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REAL-TIME DYNAMIC TRAFFIC CONTROL BASED ON TRAFFIC STATE ESTIMATION

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ABSTRACT

The accurate depiction of the existing traffic state on a road network is essential in reducing congestion and delays at signalized intersections. The existing literature in the optimization of signal timings either utilizes prediction of traffic state from traffic flow models or limited real-time measurements available from sensors. Prediction of traffic state based on historic data cannot represent the dynamics of change in traffic demand or network capacity. Similarly, data obtained from limited point sensors in a network provides estimates which contain errors. A reliable estimate of existing traffic state is, therefore, necessary to obtain signal timings which are based on the existing condition of traffic on the network.

This research proposes a framework which utilizes estimates of traffic flows and travel times based on real-time estimated traffic state for obtaining optimal signal timings. The prediction of traffic state from the Cell Transmission Model (CTM) and measurements from traffic sensors are combined in the recursive algorithm of Extended Kalman Filter (EKF) to obtain a reliable estimate of existing traffic state. The estimate of traffic state obtained from the CTM-EKF model is utilized in the optimization of signal timings using Genetic Algorithm (GA) in the proposed CTM-EKF-GA framework.

The proposed framework is applied to a synthetic signalized intersection and the results are compared with a model-based optimal solution and simulated reality. The optimal delay estimated by CTM-EKF-GA framework is only 0.6% higher than the perfect solution, whereas the delay estimated by CTM-GA model is 12.9% higher than the perfect solution.

Keywords: Cell Transmission Model; Extended Kalman Filter; Real-time Traffic State Estimation; Adaptive Signal Control; Signal Optimization; Genetic Algorithm.

INTRODUCTION

Traffic congestion has been consistently increasing despite various measures to reduce vehicular traffic demand in congested urban areas due to constraints on available resources and space for increasing road capacity. A significant proportion of delay is caused due to capacity reduction at the intersections. The conflicting movements at intersections reduce the intersection capacity, which results in traffic congestion and queues at the intersection and its approaches. These conflicts in traffic flow can be minimized by providing grade separated intersections which increase the intersection capacity, but is constrained by the limitations in the right of way and finances available to increase intersection capacity. Traffic signals provide a low-cost measure to control conflicting traffic movements at the intersections and also ensure the operation of the intersection at an optimum level. In addition to controlling conflicting movements at the intersection, traffic signals have also been used to influence commuters' route choice behavior and to achieve system optimal solutions (*1; 2*).

Optimum signal control that results in smooth traffic operation can be accomplished by estimating signal timing plans based on real-time measurements of traffic flow parameters. Various Adaptive Traffic Control Systems (ATCS) have been developed and implemented in different cities around the globe. The ATCS packages developed for optimal traffic control include Dynamit 2.0 (*3*), RHODES (*4*), SPOT (*5*), PRODYN (*6*), OPAC (*7*), SCOOT (*8*) and SCATS (*9*). SCOOT and SCATS are among the most widely implemented ATCS for optimal performance of a traffic network. These ATCS packages adjust signal timings based on real-time measurements obtained from sensors installed at appropriate locations in a traffic network. The implementation of these packages has been reported to improve the performance of the traffic network in the application areas. The implementation of SCOOT in Coventry and Glasgow resulted in a 12% reduction in delay at the signalized intersections (*8*). Similarly, a reduction of 19% in delay at signalized intersections was achieved in London by the implementation of SCOOT (*10*). Similar improvements were observed in other urban traffic networks by the implementation of ATCS. The ATCS and existing literature in real-time traffic control are extensively based only on real-time measurements of traffic flow parameters.

Adaptive traffic signal control systems usually require road occupancy and traffic flow measurements from traffic sensing devices (such as inductive loop detectors or camera vision technology). For such applications, traffic sensors are required to be placed in suitable positions and distance from each other (500m to 1 km), so as to obtain uninterrupted and sufficient information to perform the optimization task. These sensor measurements are contaminated with noises and errors, and therefore require the process of filtering and smoothing. Moreover, a fault in the local controller, sensor breakdown and communication disruption can result in insufficient data required for optimum traffic control, which can result in inefficient and inaccurate optimization and traffic operation.

Real-time traffic state estimation based on traffic flow models integrates the prediction power of traffic flow models with the benefit of real-time traffic measurements. The term *state* in traffic state estimation represents the traffic flow variables modeled using the traffic flow model employed, which are estimated using an estimation algorithm (*11*). The predicted state of traffic using traffic flow models are adjusted with the measurements from traffic sensors in the estimation process so that the final traffic state estimate is statistically more reliable than the measurement or prediction alone. Ahmed *et al(11)*, Wang *et al (12)*, Wang *et al(13)*, Wang and Papageorgiou (*14*), and Meier and Wehlan (*15*) applied Extended Kalman Filter (EKF) for traffic flow based real-time estimation of traffic state. Munoz *et al (16),* Gang *et al (17)*, Tampere and Immers (*18*), Long *et al* (*19*) and Long *et al* (*20*) estimated real-time traffic state using the Cell Transmission Model (CTM) based Kalman Filter approach.

Extensive research has been carried out in traffic flow models based offline optimization of traffic signals. Hadi and Wallace (*21*) utilize a Genetic Algorithm (GA) and TRANSYT-7F software concurrently to achieve an optimal solution to the traffic signal. Foy *et al* (*22*) examine the application of GA to produce optimal signal control timings. Lo (*23*) applied CTM and mixed integer programming technique for signal control optimization. Park *et al* (*24*) use GA based optimization by including modified delay minimization with a penalty function and throughput maximization. Park *et al* (*25*) examine the efficiency of GA based optimization on the oversaturated intersection. Li *et al* (*26*) applied GA to optimization of collaborative multi intersection traffic control under various traffic demand. Wada (*27*) proposed an optimization framework to minimize the total transportation cost by achieving an optimal state. Lo *et al* (*28*) developed Dynamic Intersection Signal Control Optimization (DISCO) algorithm which uses CTM along with GA to optimize traffic signal control. For an offline application, DISCO improved the delay up to 33% compared with TRANSYT when applied to the same traffic conditions. Numerous other studies have utilized prediction of traffic state from CTM for traffic control optimization (*28*-*33*).

This research provides an alternative to the existing real-time measurements/traffic flow model based applications for signal control optimization by replacing real-time measurements/ model-based predictions with a real-time traffic state estimation technique to determine the prevailing traffic conditions. The predicted traffic flows from CTM are combined with measurements of traffic flows from sensors in a recursive algorithm of EKF to obtain a more reliable estimate of the existing traffic state. The estimated traffic state obtained from the CTM-EKF model is utilized in the optimization of signal timings using a genetic algorithm. The proposed framework is applied to a hypothetical scenario and results show a significant improvement over the only CTM-based optimal solution while producing a solution with a negligible difference from the simulated reality.

This research presents a framework that optimizes the signal timings based on real-time estimated traffic state. The CTM-EKF algorithm employed in this research is a standard approach in real-time traffic state estimation (*11-14*). New cycle length and green times are estimated after every cycle. This makes this research more near-real-time compared to other adaptive control methods, which keep the same signal plans for a certain time period. Furthermore, the real-time traffic state is estimated based on measurements of the sensor located upstream of the signalized intersection, which is used in the background to estimate the signal timing plan that minimizes the overall network delay when the current cycle is in place. The estimated traffic state at the current time-step is projected for the duration of the candidate timing plans using GA. So, it can be inferred that the proposed framework is not only real-time but predictive in nature as well. The optimal timing plans based on the estimated traffic state during the previous cycle are immediately implemented after the previously estimated cycle is completed.

With growing interest in the potential of real-time data acquisition from connected vehicles (CVs) and its application to real-time traffic management (*34-40*), the proposed research framework can be extended to incorporate real-time data from CVs. Real-time traffic state estimation using data from CVs can replace the dependency on a capital-intensive network of sensors and communication and provide a cost-effective solution for adaptive traffic control systems.

DYNAMIC TRAFFIC ESTIMATION, CONTROL, AND FEEDBACK FRAMEWORK

The CTM-EKF-GA framework proposed in this study integrates various models from existing literature to optimize signal control devices. CTM proposed by Daganzo (*41; 42*) has been implemented by various research studies to model traffic flow on urban arterials. Lo *et al* (*28*) proposed a CTM-based traffic signal optimization model which determines optimal signal timings plans to reduce delay at a signalized intersection using the Genetic Algorithm (GA) technique. Like other model-based optimization frameworks, the CTM-GA model proposed by Lo *et al* (*28*) is useful for offline optimization of signal control devices, which cannot depict real-time variation in traffic demand or changes in capacity due to incidents and extreme weather conditions. This section first describes the selected models CTM, EKF and GA separately and then the integration of these models is described in figure-1, which explains the overall methodology of this research.

Prediction of Traffic State using CTM

The CTM proposed by Daganzo (41) has been widely used in modeling urban network traffic flows. The CTM is simpler to implement on a traffic network and it fits well with the actual field measurements (43; 44). In comparison with other higher order traffic flow models, CTM has fewer numbers of output variables and input parameters which qualifies CTM as a suitable model for real-time applications (11). The CTM has been used for real-time traffic state estimation (16-20; 45) as well as for optimization of traffic networks (23; 30; 46-52).

The CTM represents a traffic network as a collection of cells with equal lengths which is equal to the distance(l_i) that a single vehicle travel during one time-step (Δt) with free-flow speed. In free-flow condition, a vehicle would move from one cell to another in one time-step. The network is divided into i number of cells and each cell has a vehicle holding capacity of $N_i(k)$ determined by the following equation:

$$N_i(k) = \rho_i^J l_i \qquad (1)$$

where ρ_i^J is the jam density in veh/km and l_i is the length of cell i in km. The number of vehicles in cell i at time-step k is $n_i(k)$ and $q_i(k)$ is inflow to cell i at time-step k. The inflow into cell i or outflow from cell i-1 at time-step k is governed by the following equation:

$$q_i(k) = \min[n_{i-1}(k), C_{i-1}(k), C_i(k), \delta(N_i(k) - n_i(k))] \qquad (2)$$

where $C_i(k)$ represents the capacity flow of cell i at a given time-step k; N_i - $n_i(k)$ represents the available space in the cell, and δ is the ratio of shockwave speed to free-flow speed (w/v). Once inflow for all the cells at time-step is determined using equation (2), the cell occupancy for all the cells in the network for one time-step ahead is calculated as follows:

$$n_i(k+1) = n_i(k) + q_i(k) - q_{i+1}(k) \qquad (3)$$

The effect of the traffic signal is modeled by formulating the capacity of the cell containing traffic signal as a variable that switches between zero and saturation flow rate.

$$C_{i+1}(k) = \begin{cases} C_i(k) \; if \; k \in green\ phase \;\; i+1 \in signalized\ cell \\ 0 \; if \; k \in red\ phase \;\; i+1 \in signalized\ cell \end{cases} \qquad (4)$$

Based on Lo et al (28), the delay faced by vehicles in each cell i at times-step k is calculated as:

$$d_i(k) = n_i(k) - q_{i+1}(k) \qquad (5)$$

Estimation of Traffic Flow using EKF

The EKF has been established as a de facto state estimation algorithm for non-linear dynamic systems. Various traffic flow models including CTM are nonlinear in nature; therefore EKF is more suitable for CTM-based estimation framework. This paper adapts the CTM-EKF framework proposed by Ahmed et al (11) for real-time estimation of traffic state with some modifications. Ahmed et al (11) and other research studies (*16-20; 45*) estimated traffic density recursively by taking prediction of traffic density from CTM and assuming real-time measurements of traffic occupancy (density) from sensors. This study estimates inflow to cells (flow rates) instead of traffic density (cell occupancy) as flow rates are one of the basic measurements from traffic sensors. Traffic flow rates are also important in the optimization of traffic control devices as estimated flow rates will be useful in quantifying traffic demand on various approaches of a signalized intersection. Furthermore, real-time measurement devices such as inductance loop detectors directly measure the occupancy and flow rates. In the conversion of occupancy into density, the underlying error in conversion might increase the error in real-time measurements. Using flow rate as a variable for real-time estimation is more useful, as it can be directly related to the modeled flow-rate by the CTM.

In traffic state estimation, the predicted traffic flow by CTM based on equation (2) for current time-step k using estimated density at time-step *k-1* is as follows:

$$\tilde{q}_i(\mathrm{k}) = \min[\hat{n}_{i-1}(k), C_{i-1}(k), C_i(k), \delta(N_i(k) - \hat{n}_i(\mathrm{k}))] + \varepsilon \qquad (6)$$

Where $\tilde{q}_i(\mathrm{k})$ is predicted inflow by CTM, $\hat{n}_i(\mathrm{k})$ is the cell occupancy based on estimated flows at time-step k-1 and ε is white Gaussian noise in predthe iction of traffic flow. The measured traffic flow at time-step k, $m_i^q(k)$ with noise in measurement γ is related with the actual inflow to cell i as follows:

$$m_i^q(k) = q_i(k) + \gamma \qquad (7)$$

The CTM-EKF framework described in Ahmed et al. (11) for real-time traffic state estimation is then applied to obtain the estimated value of inflow $\hat{q}_i(\mathrm{k})$. This estimated inflow is used in cthe alculation of cell occupancy for the future time-step k+1.

$$\hat{n}_i(\mathrm{k}+1) = \hat{n}_i(k) + \hat{q}_i(k) - \hat{q}_{i+1}(k) \qquad (8)$$

The inflows and occupancies are estimated iteratively. $\hat{x}(k|k\text{-}1)$ contains the values of estimated inflows and occupancies and $y(k)$ contains all the measurements. The entire process of correction-estimation using EKF is further explained in figure 1 and equation-11.

Estimating Delay using Estimated Traffic State

Lo et al (28) proposed quantifying approach delay for all the cells in the network by using equation (5). This study updates equation (5) from prediction-based delay to real-time estimation-based delay as follows:

$$\hat{d}_i(\mathrm{k}) = \hat{n}_i(k) - \hat{q}_{i+1}(k) \qquad (9)$$

where $\hat{d}_i(\mathrm{k})$ is the estimated delay for cell i at time-step k; $\hat{n}_i(k)$ is the estimated number of vehicles and cell i and $\hat{q}_{i+1}(k)$ is the estimated flow proceeding from cell i to cell i+1. The link delay can be determined by adding the estimated delay of the component cells in the link. The objective function of signal optimization is to reduce the total network delay in real-time based on the dynamics of traffic flow obtained from CTM-EKF.

$$D = \min \sum_i \sum_{j=1:j} \hat{d}_i(k+j) \qquad (10)$$

where D is the sum of delays in all the cells during j time-steps and j is the number of time-steps estimated for the upcoming signal cycle. $\hat{d}_i(k+j)$ is obtained by predicting the traffic flows for the network using randomly generated signal timing plans for j number of future time-steps based on the estimated traffic state at time-step k. This study keeps the cycle length and green times as dynamic variable which results in the minimum intersection delay.

Optimal Signal Timings using Genetic Algorithm

In this study, we develop a solution approach based on an artificial intelligence technique called Genetic Algorithm to find an optimal timing plan for the traffic signal. This study utilizes the CTM-GA approach proposed by Lo et al (28) to determine the optimal signal control timings based on real-time estimated traffic state and delays. Lo et al (28) can be referred for further details about determining the optimal cycle length based on GA. The optimal cycle lengths and green times for signal phases at time-step k are estimated by simulating the traffic with candidate signal plans proposed by GA and estimated traffic state at the current time-step k is predicted for the duration of proposed cycle length.

Integration of CTM, EKF, and EKF to formulate CTM-EKF-GA Framework

In the proposed CTM-EKF-GA framework, the CTM-EKF estimates real-time traffic flow based on observations from sensors along approaches of the intersection by replacing only CTM-based traffic prediction model in CTM-GA with CTM-EKF estimation developed by Ahmed *et al* (*11*) with some modifications. The CTM-EKF-GA framework proposed in this study is elaborated in figure 1. $\sum(x, y)$ represents CTM based state-space dynamic model for the prediction of traffic flow and connecting the prediction of traffic flow to the measurements of traffic flow parameters from sensors. It predicts the traffic flow for current time-step based on the estimated traffic density that was calculated using CTM-EKF based estimated flow rates at the previous time-step (equation-6). CTM-based function, $f(\hat{x}(k|k\text{-}1, 0))$, predicts traffic flow rates for time step k, based on all available measurements until time-step k-1. $g(\hat{x}(k|k\text{-}1,0))$ is a differentiable function that maps the predicted flow-rate for time-step k to the flow rates measured by the sensor $y(k)$ (equation-7). The measurement of traffic flow rates at time-step k is compared with the predicted output from CTM and a correction factor called the Kalman Gain **K** is estimated using the variance in the prediction and the measurement of the traffic flow rates. This correction is then added to the pure model-based flow-rates and traffic density for time-step k+1 is predicted based on estimated flow rates at time-step k (equation-8). This predicted density is then used recursively for determining estimated traffic flow rates for all the time-steps in simulation horizon. The estimated flow rates and traffic density are used for determining the delay for each cell in the link and overall network delay for each simulation time-step. $\hat{x}(k+1|k)$ represents the CTM-EKF based estimated traffic flow rates and predicted densities calculated using estimated flow rates as follows:

$$\hat{\mathbf{x}}(k+1|k)= f[\hat{\mathbf{x}}(k|k\text{-}1,0),0] + \boldsymbol{K}(k)\,[\mathbf{y}(k)\text{-}g(\hat{\mathbf{x}}(k|k\text{-}1,0))] \qquad (11)$$

The network delay based on CTM-EKF estimated state at time-step k is forwarded to another CTM prediction model of the network, which simulates the current estimated traffic state with the random timing plans generated by GA. The predicted delays and corresponding signal timings are stored to determine the optimum signal control plan that results in the minimum delay. The optimum cycle length consists of j number of time-steps, which is dynamic and may change from cycle to cycle based on the existing traffic conditions. The same procedure is repeated after the completion of each signal cycle. If Δt is the duration of each simulation time-step, the proposed CTM-EKF-GA framework estimates the optimal cycle length $j \times \Delta t$ as the sum of green splits of all the phases in one cycle.

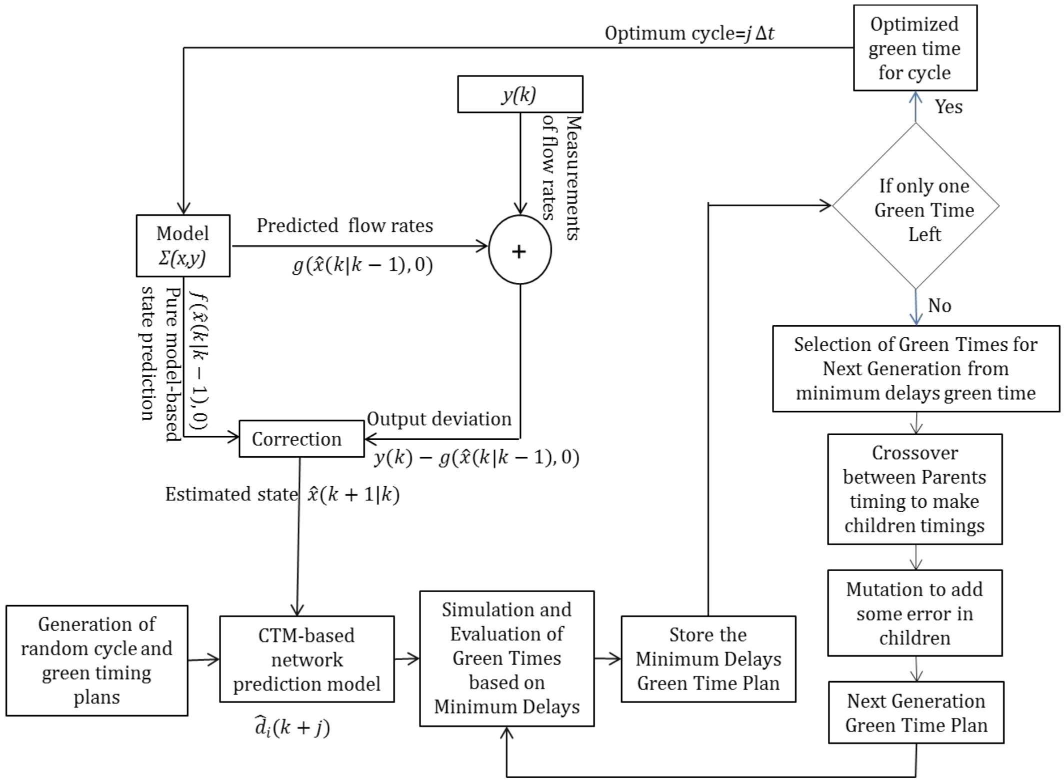

FIGURE 1 CTM-EKF-GA framework for optimal signal control

SIMULATION SETUP

The ATCS becomes more significant when there is an unexpected change in traffic demand or network capacity. This research paper highlights the significance of the proposed CTM-EKF-GA framework by simulating a signalized intersection affected with an incident. The simple network consists of three links and a signalized merging intersection. Two links (link-1 and link-2), each of two-lanes, are equipped with measurement sensors that provide real-time measurements of traffic flows in cells-10 on link-1 and cell-46 on link-2. Links 1 and 2 are intersecting at the signalized intersection **S** and merging on link-3 as shown in figure 2.

The synthetic network consists of 84 cells, each of 83.33 meters in length. The length of link-1 is 2.9 km from cells 1-36 with cell-1 as a dummy cell having the infinite holding capacity. The length of link-2 is similar to the length of link-1 with cells from 37-72. The length of link-3 is 1 km with 12 cells from cell 73-84. Free flow speed is taken as 60 km/hr, which corresponds to time-step of 5 seconds. The capacity flow rate is 1800 veh/hr/ln and shockwave speed is taken as 20 km/hr. The simulation horizon is 90mins (1080 time-steps). Traffic demand for link-1 and link-2 is constant at 2160 veh/hr for time-steps 1 to 900. After time-step 900, the traffic demand is zero for both the links to simulate the cooling-off effect. Link-1 is affected by an accident for 15 mins starting from the 30th minute (time-step=360). The accident occurs in cell-6 of link-1, which completely blocks both the lanes for 5 mins (time-step= 360 to 420), followed by one lane blockage for following ten minutes (time-step= 421 to 540).

The optimal signal timings are estimated using GA, which estimates the optimal green time between 20 and 180 seconds. Whereas, the optimal cycle length is estimated between 20 and 300 seconds in 30 iterations.

The measurement sensor is placed downstream of the accident location at cell-10 in the simulated network. The location of the sensor affects the accuracy of the estimated traffic state during an incident and the effect of the accident on traffic state is reflected at the sensor downstream of the accident location (53). Therefore, a sensor is assumed downstream of the affected cell. In a real-life scenario, the traffic sensor downstream of the accident location will be important in estimating the affected traffic state. Ahmed et al. (53) can be referred for a detailed discussion on this topic.

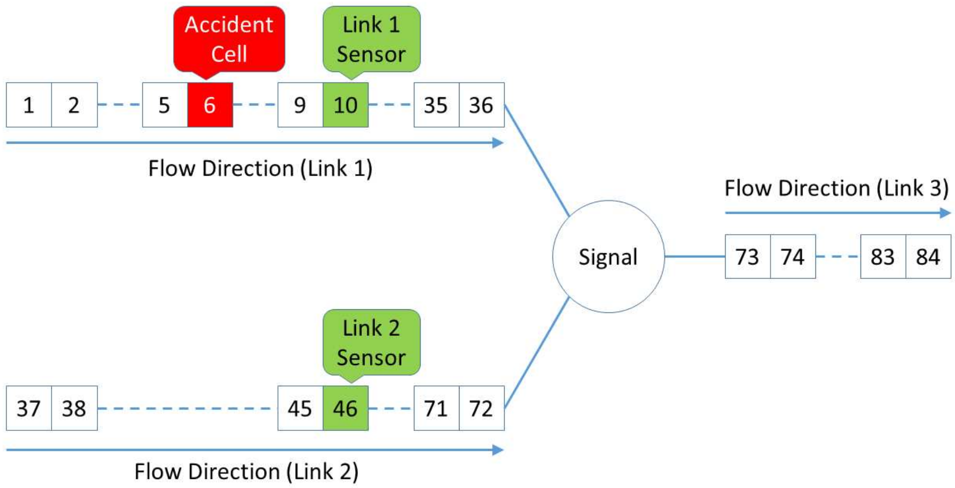

FIGURE 2 Network Diagram showing cell and signal positions

The significance and performance of the proposed CTM-EKF-GA framework are evaluated by comparing the optimal signal timing plans and resulting delays obtained by CTM-EKF-GA framework with the signal timing plans and resulting delays in CTM-GA framework and simulated reality. Thus, the network shown in figure 2 is simulated with three different frameworks as follows:

Simulated Reality (SIM)

The scenario of simulated reality estimates optimal signal timings and resulting delays using a CTM-GA model with perfect information about the duration, location, and impact of the incident. The CTM model in simulated reality scenario (SIM) is provided with the exact location of the accident, reduction in capacity and duration of the capacity drop due to the incident. SIM is considered as the base scenario for comparison of the performance of CTM-EKF-GA and naïve CTM-GA frameworks. SIM provides the best possible signal timing plan, which is based on a perfectly aware (ideal) model and results in minimum (ideal) delay.

Naïve CTM-GA

CTM-GA scenario determines optimal timing plans using a naïve CTM model for simulation of the predicted traffic state. CTM-GA and CTM-EKF-GA are simulated with exactly the same traffic demand, assuming that there is no variation in traffic demand and it is not deviating from the historic trend. The optimal signal timing plans obtained by naïve CTM-GA are applied to a perfectly aware CTM model that is provided with all the details of the accident. This will determine the actual delays that commuters will experience if the optimal timings plans obtained by naïve CTM-GA are applied to a network affected with the incident.

CTM-EKF-GA Framework

CTM-EKF-GA scenario is also based on a naïve CTM in the background for modeling traffic flow and no direct information about the incident is provided to CTM-EKF-GA model. However, CTM-EKF-GA framework is capable of estimating real-time changes using real-time measurements from the sensors and EKF technique. The synthetic measurements for sensors are generated using a perfectly aware CTM model (running as part of CTM-EKF-GA model) which provides measurements of traffic flows only for the cells with measurement sensors (cell-10 and 46) to the CTM-EKF-GA framework. A white Gaussian noise is also added in the measurements to represent the error in actual measurements corrupted with noise.

The optimal signal timing plans obtained using CTM-EKF-GA model is applied to the perfectly aware CTM model to simulate traffic state and estimate delays for optimal signal timing plans proposed by CTM-EKF-GA model. This reflects the actual delay experienced by commuters if the signal timings proposed by CTM-EKF-GA are implemented on the affected network. The delay obtained by implementing CTM-EKF-GA on perfectly aware CTM is used for evaluation of the CTM-EKF-GA performance and comparison with other scenarios.

RESULTS AND DISCUSSION

The proposed CTM-EKF-GA framework is applied to the network shown in figure 2. The performance and improvement achieved by CTM-EKF-GA framework are evaluated by comparing the network delay faced by vehicles in CTM-EKF-GA scenario with the network delay in CTM-GA model and simulated reality. The simulation results of all three scenarios are discussed in this section.

Simulated Reality

Cell occupancies for the scenario of simulated reality are shown in figure 3. Variation in cell occupancies for all the cells in links 1, 2 and 3 for the entire simulation horizon can be observed from this figure. The results of simulation obtained in this scenario are used to compare with the other two scenarios (CTM-GA and CTM-EKF-GA) to evaluate their performance. Simulated reality shows the dynamics of traffic network in a system which has perfect information about the duration and intensity of the accident.

The drop in capacity of cell-6 during the incident results in low vehicle occupancy for the cells downstream of incident location and high vehicle occupancy on the upstream of the incident location (cell-6). After the incident is cleared, the entire link-1 can be observed in congestion, due to the increased demand and stopped vehicles during the incident. These occupancies are obtained when the network is simulated with an optimal signal plan obtained using CTM-GA model with perfect information about the incident.

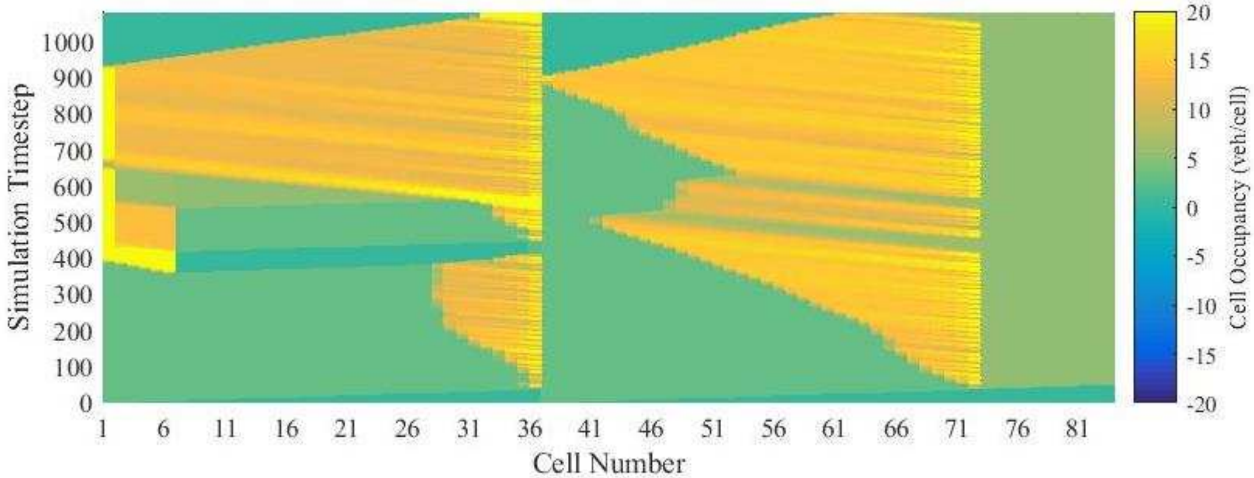

FIGURE 3 Cell occupancy for the network in simulated reality

The delay experienced (veh*time-step) with optimal timing in simulated reality is shown in Figure 4. It shows that before the incident few cells upstream of the signal were congested in link-1. During the incident, all the cells of link-1 downstream of the incident location have no delay, as the outflow from cell-6 is restricted and capacity is reduced during the incident. Link-3 always remains in the free-flow state as traffic demand for link-3 is always less than the available capacity of the link.

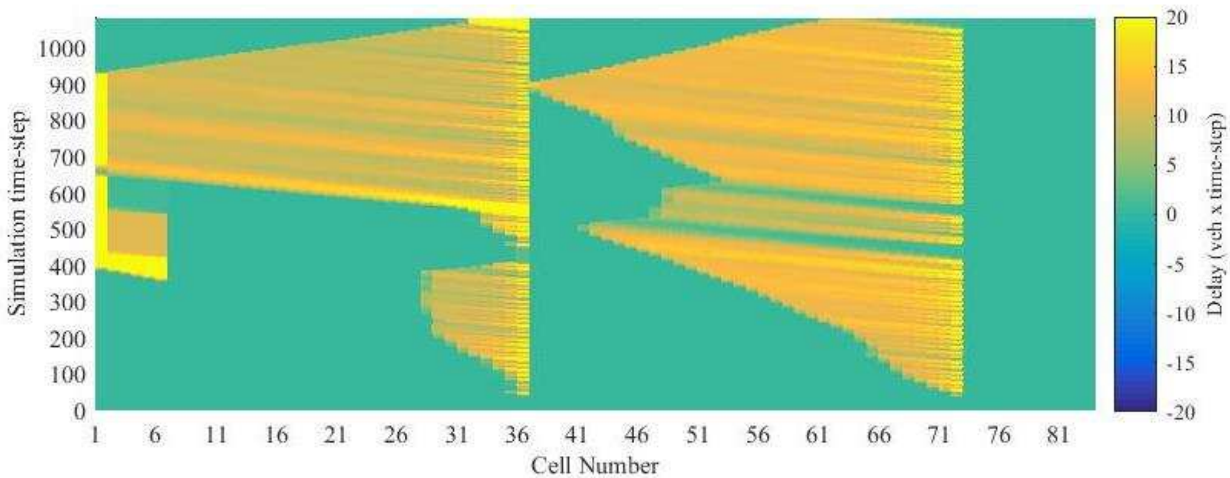

FIGURE 4 Delay experienced by the vehicles in simulated reality

Naïve CTM-GA Framework

The simulation results obtained by simulating the network with CTM-GA framework are discussed in this section. Figure 5 shows cell occupancies when naïve CTM-GA framework has no information about the incident. This figure shows cell occupancies if the network was not affected and there was no incident. The comparison of figure-5 and figure-3 reveals the difference in predicted network state using naïve CTM and the simulated reality, which highlights the importance of using real-time information for optimization during the disrupted state. Figure-6 shows predicted delays using naïve CTM-GA model for the entire simulation horizon. Figure 6 shows that the cells upstream of the signals experience congestion, as the demand is higher than the available capacity of the signalized intersection. This results in a gradual queue buildup till time-step 900, as the network is simulated with traffic demand till time-step 900. The gradual drop in cell occupancies and delay after time-step 900 can be seen from figure-5 and figure-6, respectively.

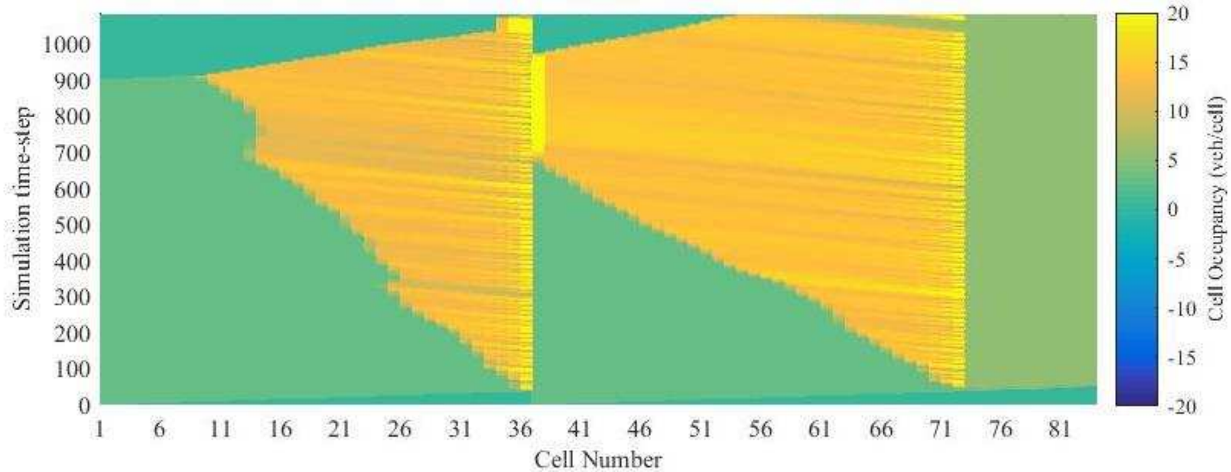

FIGURE 5 Cell occupancies from naïve CTM-GA model

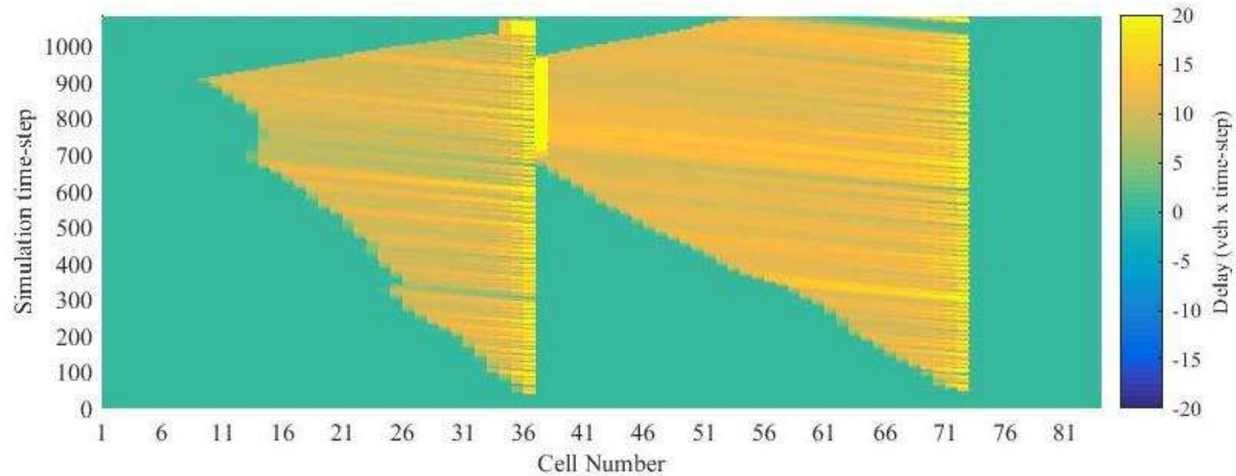

FIGURE 6 Delay from naïve CTM-GA model

CTM-EKF-GA Framework

This results obtained by simulating the disrupted network with CTM-EKF-GA framework are discussed in this section. Figure-7 shows a comparison of predicted and estimated cell occupancies with the cell occupancies from the simulated reality scenario for selected cells in link-1. While comparing the occupancies, it should be noted that the incident location is at cell-6 and sensor location is at cell-10 in link-1. In cell-5, which is upstream of the incident cell, the estimated traffic state is not much different from the simulated reality, whereas the predicted traffic state deviates significantly from the actual traffic condition during the incident. However, the CTM-EKF is unable to detect the drop in flow due to the incident from cell-6 to cell-10, as the information about reduced flow is provided by the sensor at cell-10. Ahmed et al (53) discussed this phenomenon of difference in estimated density while estimating real-time traffic state in a network affected by the incident. Thus, the traffic state estimated by CTM-EKF-GA framework might deviate from the actual traffic state from the affected cell to the cell containing the sensors, which is still better than naïve CTM or just measurements from two consecutive sensors. This shortcoming can be improved by future research in incident detection and real-time capacity estimation for all the cells in the network.

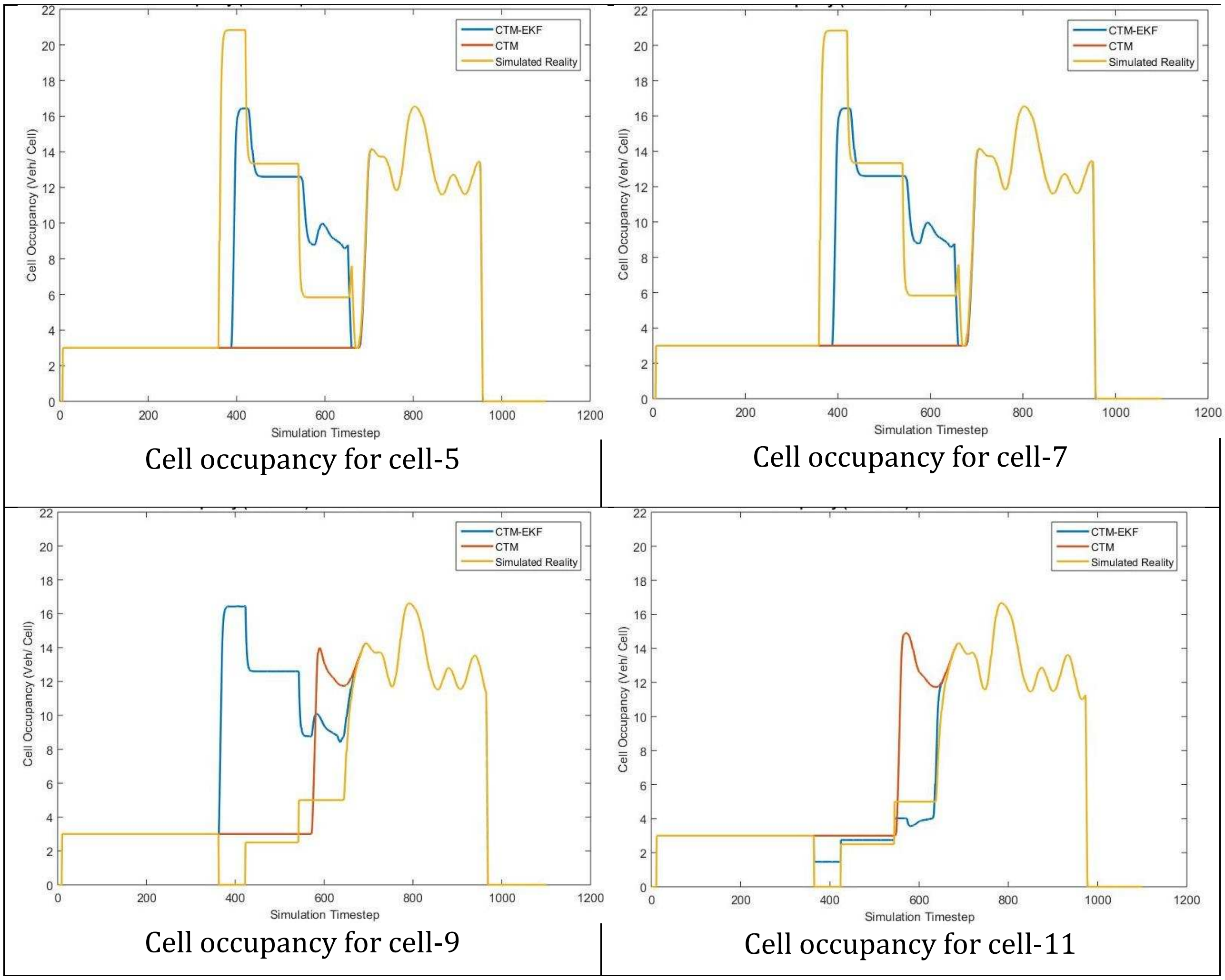

FIGURE 7 Comparison of predicted (CTM-GA) and estimated (CTM-EKF-GA) cell occupancies with the simulated reality for selected cells in link-1

Figure 8 shows estimated cell occupancies using CTM-EKF-GA framework for the network for the entire simulation horizon. The comparison of figure-3 with figure-8 indicates the difference between the estimated state and the actual state (simulated reality). It can be observed that the spillback at the upstream of cell-6 is tracked at cell-10 (sensor cell) in CTM-EKF-GA framework. Whereas for the cells downstream of sensor location, the estimated traffic state matches with the simulated reality. Figure 9 shows delay for all the cells in the network for the entire simulation horizon.

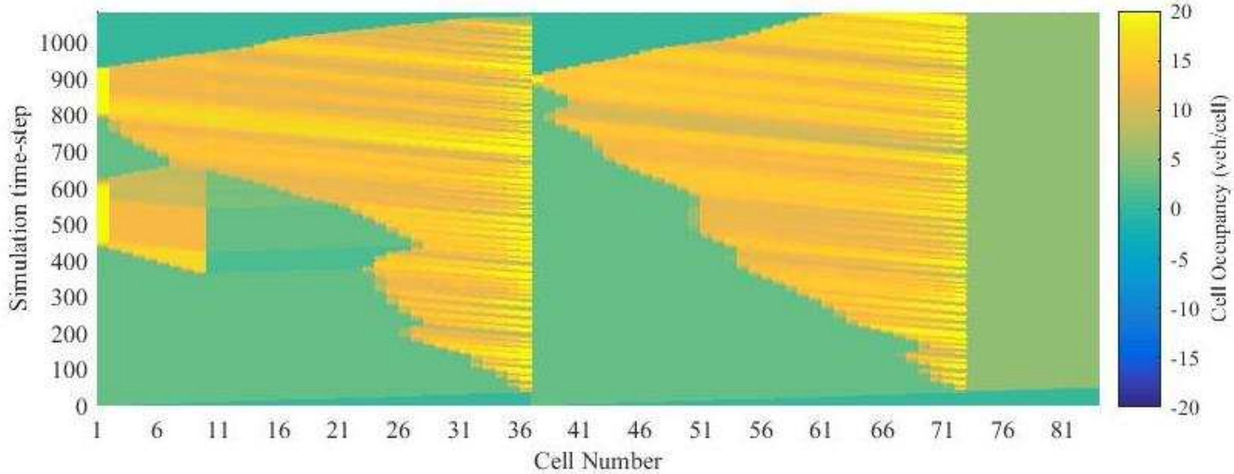

FIGURE 8 Cell occupancies obtained from CTM-EKF-GA framework

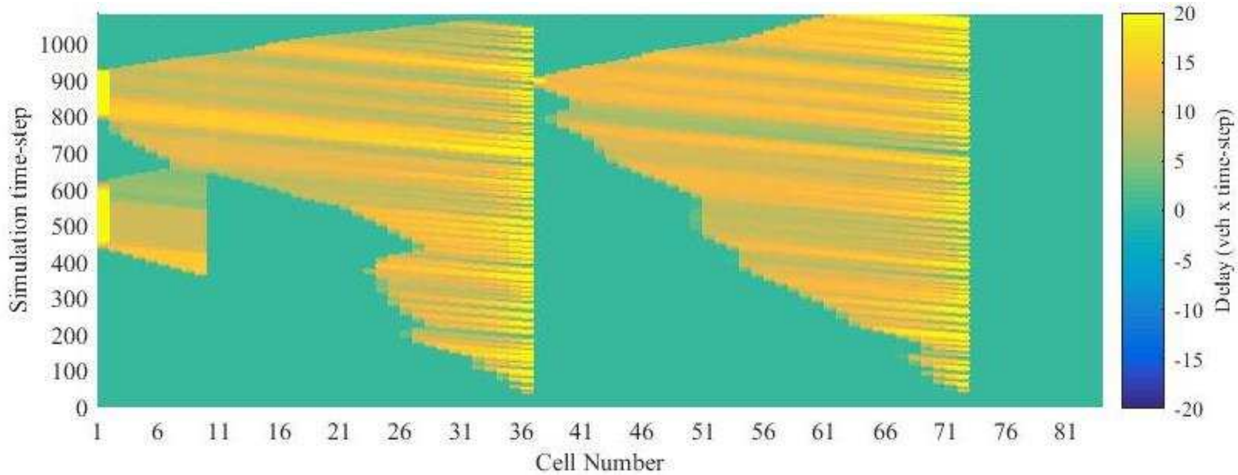

FIGURE 9 Estimated delays from CTM-EKF-GA

Comparison of Outputs from Naïve CTM-GA and CTM-EKF-GA with Simulated Reality

This section compares various outputs from simulation results obtained from naïve CTM-GA and CTM-EKF-GA framework with the simulated reality (SIM). Figure 10 compares the optimal cycle lengths obtained using CTM-GA, CTM-EKF-GA, and SIM. Figure 10 shows that the number of cycles in CTM-EKF-GA and SIM is approximately equal in the simulation horizon, while the number of cycles in CTM-GA is comparatively higher, due to the difference in duration of the cycle.

The actual reason for shorter cycle lengths estimated by CTM-GA (in comparison with CTM-EKF-GA) is that the CTM-GA model does not have any information about the incident and it estimates the optimal cycles as if there were no incident. Therefore, the cycle lengths estimated by CTM-GA are shorter and remain almost the same throughout the simulation horizon.

CTM-EKF-GA is based on a naïve CTM model and estimates the real-time traffic state based on information from limited point sensors. Thus, SIM and CTM-EKF-GA have the capability to track real-time changes in traffic state due to the incident. Therefore, CTM-EKG-GA and SIM models propose longer cycles when the network dynamics change due to the incident. However, the strategies evaluated by the CTM-EKF-GA and SIM are different due to the non-deterministic nature of the employed optimization algorithm (GA). Nevertheless, both the strategies attempt to meet the same objective, which is to minimize the network delay based on the existing traffic condition.

Figure 11 compares optimal green time estimated for link-1 by GA for three different models projecting the current state of the network. The performance of the proposed control strategies by these three frameworks can be evaluated by implementing these timings to a perfect CTM model.

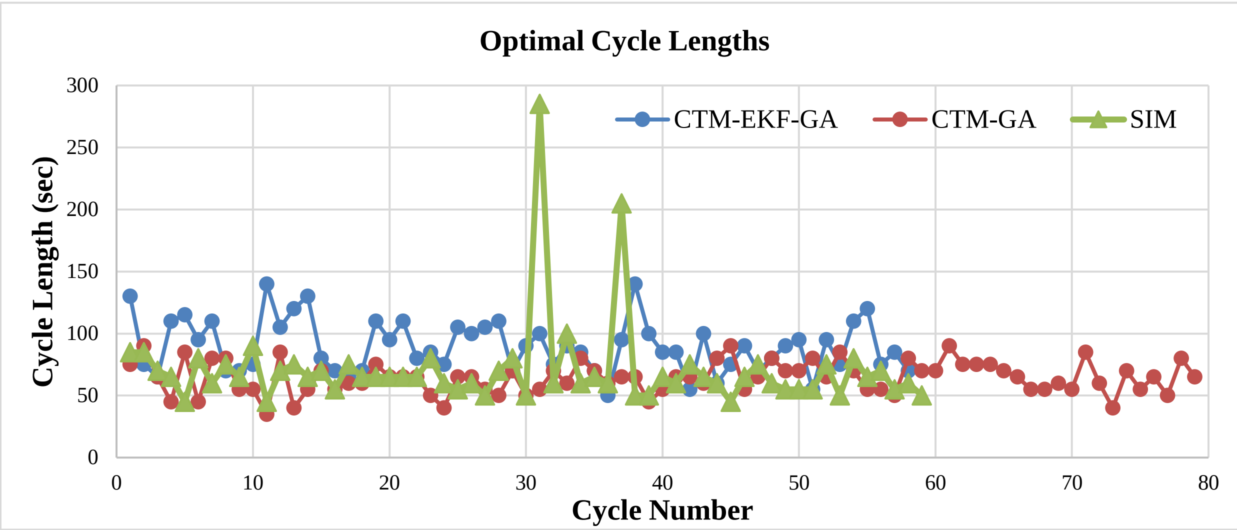

FIGURE 10 Comparison of cycle lengths proposed by naïve CTM-GA, CTM-EKF-GA, and SIM

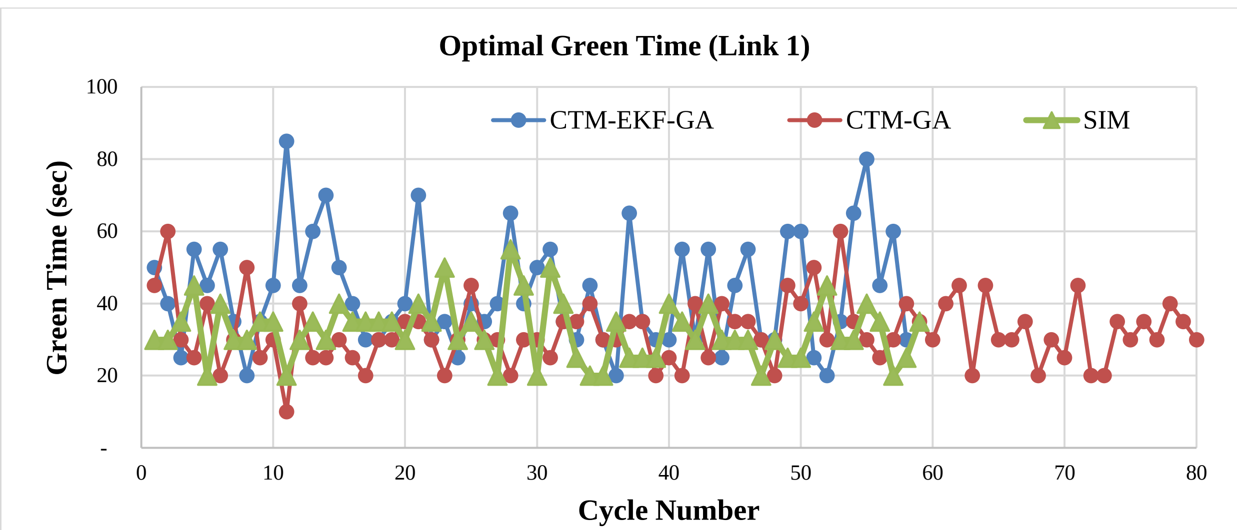

FIGURE 11 Comparison of green splits proposed by CTM-GA, CTM-EKF-GA, and SIM

The optimal signal timing plans estimated by naïve CTM-GA and CTM-EKF-GA frameworks are applied to a perfectly aware CTM network, which has the information about the location, duration and reduction in capacity due to the incident. The delay obtained by simulating perfect CTM model with CTM-GA and CTM-EKF-GA model depicts actual delays that these timing plans will produce on an affected traffic network. Figure 12 shows delay for all the cells in the network with CTM-EKF-GA proposed signal plan simulated with perfect CTM. The comparison of figures 12 and 13 shows the significance and improvement by implementing the timing plans proposed by CTM-EKF-GA to a disrupted network. Figure 14 shows the difference of network-wide occupancies during the simulation horizon by subtracting the occupancies obtained by implementing CTM-GA and CTM-EKF-GA frameworks to the perfect CTM. The implementation of CTM-EKF-GA framework shows a significant improvement in overall network delay during the incident.

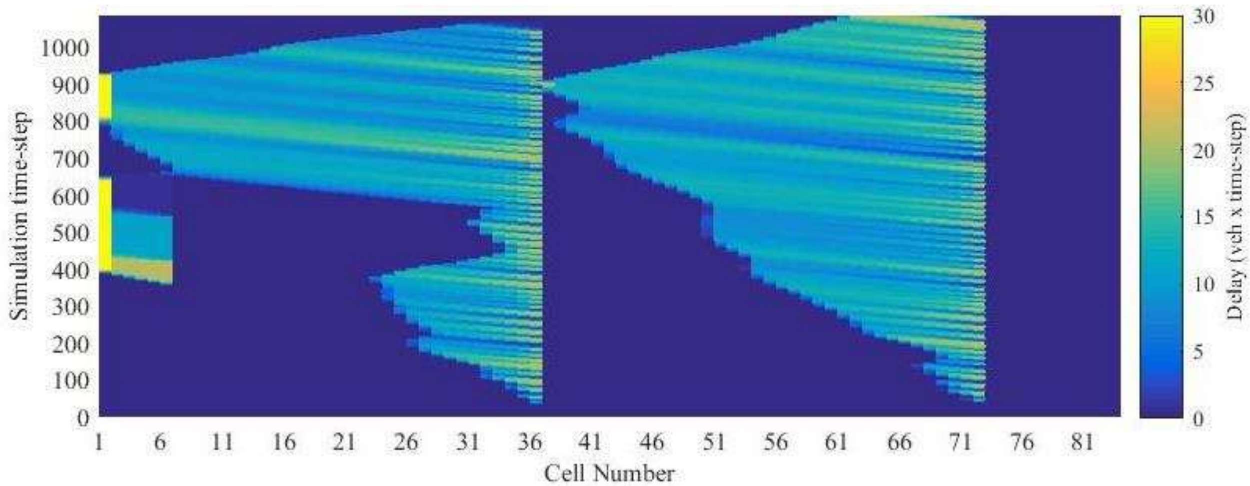

FIGURE 12 Estimated delay obtained by CTM-EKF-GA proposed plans to perfect CTM

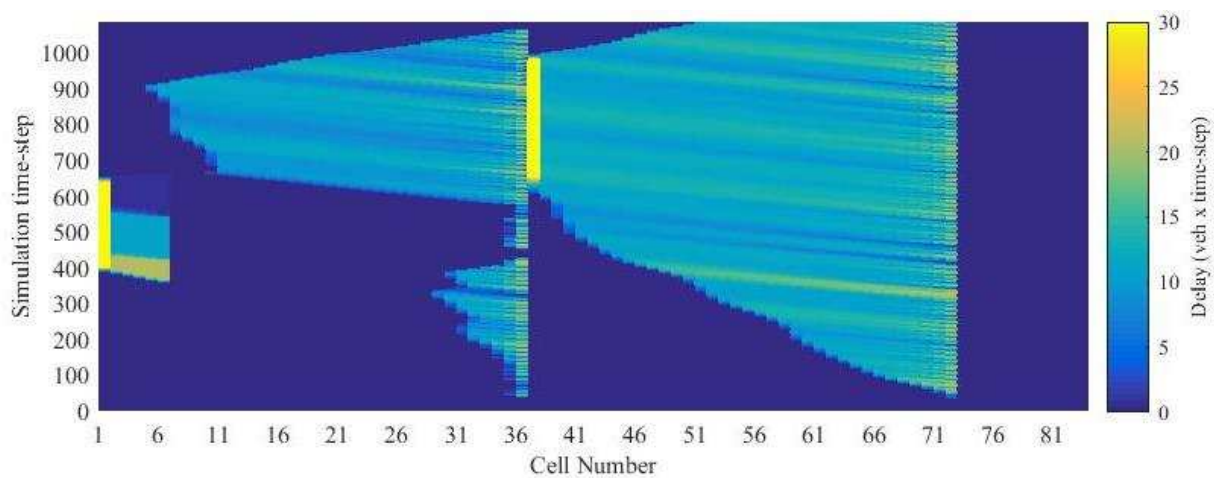

FIGURE 13 Network-wide delays obtained by implanting CTM-GA signal plan to perfect CTM model

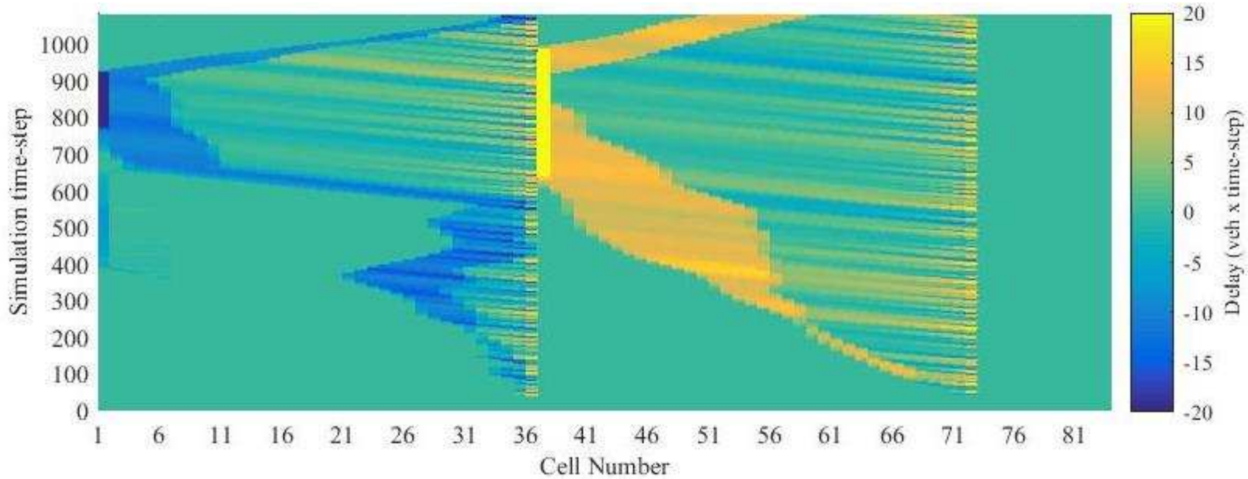

FIGURE 14 Difference of cell occupancies obtained by simulating perfect CTM with timings proposed by CTM-GA and CTM-EKF-GA (CTM-GA minus CTM-EKG-GA)

The simulated reality (SIM) scenario is considered as an ideal framework and the performance of CTM-GA and CTM-EKF-GA are compared with simulated reality. SIM proposed timing plans resulted in the lowest total delay for the entire simulation horizon (1.5 hrs) with 644.4 veh-hr. In comparison with SIM, the total network delay using timings proposed by CTM-EKF-GA is only 0.6% higher than the simulated reality scenario (648.5 veh-hrs). Whereas, the timing plans proposed by naïve CTM-GA model result in a total network delay of 727.4 veh-hr, which is 12.9% higher than the simulated reality and 12.1% higher than the total network delay resulted using CTM-EKF-GA model.

CONCLUSIONS

This research paper proposes a novel framework for optimizing traffic signal control based on CTM-based real-time traffic state estimation. The existing literature in the optimization of traffic control is mainly based on either traffic flow models or direct measurements from various real-time measurement technologies. The research, for the first time, utilizes a traffic flow model-based estimation techniques and uses CTM-EKF based real-time estimated state for optimizing traffic control using the GA technique. The proposed framework in this research does not depend on GA, but any heuristic optimization algorithms (such as cross entropy method, Simulated Annealing, etc.) can be applied in place of GA. As this optimization problem is non-smooth, this research is focused on finding a reasonably good solution, not the global one (which is impossible to obtain).

The proposed CTM-EKF-GA framework is applied to a synthetic network, disrupted with an incident. Simulation results show that a reduction of 12.1% in total network delay is achieved by using CTM-EKF-GA model instead of CTM-GA model. The network delay by CTM-EKF-GA is only 0.6% higher than the network delay estimated with a simulated reality which is based on perfect CTM model. This difference in performance on CTM-EKF-GA can also be improved if the incident location, duration, and impact of the incident are also estimated using a real-time capacity estimation of all the cells in the network. This research only utilizes GA as an optimization tool to determine optimal timing plans, which may be extended to include some other optimization algorithms to evaluate the performance of various algorithms with real-time traffic estimation. The proposed framework may also be extended to estimate real-time traffic state using the real-time data available from connected vehicles, which may reduce the dependency on a network of costly sensors installed throughout the network to provide real-time measurements, as connected vehicles can be used as mobile sensors spread throughout the network.

This research develops a framework for optimization of a standalone signalized intersection, which can be expanded for network optimization and signal coordination. Signal offset optimization can be improved by utilizing model-based real-time traffic state estimation.

Author Contribution Statement

The authors confirm contribution to the paper as follows:
Study conception and design: A. Ahmed
Simulation and Modeling: S.A.A. Naqvi, D. Ngoduy, D. Watling
Draft manuscript preparation: A. Ahmed, S.A.A. Naqvi, D. Ngoduy, D. Watling
Analysis and interpretation of results: A. Ahmed, S.A.A. Naqvi, D. Ngoduy, D. Watling

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