature of the problem and further reduce the computational complexity.

A. Distributed Optimization

The distributed optimization decomposes the network-level coordinated signal timing and speed optimization problem into several stand-alone intersection-level sub-problems. Particularly, a signal controller will be responsible for finding the optimal signal timing and the average speed of approaching vehicles. However, this decomposition is equivalent to cutting the links that connect intersections. In other words, the constraints that connect two neighboring intersection are relaxed and each intersection is optimized as a stand-alone sub-system.

Let define V as the set of all intersection nodes in a network. Fig. 2 shows a decomposed network containing intersections $\{n, m\} \in V$. Two intersections are decomposed by breaking the shared links between them. Intersection $n \in V$ is converted to a stand-alone sub-network by adding dummy source cells C_O^n

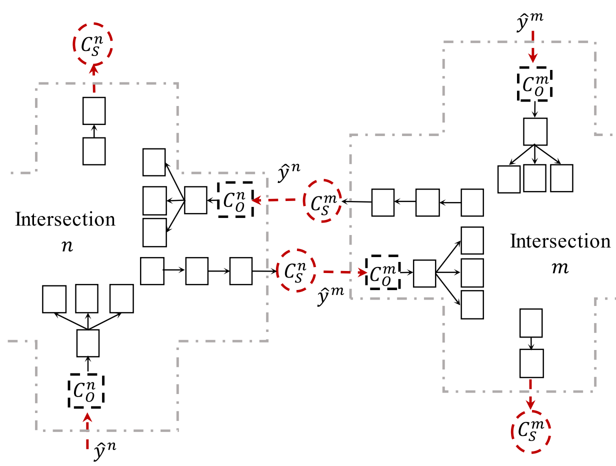


Fig. 2. The modification of the sub-problems' formulation for coordination.

and dummy sink cells C_S^n to the boundaries of the intersection. The flow $\hat{y}^n$ belongs to the broken links that enter intersection n from neighboring intersections.

Let P represents the centralized CSSO problem, where f is the objective function (19). Constraints (4), (5), (11)-(18), (21), and (22) include decision variables that belong to one sub-problem. On the other hand, constraints (6)-(10) and constraint (20) represent inter-relationship between adjacent sub-problems (when the constraints are defined for cells at the boundary). The decomposition is achieved by relaxing these constraints. Therefore, sub-problem P_n contains all constraints according to the decision variables of the intersection $n \in V$ except the relaxed constraints.

$$\begin{aligned} P: \quad & \max\ f \\ & \text{s.t. } (4)\text{-}(5);\ (11)\text{-}(18);\ (21)\text{-}(22) \\ & \qquad (6)\text{-}(10);\ (20) \end{aligned}$$

The sub-problems P_n for intersection $n \in V$ has fewer number of decision variables and constraints. As a result, each sub-network level MILP can be solved efficiently using commercial software packages. In this study, we utilized CPLEX (CPLEX 2009) to solve them.

B. Distributed Coordination

Intersection $n \in V$ has a controller to make signal timing and assigned speed decisions. An effective coordination scheme between sub-networks is needed to compensate for the impact of the proposed relaxations on solution quality and push them toward global optimality. Note that we assume that connected vehicle technology can allow communications between adjacent sub-networks and facilitate the coordination. Sub-network $n \in V$ needs to receive information about (a) the outflow of the upstream intersections, (b) the available capacity at the receiving cells at the downstream intersections, and (c) the difference of occupancy and flow at the receiving cells at the downstream intersections to harmonize the speed.

The difference of occupancy and flow between cells that belong to separate intersections is not minimized. Hence, the information about the difference of occupancy and flow $\left(\hat{x}_j^{n,t+1} - \hat{y}_{jk}^{n,t+1}\right)$ at the receiving cell $j \in C_S^n$ belonging to adjacent intersections is shared with the intersection controller $n \in V$ and added to the objective function of controller n, see (25).

$$(1-\alpha)\sum_{t\in T}\sum_{j\in C_S^n}\sum_{i\in P(j)}\left|\left(x_i^t - y_{ij}^t\right) - \left(\hat{x}_j^{n,t+1} - \hat{y}_{jk}^{n,t+1}\right)\right| \quad \forall n \in V \quad (25)$$

The outflows of the neighboring intersections are the inflows $\hat{y}^n$ to intersection $n \in V$. These flows are considered as demands in dummy source cell $i \in C_O^n$ at intersection $n \in V$, see constraint (26). The input parameter $\hat{y}_i^{n,t}$ indicates the inflow to cell $i \in C_O^n$ at time $t \in T$ at subnetwork $n \in V$.

$$x_i^{t+1} = \hat{y}_i^{n,t} + x_i^t - \sum_{j\in S(i)} y_{ij}^t \quad \forall i \in C_O^n,\ t \in T \quad (26)$$

Finally, the available capacities $(\hat{N}_j - \hat{x}_j^{n,t})$ at the receiving cells $j \in C_S^n$ at the downstream intersections are considered as inputs to intersection $n \in V$. Constraint (27) ensures that the sending flows from the intersection n to the downstream intersections are restricted by the available capacity.

$$\sum_{i\in P(j)} y_{ij}^t \le \hat{N}_j - \hat{x}_j^{n,t} \quad \forall j \in C_S^n,\ t \in T \quad (27)$$

The shared data between adjacent intersections are estimated in the prediction period by a CTM simulation run. The optimal speeds and signal timing parameters that are found by the distributed optimization are used in the CTM simulation and the network state for near future will be predicted. The simulation takes into account all CTM constraints throughout the network and always provides feasible predictions. More details are explained in Tajalli and Hajbabaie [43]. Note that the proposed distributed algorithm is non-iterative since CTM simulation provides feasible solutions as the coordination layer. Hence, there is no need to iterate the information sharing process to converge to a feasible solution.

C. Model Predictive Control

A model predictive control (MPC) approach is implemented to increase the computational efficiency of the algorithm. First, the state variables are predicted for near future. Then, the required information between sub-networks is shared through the distributed coordination. After receiving the information, each controller solves the corresponding sub-problem and finds the optimal signal timing and speeds for each sub-network. This process is repeated until the study period is finished. Note that the length of prediction horizon is selected long enough to ensure the feasibility and stability of the system with MPC.

D. Accounting for the Trade-Offs Between Traffic Operations and Speed Variations

CSSO is a multi-objective program with a trade-off between maximizing the cumulative intersection throughputs and minimizing speed variance. Thus, there is a set of Pareto optimal solutions for CSSO problem. Hwang and Masud [17] classified the solution techniques for accounting these trade-offs into three categories including Priori, Interactive, and Posteriori methods. In Priori method, the optimal solution is found in a way that satisfies the preference of decision makers. The Interactive method allows decision makers to search iteratively for the most preferred solution by receiving feedbacks. However, decision makers might not see the entire pareto. The Posterior method finds a set of pareto optimal solutions and let decision makers select among them. We utilized the Posteriori method because it provides the opportunity to observe the tradeoffs between different terms of the objective function. Based on the weighting method in [44], we multiply the intersection throughput maximization term by α and speed variation minimization term by $(1 - \alpha)$ in objective function (3). Therefore, an α of zero corresponds to minimizing speed variation and an α of one corresponds to intersection throughput maximization.

E. Benchmark

The benchmark solutions are found using the Benders decomposition technique [45]. Benders decomposition technique finds an upper and a lower bound to the objective function of the problem through an iterative process. It is proven that the gap will be reduced to zero (i.e., the exact solution is found) after a finite number of iterations. Benders technique decomposes the coordinated signal timing and speed optimization problem to master and primal sub-problems. The signal timing decision variables are found by the master problem and the average speeds are optimized by the primal problem based on the fixed values of signal timing variables. The algorithm iterates between the two sub-problems until the convergence criteria is met. For more details see Mohebifard and Hajbabaie [46].

F. Implementation of the Algorithm in Vissim

The proposed algorithm is implemented in Vissim [47] to allow a more accurate evaluation of the results in a more realistic simulated environment. We used COM interface to provide required communications between vehicles and signal controllers. In general, the network in Vissim is divided into several segments to match the cells in the CTM. Vehicle location data is passed from Vissim to DOCA through the COM interface as the initial state of the system. The optimization problem is solved, and optimized signal timing and speed variables are sent back to Vissim.

DOCA finds the average speed of a cell in CTM. This speed is assigned to the vehicles traveling in the corresponding segment of the network as their desired speed. Note that the optimal speed from the CTM should be calibrated for Vissim to ensure that both models have similar outflows in the road segment. In other words, the CTM is a macroscopic first-order model and does not consider the interaction between vehicles. Therefore, vehicles take more time to achieve the speed in Vissim than the CTM (instantaneous). As a result, we quantified this difference and accounted for it when transmitting speeds to Vissim.

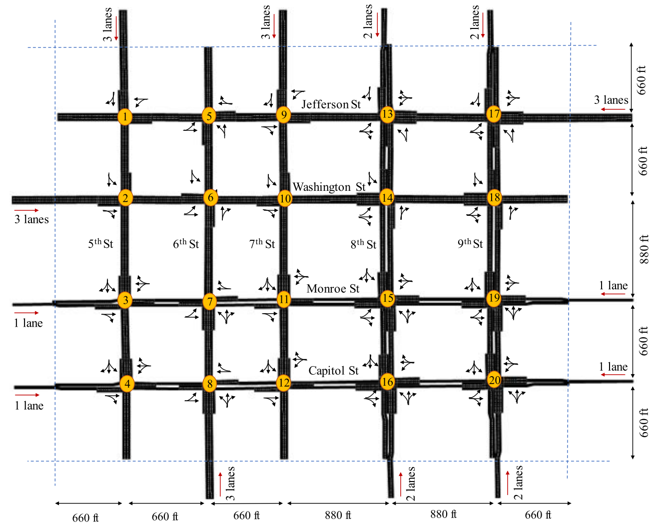


Fig. 3. Springfield network.

TABLE II
CHARACTERISTICS OF SPRINGFIELD NETWORK IN CTM

Link data	
Number of lanes per link	1, 2, or 3
Maximum free-flow speed (mph)	30
Link saturation flow (veh/hour/lane)	1800
Optimization period (time steps)	500
Prediction period (time steps)	15
Duration of each time step (seconds)	6
Number of cells	342
Cell jam density (veh/cell/lane)	12
Cell saturation flow (veh/cell/ lane)	3
Signal timing parameters	
Maximum green for through (seconds)	60
Minimum Green time for through (seconds)	18
Maximum green for left turn (seconds)	24
Minimum green for left turn (seconds)	6

V. CASE STUDY

The case study network is a portion of downtown Springfield, Illinois. The network has 20 intersections and a mix of one-way and two-way streets with different number of lanes and turning configurations at signalized intersections. Fig. 3 shows the network, which is divided into 20 sub-networks, each corresponding to a sub-problem. Table II presents the general characteristics of the Springfield network in the CTM representation and the signal timing parameters. The total study period is 500 time steps (50 minutes), where each time step is six seconds.

Four demand patterns were used in the case study network:

1- Symmetric undersaturated demand pattern: 500 veh/hr/ln on all entry points,
2- Symmetric saturated demand pattern: 900 veh/hr/ln on all entry points,
3- Symmetric oversaturated demand pattern: 1200 veh/hr/ln on all entry points, and

TABLE III

THE NETWORK MOBILITY PERFORMANCES FOR THREE SCENARIOS AND THREE DEMAND PATTERNS BASED ON CTM

Demand (veh/hour/lane)	Mobility performance	(3) CSSO			(2) Signal optimization	(1) Speed optimization
		Value	% Diff to (2)	% Diff to (1)		
500	Travel time (hour)	511.2	-2.1	-26.1	522	691.8
	Throughput	12385	0.0	1.5	12389	12197
	Average speed (mph)	21.9	2.2	36.8	21.5	16.0
900	Travel time (hour)	1863	-2.5	-36.7	1911.4	2943.0
	Throughput	18717	2.0	17.1	18342	15977
	Average speed (mph)	9.4	4.8	81.2	8.9	5.2
1200	Travel time (hour)	4187.3	-5.6	-29.9	4436.9	5969.7
	Throughput	19950	5.0	28.6	19005	15509
	Average speed (mph)	4.5	10.6	82.2	4.1	2.5

*Diff= Difference

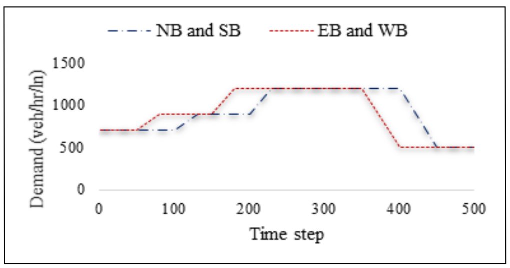


Fig. 4. Demand profile.

4- Asymmetric demand pattern covering both under and oversaturated conditions. Demand profiles for east-west and north-south streets are shown in Fig. 4.

Note that demand patterns 1, 2, and 3 are considered in the CTM to show the analytical optimality gap of DOCA. Demand pattern 4 is used in Vissim to represent a more realistic evaluation of the proposed algorithm in a more realistic simulated environment.

Three scenarios are considered to evaluate the effectiveness of CSSO in congestion management:

1- Independent speed optimization with pre-defined signals (signals are optimized using genetic algorithm [48]),
2- Independent signal timing optimization, and
3- Coordinated signal timing and speed optimization

Under independent speed optimization, the signal timing parameters are fixed and input to an optimization program who only optimizes speed across different network links. In independent signal timing optimization, the desired speed of vehicles is not changed and only signal timing parameters are optimized in the network.

VI. RESULTS

A. Mathematical Programs Results

Fig. 5 (a)-(c) shows DOCA's solutions and the best upper and lower bounds found by the Benders decomposition in the undersaturated, saturated, and oversaturated conditions, respectively. Since DOCA provides a feasible solution, it can always be considered as a lower bound for a maximization problem. Therefore, the optimality gaps are calculated from the difference between the upper bound found by the Benders decomposition technique and the DOCA-CSSO solution. Note that the optimality gaps are found when the study period was set to 200 time steps since the runtime of the Benders decomposition technique does not allow increasing the study period further. The optimality gaps were 4.9%, 5.4%, and 5.2% for the undersaturated, saturated, and oversaturated demand levels, respectively.

We used the Posteriori technique [44] to select the most preferred weight (alpha) in the objective function (19). For this purpose, the weights of objective function terms are changed incrementally. Fig. 6 shows the trade-off between the travel time and speed variations for three demand patterns based on different alpha values with an increment of 0.05. For all demand patterns, the travel time decreases by increasing alpha. This is expected since a higher value of alpha prioritizes network throughput more. The speed variance also strictly increases by increasing the value of alpha, which indicates that highly harmonized speeds can reduce the network performance. We selected the value of 0.75 for alpha in this study.

Table III shows network performance measures for CSSO, independent signal timing optimization, and independent speed optimization for the same three demand patterns. In the undersaturated demand conditions, CSSO significantly improved network performance compared to speed optimization. The travel time decreased by 26.1% and the network throughput and average speed increased by 1.5% and 36.8%, respectively. In comparison to signal timing optimization, CSSO only improved the travel time and average speed by 2.1% and 2.2%, respectively. Both signal timing optimization and CSSO yield similar improvements in network throughputs in undersaturated flow conditions when a macroscopic first-order traffic flow model is utilized.

In the saturated demand conditions, CSSO showed significant improvements in comparison with the two other scenarios. The coordinated approach reduced the travel time by 36.7% and increased the network throughput and average speed by 17.1% and 81.2%, respectively, compared to

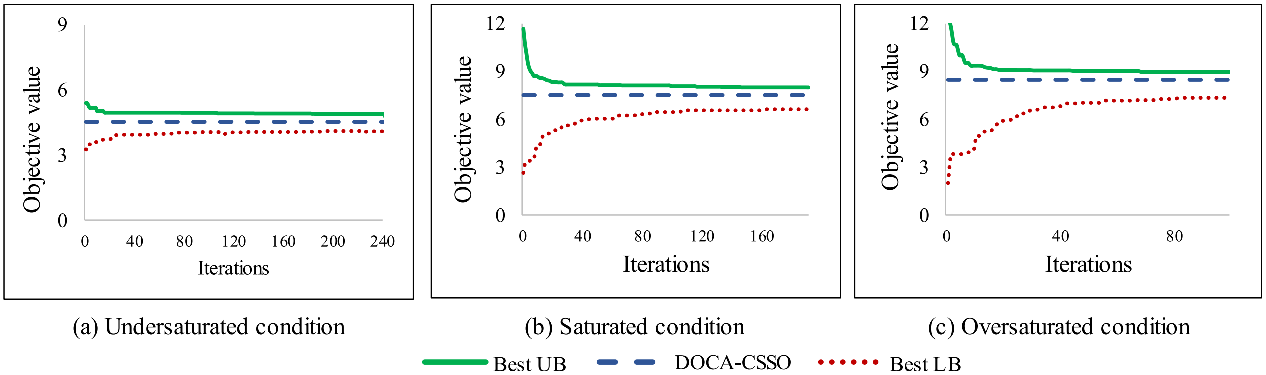


Fig. 5. DOCA and the benchmark solutions objective values ($\times 10^5$) for three demand patterns.

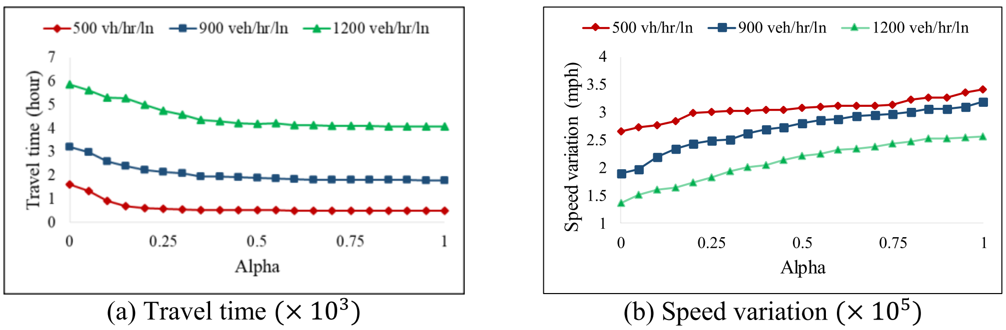


Fig. 6. Trade-off between travel time and speed variations.

speed optimization. CSSO reduced the travel time by 2.5% and increased the network throughput and average speed by 2.0% and 4.8%, respectively, compared to signal timing optimization. These trends show that the cooperation between signal timing and speed optimization offers great potential for reducing traffic congestion in saturated demand conditions, even when a first-order traffic flow model is in use.

The results of oversaturated demand conditions show trends similar to those that were observed in the saturated demand conditions. The coordinated approach reduced the travel time by 29.9% and respectively increased the network throughput and average speed by 28.6% and 82.2% compared to the speed optimization. In comparison to the signal timing optimization, CSSO reduced the travel time by 5.6% and increased the network throughput and average speed by 5.0% and 10.6%, respectively. These trends indicate that CSSO offers great potential for congestion management in oversaturated demand conditions.

Note that the signal timing optimization improved the network performance significantly in comparison with the speed optimization in all demand patterns. CSSO improved the network performance further in more congested conditions. The trends suggest that CSSO yields higher improvement in traffic operations with more congested demand levels in comparison with the signal timing optimization.

B. Vissim Results

Analyzing the effects of CSSO from a mathematical point of view showed significant improvements in traffic operations. In this section, we present the results that are obtained by incorporating the proposed methodology in Vissim. Vissim provides a more realistic representation of traffic operations on urban-street networks and accounts for the interactions between vehicles using car following and lane changing models. For this purpose, the time variant demand profile (shown in Fig. 4) is used. Table IV shows the network performance for CSSO, signal timing optimization, and speed optimization strategies in Vissim. The coordinated approach respectively reduced the travel time, average delay, average number of stops, and average delay at stops by 32.5%, 38%, 35.3% and 42.1% compared to the case that only vehicles speeds are optimized. Moreover, the network throughput and average speed were increased by 41.4% and 104.2%, respectively.

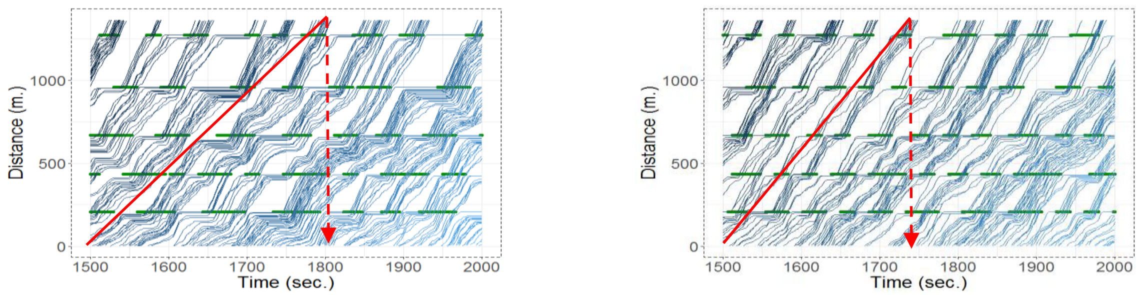
CSSO respectively reduced the travel time, average delay, average number of stops, and average delay at stops by 1.9%, 5.3%, 28.5%, and 5.4% compared to the case that only signal timing parameters are optimized. In addition, CSSO increased the network throughput and average speed by 1.7% and 3.4%, respectively. These results are consistent with the findings from the mathematical analysis indicating that the coordinated approach has a positive effect on traffic.

Fig. 7 shows vehicle trajectories when only the signal timing parameters were optimized (part a) and when both signal timing parameters and speeds were optimized (part b). Vehicles pass through five intersections on eastbound Washington St. with three lanes. The CSSO smoothened the movement of vehicles and reduced the number of stops. Moreover, it is shown that vehicles that entered the network at the same

TABLE IV

THE NETWORK MOBILITY PERFORMANCES FOR THREE SCENARIOS AND THREE DEMAND PATTERNS BASED ON VISSIM

Mobility performance	(3) CSSO Value	(3) CSSO % Diff to (2)	(3) CSSO % Diff to (1)	(2) Signal optimization	(1) Speed optimization
Travel time (hour)	3533.8	-1.9	-32.5	3600.5	5236.7
Throughput (vehicle)	15093	1.7	41.4	14839	10671
Average Delay (sec.)	464.4	-5.3	-38.0	490.5	749.0
Average speed (mph)	3.9	3.4	104.2	3.8	1.9
Average number of stops	12.0	-28.5	-35.3	16.9	18.6
Average delay at stop (sec.)	385.5	-5.4	-42.1	407.5	666.2



(a) Signal timing optimization (b) Coordinated signal and speed optimization

Fig. 7. Vehicles trajectories.

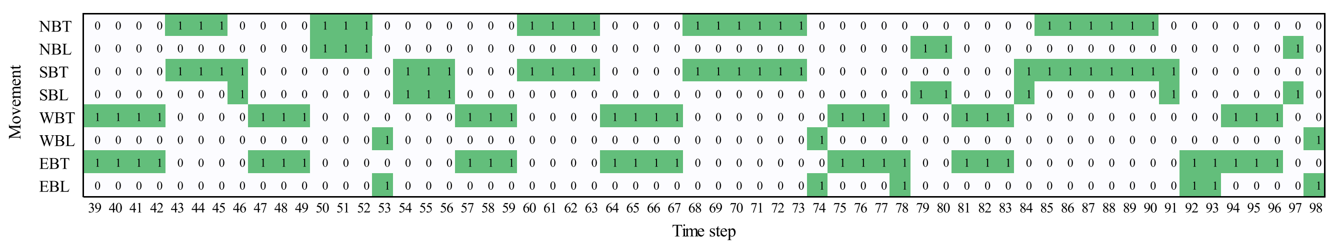


Fig. 8. Optimal signal timing parameters at intersection 19.

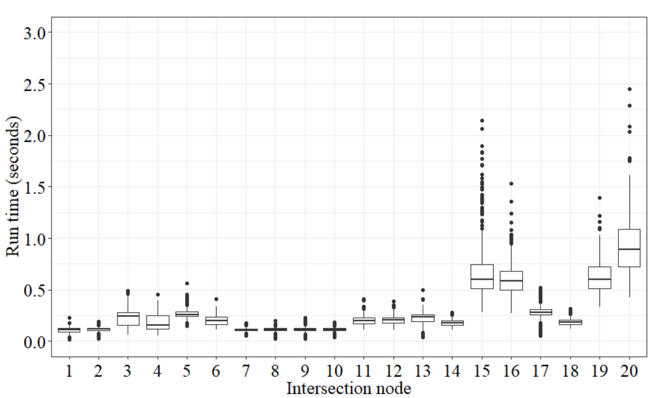


Fig. 9. DOCA runtimes at each intersection node.

time left the network earlier when signal and speeds are optimized together. Furthermore, Fig. 8 shows the optimal signal timing parameters and the green time extensions for different movement of the intersection number 19. Note that each signal timing time step is equal to 6 seconds.

The algorithm was solved for demand pattern 3 (the highest demand) on a PC with a Core i9 CPU and 64 GB of memory. Fig. 9 shows the runtime distribution for solving the optimization problem at each intersection in the network. The maximum runtime was 2.45 seconds. Since the implementation period is six seconds the algorithm works in real time even with considering a conservative time for communication between sub-problems.

VII. CONCLUSIONS

This study formulated coordinated signal timing and speed optimization problem in urban street networks as an MILP based on the CTM network loading concept. Since the problem is a mixed integer linear program, it does not scale well with the size of the network and cannot be solved in real-time. Therefore, a distributed optimization and coordination algorithm is developed to improve the scalability and provide real-time solutions. Distributed optimization decomposes the network-level problem to several sub-network level sub-problems by relaxing the constraints that represent the interrelationship between sub-problems. The decomposition significantly reduces computational complexity; however, may affect solution quality adversely. To avoid this issue, an effective coordination scheme is designed that re-enforces the re-introduced relaxed constraints by exchanging information among adjacent sub-problems and implementing them in the constraints. The required information is (a) the outflow of cells at boundaries of a computation node, (b) the available capacity of the receiving cells, and (c) the average speed in the receiving cells. The problem formulation was modified for each computation node to accommodate the incorporation of the information.

We tested the proposed algorithm in a network with twenty intersections. Compared to the Benders decomposition algorithm (benchmark), DOCA found solutions with at most 5.4% optimality gap. Moreover, it was shown that the CSSO is more effective when the network is congested. In comparison to the signal timing optimization, DOCA-CSSO reduced the travel time by 0.5%, 1.1%, and 2.7% in the undersaturated, saturated, and oversaturated demand conditions, respectively. Results that were obtained by implementing the proposed algorithm in Vissim were positive too. Compared to the speed optimization, CSSO reduced the travel time, average delay, average number of stops, and average delay at stops by 32.5%, 38%, 35.3%, and 42.1%, respectively. In addition, the network throughput and average speed increased by 41.4% and 104.2%, respectively. In comparison with the signal optimization, CSSO reduced the travel time, average delay, average number of stops, and average delay at stops by 1.9%, 5.3%, 28.5%, and 5.4%, respectively. Moreover, the network throughput and average speed increased by 1.7% and 3.4%, respectively.

This study assumed that all vehicles are connected and automated and the information about their position and speeds are available. In addition, it was assumed that all vehicles follow the assigned speeds. Further research is needed to investigate how CSSO performs under various market penetration rates of connected and automated vehicles or their compliance with the assigned speed. Moreover, this study assumed that vehicle positions are accurate, and the communications are instantaneous. Further research on the effects of error in vehicle positions and communication latency is needed.

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