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Research Paper

Identification of optimal locations of adaptive traffic signal control using heuristic methods ☆

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A B S T R A C T

Adaptive Traffic Signal Control (ATSC) adjusts signal timings to real-time traffic measurements, increasing operational efficiency within a network. However, ATSC is both expensive to install and operate making it infeasible to deploy at all signalized intersections within a network. This study presents a bi-level optimization framework that applies heuristic methods to identify a limited set of locations for ATSC deployment within an urban network. At the upper-level, the Population Based Incremental Learning (PBIL) algorithm is employed to generate, evaluate, learn, and update different ATSC configurations. The lower-level uses the delay-based Max-Pressure algorithm to simulate the ATSC configuration within a microsimulation platform. The study proposes improvements to the PBIL algorithm by considering constraints on the maximum number of intersections for ATSC deployment and incorporates prior information about the intersection performance (i.e., informed search). Simulation results on the traffic network of State College, PA reveal that the proposed PBIL algorithm consistently outperforms baseline methods that select locations only based on queue-lengths or delays in terms of reducing overall network travel times. The study also reveals that intersections experiencing the highest delays or longest queues are not always the best candidates for ATSC. Moreover, applying ATSC at all intersections does not always provide the best performance; in fact, ATSC applied to some locations could increase travel times by contributing additional congestion downstream. Additionally, the modified PBIL algorithm with the informed search strategy is more efficient at identifying promising solutions suggesting it can be readily applied to more generalized optimization problems.

1. Introduction

Traffic signals play a critical role in street networks by alternating the right of way between competing traffic streams to prevent conflicts. However, they often serve as bottlenecks and create congestion as they frequently interrupt traffic flows to accommodate other movements. As a result, traffic engineers have long been concerned with developing the most efficient

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signal phasing and timing plans. The most common type of signal timing plan is fixed-time control, which operates on predetermined fixed signal timings throughout the day. However, this fails to adapt to the changing traffic patterns and volume fluctuations (Urbanik et al., 2015) and can lead to significant delays and congestion during incidents such as crashes, lane closures, and work zones.

One option to mitigate these drawbacks is to apply adaptive traffic signal control (ATSC), which measures traffic patterns and adjusts signal timings dynamically. Some ATSC algorithms utilize a centralized controller to make signal timing decisions for multiple intersections together in a coordinated way (Douglas Gettman et al., 2006; Gartner, 1983; Mirchandani and Head, 2001; P B Hunt et al., 1981). However, centralized ATSC systems impose a heavy computational burden and are not generally scalable (Liu and Gayah, 2022). Decentralized ATSC systems, on the other hand, optimize signal timings at individual intersections independently of other intersections. These are easier to implement and have been shown to be effective at increasing average flows when the network is moderately congested and preventing gridlock (Abdelghaffar and Rakha, 2019; Carlson et al., 2011; Chow et al., 2020; Gayah et al., 2014; Lämmer and Helbing, 2008; Liang et al., 2021; Priemer and Friedrich, 2009).

An increasingly popular and effective branch of decentralized ATSC is the Max Pressure (MP), which was initially proposed for packet transmission scheduling in wireless networks (Tassiulas and Ephremides, 1990) but later extended to traffic signals in (Varaiya, 2013). MP-based traffic signal control algorithms only require local information from approach links upstream and downstream of the subject intersection and can operate on each intersection independently without knowledge of future demands. MP algorithms are reputed for their ability to maximize throughput, defined as the algorithm's ability to serve vehicle demand if the demand can be accommodated by any control strategy. This property was proven in (Varaiya, 2013) and supported through subsequent research (Barman and Levin, 2022; Gregoire et al., 2014; Le et al., 2015; Levin et al., 2020; Li and Jabari, 2019; Pumir et al., 2015; Wu et al., 2018; Xiao et al., 2014). Most of these studies have reported significant improvements in network performance by implementing MP either at isolated intersections or at all intersections in a network (i.e., global deployment).

Although decentralized ATSC systems do not have the heavy computational burdens of centralized systems, they still require detection infrastructure to measure conditions in adjacent links in real-time. Due to budgetary constraints, however, it may not always be feasible to apply such technology at all intersections in a network. Very few studies have focused on where decentralized ATSC systems should be implemented in a traffic network. The first study combined MP with perimeter control and proposed a strategy to identify optimal locations to deploy ATSC based on a few criteria (Tsitsokas et al., 2023). Specifically, intersections are selected based on a linear combination of the mean link occupancy, variance of link occupancies and experienced level of congestion under a fixed control scheme. However, a drawback to this study is that the weights assigned to each of these criteria rely on trial and error. Further, while this strategy provides a simple rule for selecting potential ATSC locations, there is no guarantee that even more benefits could not be obtained by another configuration or that performance may not degrade with the implementation of additional ATSC signals. For example, long queues at an intersection may be due to improper signal timings at an adjacent intersection that causes queues to spillback onto the subject intersection; applying ATSC at such locations might not be beneficial if the problems at the adjacent locations are not first properly addressed. Another related study (Barman and Levin, 2023) presented a mixed-integer linear programming (MILP) to find the optimal intersections to install MP control and a greedy algorithm to solve the MILP efficiently. However, the greedy algorithm does not search for optimal deployment from a network-level perspective. Instead, the greedy algorithm makes locally optimal choices at each step, sequentially adding intersections based on the maximum increase in the network throughput per unit of cost until a budget is exhausted. Therefore, it is important to carefully consider the assumptions and limitations of the method when applying it to determine the best intersections to implement MP in a particular network.

This paper proposes a bi-level optimization framework to identify both the optimal number and locations of intersections at which to deploy decentralized ATSC systems in a signalized traffic network. At the upper level of this problem, the Population Based Incremental Learning (PBIL) algorithm is applied, given its successful performance on other types of transportation treatments that exhibit interdependence (Bayrak et al., 2023, 2021; Bayrak and Gayah, 2021). Two extensions to the PBIL algorithm are proposed here to improve its applicability to this problem and its overall performance. The first is the integration of constraints within the PBIL framework to consider a maximum number of ATSC deployments that may be considered at any given time. Such constraints are useful in scenarios where deployments must be limited, perhaps due to resource constraints. The second is the integration of prior knowledge to improve the quality of solutions provided by the PBIL algorithm (referred to as informed decision-making). At the lower level, a cyclic version of the delay-based MP algorithm (D-MP) (Liu and Gayah, 2022) was used as a representative ATSC scheme. The impact of the ATSC is tested via the micro-simulation platform AIMSUN in the traffic network of State College, PA. The result suggests that a limited number of ATSC configurations can yield better performance than global deployment. The results of the proposed method are also compared with baseline methods to verify its effectiveness.

The remainder of this paper is organized as follows. First, detailed descriptions of the proposed optimization method and baseline comparison methods are presented. Then, the simulation setup used to evaluate the performance of these methods is provided. Next, the results of the experiments are shown, including a comparison of the proposed methods with baseline approaches, and the implications of these results are discussed. Finally, the paper concludes with remarks on the significance of the findings and potential avenues for future research.

2. Methods

This section describes the bi-level optimization framework and PBIL algorithm (as well as novel extensions proposed here) to determine the optimal location and number of ATSC deployments in a signalized traffic network. Two baseline methods of identifying the optimal location of ATSC intersections are also described. In addition, the MP algorithm used here as the proposed ATSC is introduced.

2.1. Bi-level optimization framework

The determination of optimal locations of transportation treatments in a network – so called *facility location problems* – are generally classified as NP-hard optimization problems (Drira et al., 2007). The complexity of these problems increases drastically as the number of treatments or potential locations increases. Therefore, it is difficult to develop an analytical model with a precise solution to determine the optimal location. Furthermore, the placement of individual transportation improvements is also interdependent. For example, making one signal adaptive alters traffic flows both downstream and upstream and might influence whether an adjacent intersection also needs to be adaptive. To overcome these challenges, the method proposed in this paper is a bi-level optimization framework. Such frameworks have previously been used to solve optimal location problems in the transportation literature (Bayrak and Guler, 2020, 2018; Chen, 2015; Ferro et al., 2020; Jung et al., 2016; Mesbah et al., 2011, 2008).

The structure of the bi-level optimization framework is depicted in Fig. 1. In a generic sense, the upper level of a bi-level optimization problem identifies sets of decision variables (i.e., set of intersections equipped with ATSC) that continually improve network performance quantified in the lower level of the problem. Genetic Algorithms (GA) are a popular method for solving optimization problems in the upper level of bi-level optimization (Bingfeng et al., 2017; Chen, 2015; Mesbah et al., 2011, 2010; Yao et al., 2012). GA mimics the process of natural selection by using a population of potential solutions to a problem and then selecting the best solutions for the next generation. Through the process of selection, crossover, and mutation, the genetic algorithm iteratively improves the quality of the population until a near optimal solution is reached (Sivanandam and Deepa, 2008). A critical drawback to GA is that they do not consider the interdependence of the solutions (Goldberg, 1989a, 1989b). To alleviate this drawback, the Population Based Incremental Learning (PBIL) algorithm is used here. PBIL is an evolutionary algorithm that is stochastic, unconstrained and is capable of accounting for the dependence between solutions (Baluja, 1994). This algorithm has been used to determine the optimal implementation sequence (Bayrak et al., 2021) and location (Bayrak et al., 2023; Bayrak and Gayah, 2021; Bayrak and Guler, 2023) of treatments in a transportation network. The configurations are passed down to the lower level, where its performance is evaluated either via an analytical or simulation model. An objective function is defined that measures how well the configuration satisfies the optimization criteria. The objective function is used to assign a score to each configuration (i.e., travel time or cost), which is then passed back to the upper level. The algorithm then learns from the best and the worst solutions to propose even better configurations. The framework continues to iterate and generate sets of configurations for further evaluation until termination.

2.1.1. Lower level simulation

2.1.1.1. AIMSUN. The lower level illustrated in Fig. 1 provides a measure of performance for a given ATSC configuration tested. In this case, the measure of performance is the total vehicle travel time obtained by simulating the ATSC configuration in the AIMSUN microsimulation platform. AIMSUN is selected due to its ability to accurately model traffic dynamics—such as queue formation and spillbacks—and ease of programming (Barceló and Casas, 2005).

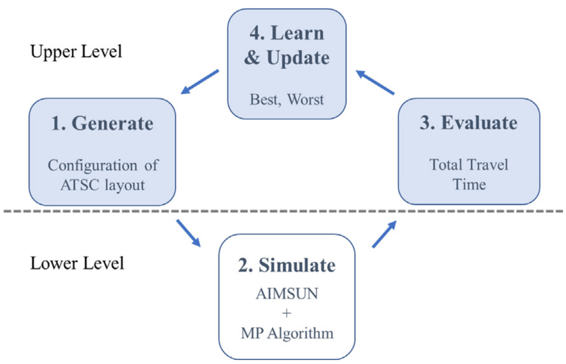

Fig. 1. Proposed bi-level optimization framework.

2.1.1.2. Delay-based cyclic MP. In this paper, the MP control algorithm is used as the ATSC strategy that is to be implemented. All MP-based algorithms allocate green time according to the value of a pre-defined metric, such as number of vehicles (Kouvelas et al., 2014; Le et al., 2015; Lioris et al., 2016; Varaiya, 2013; Xiao et al., 2014) travel time (Mercader et al., 2020) and travel delays (Dixit et al., 2020; Liu and Gayah, 2023, 2022), from all movements at each intersection. Specifically, an MP algorithm first calculates the weight for a movement as the difference of this metric between this movement and the average value from its downstream movements. Then, it computes the pressure for each phase as the sum of the weights multiplied by the saturation flow over all served movements. Finally, it activates the phase with the largest pressure for the next time step in acyclic MP algorithms (Li and Jabari, 2019; Lioris et al., 2016; Liu and Gayah, 2023, 2022; Varaiya, 2013; Wu et al., 2018; Xiao et al., 2014) or allocate green time according to the proportion of pressures for the next cycle in cyclic MP algorithms (Kouvelas et al., 2014; Le et al., 2015; Mercader et al., 2020). Thanks to the ease of implementation and computational efficiency, MP has drawn considerable research efforts in the past decade. Additionally, numerous calibrated microsimulation models have shown that it outperforms existing signal timing methods (Anderson et al., 2018; Barman and Levin, 2022; Li et al., 2021; Li and Jabari, 2019; Pumir et al., 2015; Ramadhan et al., 2020; Sun and Yin, 2018; Wang and Abbas, 2019; Wongpiromsarn et al., 2012; Xiao et al., 2015). Some researchers have even tested max-pressure control on real roads, demonstrating its potential for practical use (Dixit et al., 2020; Mercader et al., 2020). In this paper, a delay-based cyclic MP model is used specifically as the ATSC logic due to its superior performance compared to other MP models (Liu and Gayah, 2022). Moreover, the benefit of using a cyclic MP is the consistency in phase sequences, which means the same order of phases is maintained across each signal cycle (Levin et al., 2020). The remainder of this section describes the control logic implemented.

For MP-controlled intersections, the pressure for each phase is computed at the beginning of each cycle, and the green time to each phase is allocated proportionally to the pressure. For intersections not equipped with the MP, the signal timing is pre-defined and fixed. The notation that is used in the following sections is as follows. Every intersection contains multiple upstream and downstream links that facilitate incoming and outgoing vehicle movements. A movement from an upstream link l to a downstream link m is represented by (l, m). Here, $l \in U(i)$, the set of upstream links at intersection i, and $m \in D(l)$, the set of links that receive vehicles from link l. The turning ratio of traffic from link l to link m, denoted by $r(l, m)$, represents the proportion of traffic that turns from link l to link m. The saturation flow is expressed by $s(l, m)$ which represents the maximum flow rate of vehicles that can pass through link l to link m per unit time. The set of movements that are served by phase ϕ at intersection i is denoted by set L_i^{ϕ}. The set of phases at intersection i is symbolized by Φ_i.

The metric used to calculate the weight of a movement is the vehicle delay of this movement incurred in the previous cycle. Hence, the weight of the movement (l, m) in cycle T_x can be calculated as:

$$w(l, m, T_x) = \max\left(0, \sum_{t=T_{x-1}+1}^{T_x} d(l, m, t) - \sum_{n \in D(m)} r(m, n) \times \sum_{t=T_{x-1}+1}^{T_x} d(m, n, t)\right) \tag{1}$$

where $d(i, j, t)$ is the delay from movement (i, j) at time t; and T_x is the time of the end of the x^{th} cycle. Therefore, its weight is the difference between the experienced delay and the average delay over all downstream movements in the x^{th} cycle. To prevent negative weights of a movement, if downstream delays are higher than upstream, the weight of that movement is set to zero as in (Gregoire et al., 2015). At the end of each cycle, the pressure of phase ϕ at intersection i is computed as the sum of products of the weights and saturation flow over all movements in this phase, which can be expressed as:

$$P_i^{\phi} = \sum_{(l,m) \in L_i^{\phi}} w(l, m, T_x) \times s(l, m), \forall \phi \in \Phi_i \tag{2}$$

where L_i^{ϕ} is the set of movements in the phase . Finally, the duration of green time on each phase is distributed according to its pressure as follows:

$$G_i^{\phi} = G_{min} + (\mathscr{T} - n_{\Phi} \times (G_{min} + e)) \times \frac{P_i^{\phi}}{\sum_{\phi \in \Phi_i} P_i^{\phi}} \tag{3}$$

where G_i^{ϕ} is the assigned green time for phase ϕ at intersection i; n_{Φ} is the number of phases; $\mathscr{T}$ is the cycle length; G_{min} is the minimum green time of each phase; and e is the lost time between each phase change. The quantity $\mathscr{T} - n_{\Phi} \times (G_{min} + e)$ calculates the effective green in addition to the minimum green time that can be allocated among competing phases according to the pressures. The minimum green time is set to ensure every phase is served at least once despite its pressure. Although this may decrease the effective green time and reduce network throughput, it helps maintain consistency and improve driver expectancy. If the sum of pressures of all phases is zero, then the green time is evenly split between the phases.

2.1.2. Upper level PBIL

At the upper level, candidate configurations of ATSC deployments are identified to minimize travel time in the network using the PBIL algorithm, which is an unconstrained algorithm that combines elements of genetic algorithms with learning processes. The PBIL algorithm consists of the 5 steps shown in Fig. 2 and described below.

2.1.2.1. Step 1: Initialization. The first step involves initialization of the algorithm's parameters. This includes defining the generation size $\mathscr{G}$, which specifies the number of times the algorithm will iterate and generate a new set of configurations; the population size $\mathscr{P}$, which determines the number of generated ATSC configurations in each generation; and the candidate size $\mathscr{C}$, which indicates the number of intersections that are candidates for ATSC implement in the network. A Probability Vector $\mathscr{p}^g$ is also created, which is a one-dimensional vector of size $\mathscr{C}$ in which each element $\mathscr{p}_i^g$ represents the probability of ATSC being applied at intersection i in generation g. The values of the initial vector $\mathscr{p}^0$ are input in this initialization step and this vector is updated every generation as the algorithm proceeds.

The PBIL algorithm assumes that there is no prior information on what the final solution might look like, e.g., there is no information on which intersections are the best candidates for ATSC. In this case, every candidate is assigned a probability of $\mathscr{p}_i^0 = 0.5$ in the first generation, which indicates that each intersection has an equal chance of being selected without any bias in the first generation. This case is denoted as the "uninformed" optimization case. This case should ensure maximum exploration of the solution space but would likely take longer to converge to a final solution.

However, in any optimization problem, it is possible that some information exists on what the final solution is likely to look like. For example, in the context of this paper, one might expect that ATSC would be better served at the most congested intersections. To account for this, an informed decision-making initialization method is proposed that purposefully sets the initial direction of the optimization process based on this prior knowledge. This information can be used to guide the optimization process towards selecting the best configuration more efficiently. In this study, the delays and normalized queues are used at individual intersections as a measure of how likely an intersection is to benefit from ATSC, as suggested in (Tsitsokas et al., 2023). Intersections with higher queues/delays without ATSC are then given a larger value in the initial probability vector $\mathscr{p}_i^0$, while those with smaller queues/delays have a reduced probability. Doing so initially directs the PBIL algorithm towards these poor performing intersections as candidates for ATSC but does not either eliminate the possibility of other intersections from receiving ATSC or force these intersections to always receive ATSC. This approach should both speed up the optimization process and increase its effectiveness by focusing on the intersections that are most likely to benefit from ATSC.

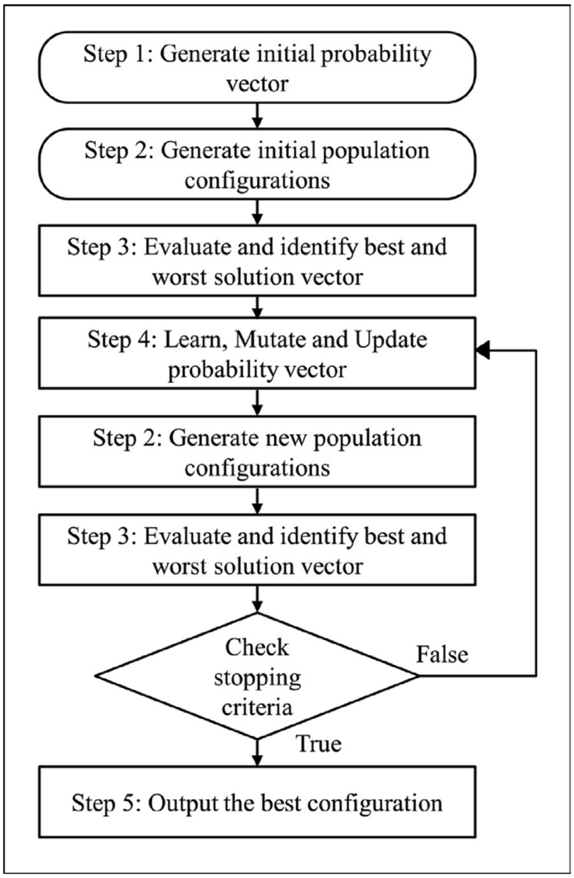

Fig. 2. Flowchart of PBIL.

More specifically, let $\bar{D}_i$ denote the average delay experienced by vehicles at intersection i without ATSC. First, the intersections are ranked based on their delay, with $i = 1$ being the intersection with the highest delay and $i = \mathscr{C}$ being the intersection with the lowest delay. Next, the initial probability of each intersection being selected in the first generation, denoted by $\mathscr{p}_i^0$, is calculated as:

$$\mathscr{p}_i^0 = 0.25 + 0.5 \times \frac{\mathscr{C} - i}{\mathscr{C} - 1} \tag{4}$$

This assigns the highest probability of 0.75 to the intersection with the highest delay and the lowest probability of 0.25 to the intersection with the lowest delay, while probabilities of the other intersections are uniformly distributed between 0.75 and 0.25 based on their rank.

2.1.2.2. Step 2: Generation. The second step generates potential ATSC configurations to be tested. A total of $\mathscr{P}$ configurations are generated in each step. Each configuration p is denoted by a one-dimensional vector of size C. Each element is a binary indicator that represents whether a given intersection is equipped with ATSC (value of 1) or not (value of 0). These values are determined randomly using the associated probability vector for that generation, $\mathscr{p}_i^g$. The number of intersections selected in configuration, p is denoted, V^p. As PBIL is an unconstrained optimization algorithm, the feasible region is not restricted by constraints, and any number of intersections can be selected as having ATSC in each configuration.

In real-world scenarios, there are practical limitations on the number of ATSC intersections that can be implemented in a network. Therefore, the PBIL algorithm is modified to incorporate constraints on the maximum number of intersections, N_{max} that can be equipped with ATSC. Specifically, if the number of generated intersections in a configuration , V^p, exceeds the set maximum number N_{max}, one of two methods are used to prune the candidate ATSC locations to a feasible number:

1. Exploitation: the $(V^p - N_{max})$ candidate locations with the lowest probabilities are dropped from the configuration; or
2. Exploration: some $(V^p - N_{max})$ candidate locations are randomly selected and dropped from the configuration.

To ensure the balance between exploitation and exploration, one of these two methods is randomly selected each time the constraint on number of intersections with ATSC is violated.

2.1.2.3. Step 3: Evaluation. This step involves evaluating the total travel time of each configuration by implementing ATSC using D-MP in the network and simulating using AIMSUN in the lower level of the algorithm. The configurations corresponding to the minimum and maximum total travel times from the population are then identified as the best (B^g) and worst (W^g) solutions in generation g.

2.1.2.4. Step 4: Learn, mutate and update. Step 4 involves updating the probability vector via positive and negative learning, as well as a mutation operation. Positive learning updates the probability vector of the next generation to favor the intersections present in the best solution of the current generation by increasing their probabilities using a positive learning rate, LR^+. This is done by reducing the probabilities of all candidate locations while increasing the probabilities of candidate locations present in the best solution:

$$\mathscr{p}_i^{g+1} = \mathscr{p}_i^g \times \left(1 - LR^+\right) + \left(B_i^g \times LR^+\right);\ \forall i \tag{5}$$

Negative learning, on the other hand, allows the algorithm to move away from inferior solutions in the current generation by decreasing the probabilities of candidate locations present exclusively in the worst configuration but not present in the best configuration using the negative learning rate, LR^-. It also increases the probabilities of candidates present in the best solution but not in the worst solution without modifying the probabilities of candidates that appear in both best and worst configurations. By updating the probabilities of elements twice, we are essentially emphasizing the importance of intersections that contribute to the best solution while simultaneously penalizing elements that hinder performance. This dual update approach helps to fine-tune the probabilities, making the algorithm more adaptive and responsive.

$$\mathscr{p}_i^{g+1} = \begin{cases} \mathscr{p}_i^g \times (1 - LR^-); & \forall i\ s.t.\ B_i^g = 0,\ W_i^g = 1 \\ \mathscr{p}_i^g \times (1 - LR^-) + LR^-; & \forall i\ s.t.\ B_i^g = 1,\ W_i^g = 0 \\ \mathscr{p}_i^g; & \forall i\ s.t.\ B_i^g = W_i^g \end{cases} \tag{6}$$

Mutation is also applied, which allows greater exploration of the solution space by randomly mutating the probabilities by a mutation rate, Δ_m. The mutation vector, M^g is a set of C binary values that each take a value of 1 randomly with a mutation probability, m to indicate which intersections in the set will undergo mutation.

$$\mathscr{p}_i^{g+1} = \mathscr{p}_i^g \times (1 - \Delta_m) + \Delta_m;\ \forall i\ s.t.\ \mathrm{M}_i^g = 1 \tag{7}$$

Finally, the probability vectors are modified as follows to ensure that they are within a feasible range and all intersections have some probability of being selected (or not selected) to ensure exploration:

$$if\ \not{p}_i^{g+1} > 0.95,\ \not{p}_i^{g+1} = 0.95 \tag{8}$$

$$if\ \not{p}_i^{g+1} < 0.05,\ \not{p}_i^{g+1} = 0.05 \tag{9}$$

Overall, the learning and mutation operations of PBIL help to gradually converge towards optimal solutions by favoring the best solutions and moving away from inferior ones, while the mutation operation adds diversity to the population to avoid premature convergence. The speed of convergence of the algorithm can be adjusted by changing the positive and negative learning rates. Higher values allow the algorithm to quickly converge whereas, lower values allow more exploration.

2.1.2.5. Step 5: Termination. Step 5 involves checking the termination criterion after every generation. The termination criterion is crucial as it indicates when the algorithm has converged toward the optimal solution. Of two commonly applied termination criteria the first is based on the convergence ratio between the travel time of the previous generation and the current generation. If this ratio is less than a defined threshold, the algorithm is considered to have converged. The second termination criterion is based on the maximum number of generations, whereby the algorithm will stop if the number of generations reaches the defined maximum. In the case that the termination criterion has not been met, the algorithm will continue to iterate until a stopping criterion is met. Conversely, if the algorithm has reached the maximum number of generations, it will stop regardless of whether it has met the convergence criterion or not. Finally, the configuration with the lowest travel time is output as the best solution.

2.2. Baseline comparison methods

Two baseline methods are considered for comparison with the proposed PBIL results.

2.2.1. Delay-based selection method

The first method, which is referred to as the "Delay-based" selection method in the remainder of this paper, selects intersections based on the hypothesis that those with higher average delays are better candidates for ATSC installation. To identify these intersections, the average delay $\bar{D}_i$ at each intersection i is calculated as:

$$\bar{D}_i = \frac{1}{U(i)} \frac{1}{\mathbb{T}_p} \sum\nolimits_{l \in U(i)} \sum\nolimits_{t \in \mathbb{T}_p} d_l(t) \tag{10}$$

where $\mathbb{T}_p$ is the number of signal cycles in the peak period and $d_l(t)$ is the total delay experienced on link l in cycle t. The intersections are then ranked based on these values from highest to lowest. The top N_{max} intersections from this ranked list are then equipped with ATSC to test the effectiveness of the selection method in limited deployment scenarios.

2.2.2. Queue-based selection method

The second method, referred to as "Queue-based" selection method, is adopted from (Tsitsokas et al., 2023) and selects intersections for ATSC implementation based on their experienced levels of congestion. In this method, the average normalized queue, and the variance on upstream links of an intersection is calculated to obtain a rank of intersections as candidates for ATSC. The normalized queue is the ratio of the number of vehicles queued on a link and its capacity. For each intersection i, this is defined as follows:

$$K_i(t) = \frac{1}{U(i)} \sum\nolimits_{l \in U(i)} \frac{\bar{k}_l(t)}{kj_l} \tag{11}$$

where $\bar{k}_l(t)$ is the average density experienced on link l in cycle t and kj_l is the jam density of link l. A value of 0 indicates that there are no vehicles in the link, while a value of 1 indicates the entire link is congested. The average normalized queue, Y_1^i, at intersection i is the mean over time of the normalized queues:

$$Y_i^1 = \frac{1}{\mathbb{T}_p} \sum\nolimits_{t \in \mathbb{T}_p} K_i(t) \tag{12}$$

The other metric used to rank the intersections is the mean over time of the variance of the normalized queues, Y_2^i:

$$Y_i^2 = \frac{1}{\mathbb{T}_p} \sum\nolimits_{t \in \mathbb{T}_p} var(K_i(t)) \tag{13}$$

To mimic the selection strategy in (Tsitsokas et al., 2023), in this study, a linear combination of Y_i^1 and Y_i^2 is used to rank the intersections as follows:

$$Y_i = Y_i^1 + \alpha \times Y_i^2 \tag{14}$$

Different values of the coefficient α were tested to determine the value that best relates the average queue and variance. Similar to the previous selection method, intersections are sorted from highest to lowest based on this combined queue information Y_i and, ATSC is incrementally deployed on the top N_{max} intersections.

3. Simulation setup

3.1. Network setup

The proposed method to identify the best locations to implement ATSC was tested on the State College, PA traffic network via micro-simulation. As depicted in Fig. 3. Locations of candidate ATSC intersections in State College, PA, the considered network contains 33 signalized intersections that are candidates for ATSC deployment. The simulated period is the PM peak generated using turning movement count and signal timing data from an unpublished report provided by the Borough of State College. Data of traffic signals that were not available was later collected from the field. Since travel time was used as the metric to evaluate each adaptive traffic signal control (ATSC) configuration, it was critical to ensure that the network was populated at the beginning of the simulation. Therefore, the simulation comprises: 1) a 15-minute warm-up period to allow vehicles to enter the network from all entry nodes; 2) a 2-hour peak period in which demand gradually decreases over time; and finally, 3) a 1-hour cooldown period by setting the inflow of vehicles to zero ensuring that all queues could dissipate, and vehicles within the network complete their trips. This is a common practice in the evaluation of networks using micro-simulation (Abdeen et al., 2023; Bayrak et al., 2023; Saad et al., 2019; Shalaby et al., 2003; Tsitsokas et al., 2023; Wang et al., 2017). All signals shared a common 100-second cycle length with 5 seconds of lost time and a minimum green time of 4 seconds. While this paper simulates the PM peak to identify candidate intersections to deploy ATSC, it is imperative to account for variations in traffic conditions for which optimal locations may differ. When making recommendations for a region, average results from the simulation of multiple traffic scenarios such as the AM peak, special events, incidents, and recurrent bottlenecks, can be used to obtain a robust configuration.

3.2. Scenarios

Various scenarios were simulated to evaluate the benefits of the proposed PBIL method to identify the best locations for ATSC deployment. The same random seed was used for all simulation tests to ensure that the comparison of results was fair. These scenarios include 3 control scenarios:

- "No ATSC" – consists of fixed-time control applied to all 33 signalized intersections in the network. Total travel time, delay, and normalized queue on all approaches of signalized intersections during each cycle were used to identify potential ATSC locations for the baseline comparison methods described above.
- "All ATSC" – consists of ATSC applied to all 33 candidate intersections.
- "1 ATSC" – tests ATSC being applied individually to each of the candidate intersections to understand their individual impacts on network performance.

The "Delay-based" and the "Queue-based" baseline methods defined in section 2.2. were also performed to evaluate the effectiveness of the proposed PBIL method. Similar to (Tsitsokas et al., 2023), Varying values of α were used in Eq. (14) to

Fig. 3. Locations of candidate ATSC intersections in State College, PA.

determine the optimal combination to calculate the queue rank; a final value of $\alpha = 4$ was selected since this maximized its performance. For each method, 33 different configurations were tested from the obtained ranks, with the number of intersections, N_{max} increasing from 1 to 33.

The PBIL algorithm was also run under a variety of conditions. For one, the algorithm was run both ignoring and considering constraints on the number of intersections at which ATSC could be deployed. In the constrained case, a limit on the maximum number of equipped intersections, N_{max}, was imposed ranging from 2 to 14 in increments of 1; in the unconstrained scenario, $N_{max} = \infty$. Second, the impact of informed and uninformed decision-making methods on the optimization process was tested. In the uninformed decision-making scenario, an initial probability of 0.5 was used for all intersections, which represents completely random initialization of the PBIL process. By contrast, informed decision-making scenario sets probabilities based on the average delays at each intersection according to (4) to guide the selection of candidate locations. Other parameters of the PBIL algorithm used are as follows: generation size, $\mathscr{G} = 10$ (constrained optimization) or 20 (unconstrained optimization); population size $\mathscr{P} = 50$; positive learning rate, $LR^{+} = 0.01$; negative learning rate, $LR^{-} = 0.075$; mutation probability, m = 0.02; and, mutation rate, $\Delta_m = 0.05$. The specific values of these parameters are inspired by previous literature that employed PBIL for similar problems, then finetuned using engineering judgement based on our problem.

4. Results

This section discusses the results of the simulations and assesses the performance of the control scenarios and compares the proposed methodology against the baseline methods.

4.1. Control scenarios

4.1.1. No ATSC scenario

The simulated scenario was first run without any ATSC implemented (No ATSC scenario). This resulted in the formation of large queues at some of the intersections that eventually spilled back on its adjacent links causing large delays and a total travel time of 9324.15 vehicle-hours. Fig. 4a shows the experienced average vehicle delay on each link as a percentage of their travel times. Individual delays and queue lengths at each approach were also recorded for use in the informed decision-making process for the PBIL, as well as the baseline comparison methods for ATSC implementation selection.

4.1.2. ATSC scenario

Fig. 5 shows the change in total travel time compared to the No ATSC scenario when ATSC was installed at a single intersection (1 ATSC scenario). The performance ranges from an improvement (decrease) in total travel time of 4.9 % to an increase in total travel time of nearly 1 %. However, most intersections were generally associated with modest decreases in total travel time. The results suggest that while ATSC generally improves conditions, it may be unsuitable at some locations, particularly those in which congestion occurs downstream. These findings highlight the importance of considering the specific characteristics of each intersection when selecting ATSC intersections in urban networks.

4.1.3. All ATSC scenario

When ATSC was implemented at all 33 signalized intersections (All ATSC scenario), the total travel time dropped to 8559.4 vehicle-hours, which represents an 8.2 % improvement over the No ATSC scenario. Interestingly, the improvement is less than twice the improvement obtained from the best intersection alone. This suggests that the impact of ATSC may not be additive when applied in combination. This further strengthens the rationale for the identification of optimal number and location of adaptive traffic signals.

4.2. Optimal ATSC deployment using PBIL

In this section, the performance of the proposed PBIL method is compared with the two baseline methods defined in section 2.2. Fig. 6 illustrates the improvement in travel time achieved by each of these methods compared to a network without ATSC as a function of the maximum number of ATSC (N_{max}) that are considered for installation. For the PBIL method, while this maximum number represents a constraint in the optimization process; it is possible that the actual number implemented may be less than the maximum number if implementing ATSC at more intersections would deteriorate performance. However, the best configurations obtained from the constrained optimization shown in Fig. 6 all contained N_{max} number of intersections. For the baseline methods, this maximum number represents the exact number of intersections equipped with ATSC, based on the delay or queue rankings. The green solid line in Fig. 6 represents the improvements achieved using the constrained PBIL strategy with informed decision-making, while the purple diamond indicates the result of the unconstrained PBIL method. The blue and orange solid lines represent the improvements using the delay-based and queue-based methods, respectively. Each dashed horizontal line represents the best performance achieved for that specific method (PBIL-constrained and unconstrained, delay-based, queue-based); additionally, the red dashed horizontal line is the performance obtained by implementing all traffic signals with ATSC, for reference.

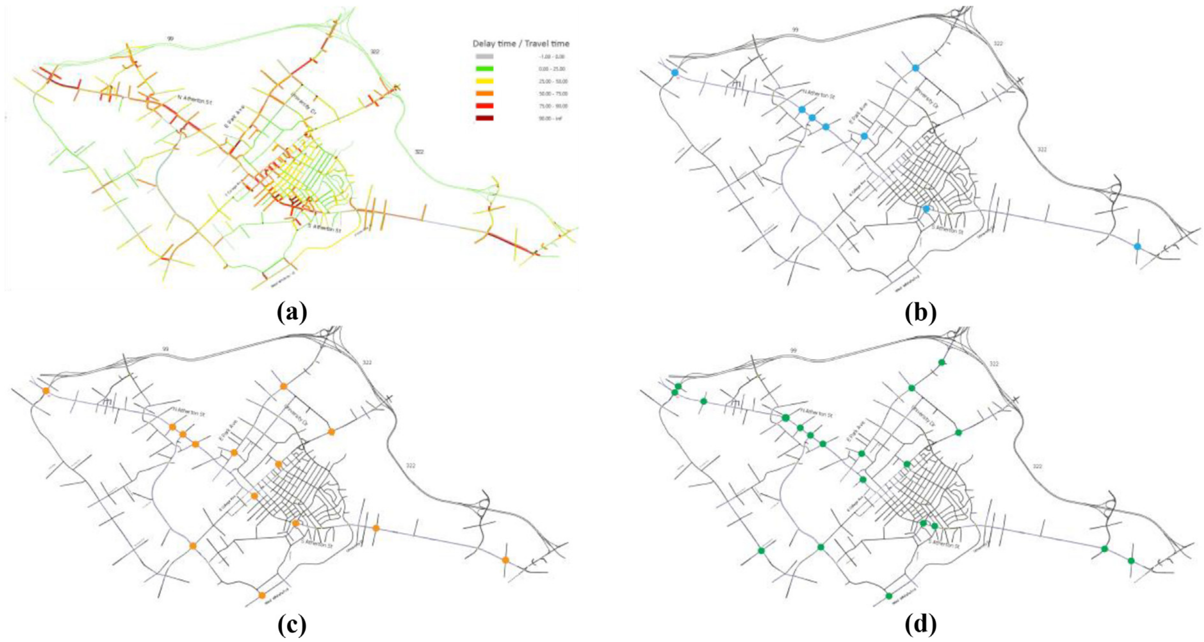

Fig. 4. (a) Simulated delay during peak period; (b) Locations of 8 intersections selected using constrained PBIL ($\boldsymbol{N_{max}} = 8$); (c) Locations of 14 intersections selected using constrained PBIL ($\boldsymbol{N_{max}} = 14$); (c) Locations of 20 intersections selected using unconstrained PBIL ($\boldsymbol{N_{max}} = \infty$).

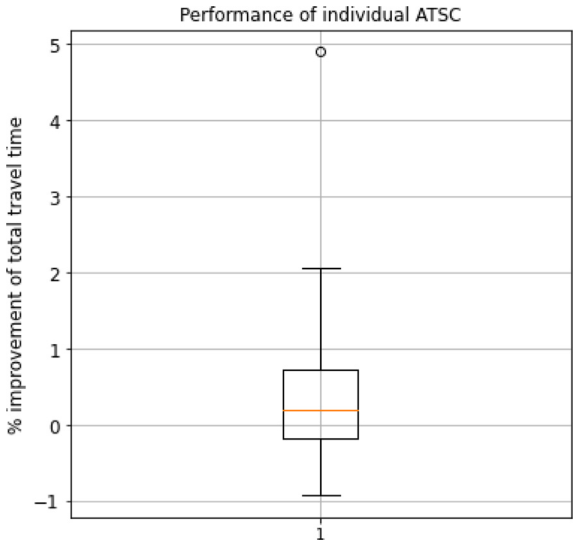

Fig. 5. Boxplot of performance of individual intersections.

4.2.1. Performance of proposed PBIL method

From Fig. 6, it is evident that the proposed PBIL strategy provides the best travel time improvements across all methods for any given number of intersections being considered for ATSC. The results from the constrained optimization show that as N_{max} increases, the travel time of vehicles in the network begins to improve. However, the improvements do not increase proportionally with the number of intersections considered for ATSC. In fact, an improvement of 10.39 % can be achieved when only 8 intersections are equipped with ATSC. The locations of these intersections are illustrated in Fig. 4b. Adding more intersections with ATSC beyond 8 provides only marginal benefits with a maximum improvement of 11.23 % obtained by selecting 14 intersections shown in Fig. 4c.

In the unconstrained optimization, the PBIL method achieves the maximum performance increase of 11.35 % travel time improvement over the base network that generates a configuration of 20 intersections. Beyond this value, further improvements were not observed. Therefore, this configuration of 20 intersections selected for ATSC as shown in Fig. 4d serves as the

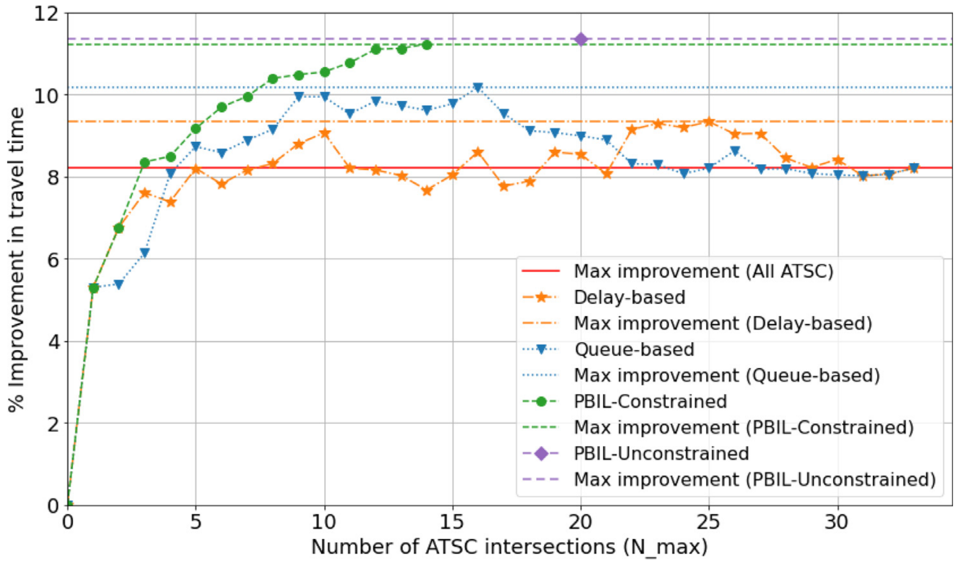

Fig. 6. Travel time improvement vs number of ATSC intersections using "Delay-based", "Queue-based" and, PBIL method.

solution observed in an unconstrainted optimization process, when no limits were placed on the maximum number of signals considered. However, this improvement is nominal compared to the best configuration from the unconstrained case when $N_{max} = 14$. Adding 6 intersections with ATSC results in further improvement of only 0.12 % which, considering the additional complexity and cost associated with implementing and managing these additional ATSC intersections is not financially viable in terms of benefit-to-cost ratio. While the obtained configuration is a near optimal solution, the findings suggest that the globally optimal solution may not be the most cost effective strategy.

4.2.2. Performance of baseline methods

The delay and queue-based methods show trends similar to the PBIL strategies. Specifically, large travel time improvements are observed when a small number of intersections are considered for ATSC. However, the benefits quickly diminish and – eventually – travel time performance degrades as more intersections are equipped with ATSC. This trend is consistent with results observed by (Tsitsokas et al., 2023) and further backed by the observation that not all intersections contribute equally to improving network traffic conditions when controlled with the delay-based method or the queue-based method, as evidenced by the results shown in Fig. 5. The best configuration from the delay-based method contains 25 intersections and results in a travel time improvement of 9.34 %. On the other hand, the queue-based method was able to find a better configuration that consists of 16 ATSC controlled intersections resulting in a 10.17 % reduction in travel time over the No ATSC scenario. However, neither of the strategies are as effective as the PBIL in identifying a configuration of limited ATSC deployment that results in the highest benefit-to-cost ratio. Thus, for any N_{max} (i.e., any budget limit), PBIL can always achieve the largest improvement in travel time. Also, for all three cases, the implementation of a subset of intersections with ATSC can outperform the implementation of ATSC at all signalized intersections. This reinforces the need for agencies to select these deployment locations carefully so as to not unintentionally degrade operational performance.

4.2.3. Benefits of informed decision-making in PBIL

This section explores the use of prior knowledge applied to the PBIL algorithm in the form of informed decision-making. As described in the Methods section, the PBIL algorithm is typically initialized randomly. However, knowledge about which intersections are likely to benefit from the implementation of ATSC can provide the PBIL with a priori knowledge that can help the optimization process. Existing literature on evolutionary algorithms typically visualizes the performance of the algorithms through convergence plots that show the best value of the objective function achieved during each generation, see (Baluja, 1994; Bayrak and Guler, 2018; Mesbah et al., 2011a). Similarly, Fig. 7 compares the travel time improvements achieved during each generation of the PBIL optimization process between the random initialization (uniformed optimization) denoted by the dotted lines, and informed decision-making case denoted by the solid lines for the unconstrained and constrained optimization cases respectively. Four randomly selected constrained optimization cases are shown in Fig. 7b whereN_{max} = 7, 8, 10, and 14. Note that the PBIL algorithm is a stochastic optimization technique that relies on random sampling of the solution space to identify high-quality solutions, albeit not necessarily the global optimum. To overcome this limitation, it is common practice to run the algorithm multiple times to obtain a pool of candidate locations, given that each independent run has a chance of finding a better solution. Additionally, running the algorithm multiple times enables the evaluation of the stability and variability of the obtained solutions (Katoch et al., 2021). This is illustrated by presenting

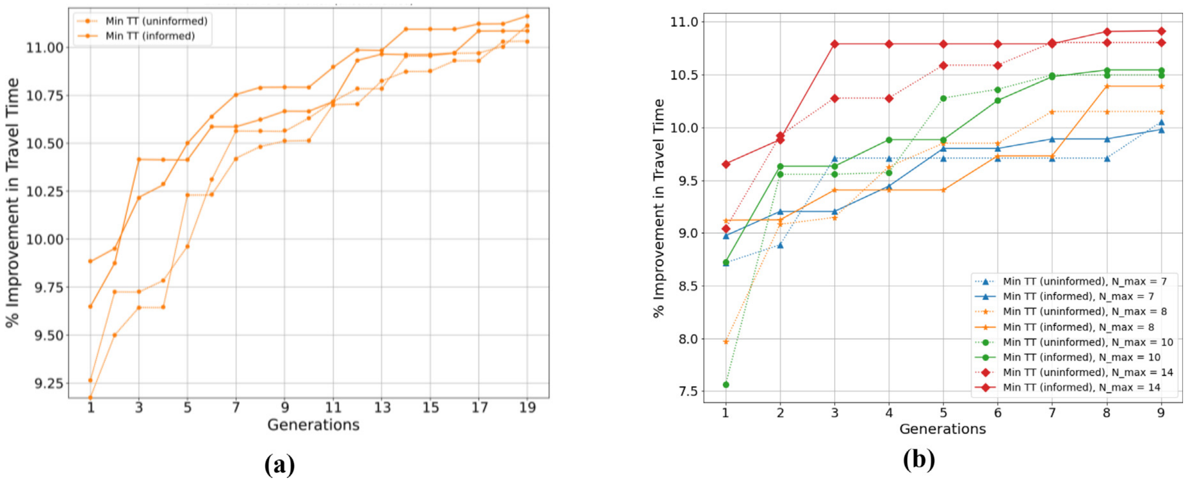

Fig. 7. Convergence of the PBIL algorithm for informed and uninformed tests: (a) Unconstrained optimization ($\boldsymbol{N_{max}} = \infty$); (b) Constrained optimization, ($\boldsymbol{N_{max}} = 7, 8, 10, 14$).

the results of two separate simulations of the unconstrained case, where the informed and uninformed optimization strategies yielded similar results after 20 generations, as depicted in Fig. 7a.

Fig. 7 clearly demonstrates the benefits of using informed decision-making in determining the optimal locations. The PBIL algorithm, when guided by the delay of each intersection, generally converges to better solutions – and does so faster – than when no prior information was used. However, there is a risk of the algorithm converging to a local optima when relying solely on the delay information. This is why a balance of exploration and exploitation strategies were implemented in the algorithm using constraints and mutation operations– a technique commonly applied in optimization to avoid convergence to local optima (Baluja, 1994; Conti et al., 2017; Hussain and Muhammad, 2020). On the other hand, the uninformed approach led to slower convergence and, in some cases, sub-optimal results, as expected. However, cases did exist in which the uninformed PBIL algorithm was able to discover better a better solution than the informed approach; e.g., see $N_{max} = 7$ in Fig. 7b. This is because the uninformed algorithm systematically explores the search space in a blind manner without any bias, which can lead to the discovery of better solutions that are not immediately apparent to the informed algorithm. And, this is also expected, since the PBIL – like any heuristic optimization – is a random process. However, in general, the informed PBIL algorithm is more efficient and leads to more efficient solutions than its counterpart. Thus, in an urban network with hundreds of signalized intersections where the relative delay at each intersection is known, using the informed PBIL optimization approach can provide significant benefits in terms of optimizing traffic signal control systems.

5. Concluding remarks

This study proposes a bi-level optimization framework using the Population Based Incremental Learning (PBIL) algorithm to identify the optimal number and location of adaptive traffic signal control (ATSC) in an urban network. The study introduces two novel modifications to the PBIL algorithm: 1) integrating constraints on the maximum number of ATSC-enabled intersections; and 2) incorporating informed decision-making by utilizing prior information of the intersection delays. The proposed algorithm is tested against baseline methods in a micro-simulation of the State College, PA traffic network using a delay based max pressure algorithm as the ATSC logic; however, it is general to any ATSC logic or broader facility location problem where constraints exist and some information is known about where the optimal locations might be.

The simulation tests reveal that the presence of ATSC in a network improves overall performance. However, the benefits are not linear, as certain intersections may experience travel time reductions while others lead to increased congestion downstream. As a result, the proposed algorithm finds that a 10.39 % travel time savings can be achieved when ATSC is applied at only 8 intersections. This is in contrast to a travel time savings of just 8.2 % when ATSC is applied at all signalized intersections. Beyond 8 intersections, a maximum of 11.35 % improvement in travel time was observed when 20 intersections were selected using the unconstrained PBIL. This results in only marginal benefits, highlighting the potential cost-effectiveness that can be achieved from limited deployment. Compared to baseline methods in literature, the proposed method is able to identify locations that provide higher travel time savings under different constraints on the maximum number of ATSC locations. Furthermore, the incorporation of prior knowledge accelerates convergence via an informed search process, making it particularly valuable in networks with a higher number of signalized intersections.

While the proposed method was tested during the PM peak based on the best information available about the State College traffic network, different traffic scenarios that reflect the conditions of a particular region should be considered to ensure a more comprehensive analysis for practitioners. Nevertheless, the results suggest that the proposed PBIL strategy should still be able to provide configurations for ATSC deployment that improve overall performance of more complex urban networks. State College, PA is characterized by a limited number of unsignalized intersections, with predominantly stop-controlled intersections in residential neighborhoods. In contrast, urban networks often feature denser grids with a higher percentage of signalized intersections, which could potentially yield greater benefits from ATSC. How performance of ATSC varies with percentage of signalized intersections in a network presents an interesting future research direction. While this research demonstrates travel time improvements over fixed-time control, future studies should explore comparisons with actuated or coordinated traffic signals, and may consider multimodal traffic, to enhance the applicability of ATSC. Future work could also consider the inclusion of spatial constraints into the optimization framework as it may be beneficial to keep ATSCs in close proximity to one another, either to ensure adequate coverage of the network or to minimize the number of ATSCs required.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Tanveer Ahmed: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Hao Liu:** Writing – review & editing, Supervision, Software, Investigation. **Vikash V. Gayah:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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