Network-Wide Optimization of Transit Signal Priority

Mehdi Bagherian*
PhD Candidate  
School of Civil Engineering  
The University of Queensland  
Brisbane 4207 QLD, Australia  
Phone: 61-431-694066  
Fax: 61-7- 336 54599  
E-mail: m.bagherian@uq.edu.au

Mahmoud Mesbah  
Lecturer  
School of Civil Engineering  
The University of Queensland  
Brisbane 4207 QLD, Australia  
Phone: 61-7-33651569  
Fax: 61-7- 336 54599  
E-mail: mahmoud.mesbah@uq.edu.au

Luis Ferreira  
Professor  
School of Civil Engineering  
The University of Queensland  
Brisbane 4207 QLD, Australia  
Phone: 61-7-33651569  
Fax: 61-7- 336 54599  
E-mail: l.ferreira@uq.edu.au

Philip Charles  
Professor  
School of Civil Engineering  
The University of Queensland  
Brisbane 4207 QLD, Australia  
Phone: 61-7- 33654356  
Fax: 61-7- 336 54599  
E-mail: p.charles@uq.edu.au

Majid Khalilikhah  
Graduate Research Assistant  
Civil & Environmental Engineering  
Utah State University  
4110 Old Main Hill  
Logan, UT 84322-4110  
E-mail: majid.khalilikhah@gmail.com

* Corresponding author

Paper number: 15-1146  
Submitted for publication and presentation,  
Transportation Research Record, 94th Annual Meeting, January 11-15, 2015  
Suggested Committee: Bus Transit Systems (AP050)  
July 2014  
Words: 4821 +5 figures (1250) +3 tables (750) = 6821
ABSTRACT

Transit signal priority (TSP) is widely accepted as a viable solution to reduce the delay of transit services at intersections. TSP changes signal timing settings in favour of buses, with possible marginal negative impacts on the traffic stream in the non-prioritized approach. Travel time value and variability of both private cars and transit services are affected through TSP implementation. Despite significant past research related to TSP deployment and operation, less attention has been given to the planning phase of this strategy. Specifically, there is a need to shift from the local or corridor level studies to a network level analysis. In addition, there is no mathematical formulation that considers the impact of TSP deployment as a generalized cost function.

In this paper, a framework to find optimum settings and location of TSP treatments is presented. This framework comprises three modules. Firstly, a generalized cost function is proposed which considers the impacts of TSP deployment on delay and reliability of private vehicles and transit services. Secondly, a simulation-based model (a package which employs VISSIM and SIDRA Intersection software) is developed to evaluate each scenario using the data for individual buses and cars. This model can be utilized for a variety of TSP logic. A heuristic algorithm was then linked to the simulation-based model to find the optimum solution throughout all possible combinations. The outputs of the proposed framework are an optimum set of intersections to install TSP as well as TSP eligible bus lines at each intersection. The method was applied to an example network and the results confirmed the potential of this framework to find optimum TSP locations at the network level.
INTRODUCTION

A rapid increase in traffic congestion on urban roads and limitations in developing infrastructure urge a better operation of available facilities. To this end, maximizing the efficiency of public transport can play a crucial role since a good transit service can serve more demand thus mitigating traffic congestion. A wide range of strategies has been suggested to improve public transportation performance. These treatments, known as transit preferential treatments, seek to allocate time or space in favour of buses. They may increase reliability, reduce transit operating costs, and provide greater ridership (1). Among the suggested treatments, Transit Signal Priority (TSP) is known as a viable solution to lessen transit delay at intersections with negligible negative effect on vehicular traffic flow (2).

Three questions are raised upon implementation of TSP treatments. Firstly, “what is the effect of TSP on transit and vehicular flows?” and essentially, what is the aim of deploying these strategies. Indeed, identifying the potential benefits of TSP on transit services and the negative impacts on competent modes is a seminal part of TSP deployment. Secondly, “how can TSP be successful in achieving the objectives?” should be answered. In this regard, a variety of logic has been developed, implemented and described in the literature to maximize the performance of TSP policies in different conditions. Finally, the question “which intersections are potentially the best to deploy TSP equipment?” should be answered. This is particularly important if two (or more) simultaneous TSP requests occur at one intersection and granting priority for one can potentially disbenefit the other. Moreover, considering the required cost of utilizing TSP treatments and the potential limitations in budget or equipment, it seems reasonable to determine the optimum locations of TSP deployment, aimed at maximizing the benefits of both system and users. Despite extensive research performed in each of these areas, a framework to systematically consider all these concerns is not yet available. Developing such a scheme is the main objective of this research.

In this paper, a framework to optimize the location of TSP treatments is presented. It comprises three major modules: firstly, a mathematical formulation for the problem is suggested in which both travel times and reliability Indices (for buses and cars) are considered. Secondly, a microsimulation model is implemented to evaluate different TSP scenarios. Finally, a Binary version of the Particle Swarm Optimization (BPSO) algorithm is implemented as the search methodology to find optimal solutions of the defined problem. The model is applied on a case study example and the results are compared with the ones obtained from the available models in this field.

LITERATURE REVIEW

TSP has attracted considerable attention in the literature. Its strategies can be classified as passive, active, and real-time (3). Passive strategies have an established pre-set timing that considers the arrival of transit services. They are particularly useful when the vehicle arrival is predictable. Active TSP strategies utilize detectors and update signal timing after detecting a bus approaching an intersection. They can either be unconditional (giving priority to all vehicles) or conditional (considering criteria such as number of passengers, being behind schedule). Finally, real-time strategies adjust signal timings based upon both transit services and general traffic states. Each group can be developed in different ways. Further explanations on different TSP strategies can be found in references like Danaher (2), Smith, et al. (4), and Baker, et al. (3).

The majority of the available literature on TSP deployment utilizes microsimulation models (e.g. 5, 6, 7). This is mainly due to the sensitivity of TSP efficiency on several parameters such as intersection layout, vehicular flow rates, bus headway, bus stop locations, and signal coordination(8, 9). Microsimulation models are able to consider a wide range of parameters and can capture agent (i.e. individual cars and buses) records and thus measure TSP performance in terms of variability. Nevertheless, they are claimed to require a significant amount of effort and expertise and are much more costly than analytical methods (10, 11).

While numerous signal timing optimization packages and models are described in the literature (e.g. 6, 12, 13), few studies are available in the area of TSP optimization. This is particularly
surprising since much research exists on the optimization of transit preferential treatments such as exclusive bus lanes (e.g. 14, 15, 16). Regarding TSP optimization, Stevanovic, et al. (17) presented a model to optimize basic signal timings and transit priority settings of intersections using a microsimulation method. This optimization tool was introduced as a VISSIM based Genetic Algorithm Optimization of Signal Timings (VISGAST). They developed an optimization method considering car delays, transit services delays, and person delays as the performance measures. However, their area of study was limited to corridors that are basically simplified cases of more general grid networks. Indeed, developing a network-wide optimization process has begun to attract researchers’ attention. In a recent study, Shourijeh, et al. (18) presented a planning framework to locate bus signal priority equipment in a grid network. In their research, average delays of both private and public vehicles were considered as the only measure the effectiveness. Furthermore, they evaluated each prioritized intersection and aggregated the marginal impacts of TSP on each independent intersection. Consequently, the possible impacts of signal status on the performance of the neighbouring intersections were ignored. This assumption has made the operation of the optimization module a ranked-based prioritization. In another study, Bernknopf, et al. (19) developed a framework to evaluate network segments and rank them based on appropriateness of deploying TSP equipment at intersections. They considered 14 different measures, classified in four different categories: traffic supply, transit supply, transit demand, and planning priorities. They implemented a GIS-based analysis tool to evaluate each segment and identify viable locations for TSP deployment. Maximization of the operating speed was defined as their objective function.

A set of shortcomings are identified from the literature review. Firstly, to the best of our knowledge, there is no research covering the wide range of TSP deployment as a generalized evaluation measurement. Indeed, there is a lack of studies proposing mathematical formulations for the TSP optimization problem, considering the parameters TSP deployment may affect. Secondly, there is no method of optimizing TSP locations in a general grid network, considering the network-wide effect of this strategy. The available literature has proposed a ranked-based prioritization only, circumventing the complex nature of the problem. Finally, this is the first research in which Particle Swarm Optimization algorithm has been applied to TSP optimization.

**RESEARCH METHODOLOGY**

The proposed framework consists of three main modules: a TSP optimization formulation, microsimulation model, and a search methodology (FIGURE 1). In this section, the model to evaluate TSP performance is presented. Then the optimization method and its integration with the model are explained. A microsimulation model that was modelled to test the approach is introduced in the next section.

![FIGURE 1 Proposed Framework for TSP location optimization problem](image)
Mathematical Formulation

To reflect the impact of TSP deployment, a generalized cost function is proposed. This model considers both travel time and reliability indexes as measures of performance. For each travel mode (either private car or bus), a measure of reliability index is defined. The reliability index is calculated using adherence to the schedule and headway (buses) and the deviation from average travel time (passenger cars). These indexes along with the travel time measurements are then combined using a set of weighting parameters. Mathematical formulation of the model can be stated as follows:

\[
\min Z = \sum_{p=1}^{P} O^p(\alpha t_p + \beta \text{var}_p) + \sum_{b=1}^{B} O^b(y t_b + \delta \text{var}_b) \quad (1)
\]

\[
S.T.
\]

\[
\sum_{s=1}^{S} \sum_{m=1}^{M_s} Y^s_m < N \quad (2)
\]

\[
D^s < \sigma D^s_0 \forall s \in S \quad (3)
\]

\[
G^s_{\text{min}} \leq e \leq G^s_{\text{min}} \forall s \in S \quad (4)
\]

\[
t_p, \text{var}_p, t_b, \text{var}_b \rightarrow \text{Simulation results} \quad (5)
\]

Where:

- \(t_p, t_b\): Travel time of private car \(p\) and bus \(b\) (from origin to destination), respectively
- \(\text{var}_p, \text{var}_b\): The measure of variability of the private car \(p\) and bus \(b\), respectively
- \(O^p, O^b\): Occupancy of car \(p\) and bus \(b\), respectively
- \(P, B\): Total number of private cars\((P)\) and buses\((B)\) in the network
- \(Y^s_m\): Binary variable of TSP deployment which is 1 if movement \(m\) of junction \(s\) is selected for TSP implementation and 0 otherwise
- \(D^s\): Average car delay at intersection \(s\)
- \(D^s_0\): Average car delay when no TSP strategy is implemented
- \(\sigma\): Parameter to control the threshold of giving priority to buses
- \(S\): Total number of intersections in the network that are candidates for TSP installation
- \(M_s\): The number of movements of intersection \(s\) with the possibility of sending TSP request
- \(N\): Total number of TSP equipment
- \(e\): Maximum amount of extension time of a signal phase
- \(C\): Cycle length of the intersections in the network (fixed)
- \(G^s_{\text{min}}\): Minimum green time of the intersections
- \(G^s_{\text{min}}\): Minimum green time of the intersection \(s\)
- \(\alpha, \beta, \gamma, \delta\): Weighting factors to convert values to a monetary measure

The first equation of the presented formulation is the objective function \((Z)\), incorporating travel time value and variability (i.e. unreliability) for both private and public systems. Constraint \((2)\) guarantees the total number of implemented TSP schemes to be less than (or equal to) the total amount of available equipment. This constraint is important in considering issues such as budget or equipment limitations. Constraint \((3)\) caps the level of priority and the maximum amount of permitted adverse effect on the cars at each intersection. Finally, Constraint \((4)\) controls the amount of priority (extension value) that can be given to an intersection. Travel time value and variability (for both buses and cars) are the parameters that should be obtained for each TSP scenario, as mentioned implicitly in Equation \((5)\); a microsimulation model was implemented to obtain these values. This model is explained in the next section.
Microsimulation Model

As discussed in the literature review, using a microsimulation method is the most common strategy used in performance evaluation of TSP treatments. A set of simulation software is available and can be implemented for different transportation analysis. Among them, the VISSIM package (20) is popular and numerous studies exist in the literature of TSP in which this powerful simulation software has been implemented (e.g. 17, 21, 22). VISSIM is a behaviour-based discrete traffic simulator that can be implemented to evaluate transportation policies and scenarios. To model TSP, packages such as Ring Barrier Controller (RBC) emulator and Vehicle Actuated Programming (VAP) have been integrated into the software. VAP is an add-on that allows users to define signal timing logic for microsimulation models. VISSIM takes the coded VAP logic as one of the parameters and processes it in each simulation step. TSP logic of this study are developed using VAP add-on.

To be able to set the initial signal settings in this study, the SIDRA Intersection package (23) was linked to the microsimulation model to extract traffic states and process the intersection. The outputs from SIDRA (cycle length, offsets, splits, and phase sequences and timings) were then used to update VISSIM VAP files. This interaction is beneficial not only for saving a significant amount of time of setting signal timings but also making an iterative optimization procedure feasible. Further details of the utilized TSP logic, the interaction with the microsimulation module and evaluation of the scenarios is presented in the next sections.

TSP Optimization Module

Considering the combinatorial nature of the problem and high computational cost of evaluating TSP scenarios using a microsimulation model, utilizing an efficient search method seems justified.

Over the past few years, application of metaheuristic algorithms in engineering problems has attracted researchers’ attention. Swarm intelligence is a branch of such methods, which is based on the study of individual’s behaviour in various decentralized systems(24). The Particle Swarm Optimization (PSO) algorithm is one of the most popular swarm-based methods which has been successfully utilized in different transportation problems (e.g.25, 26, 27). The binary version of this algorithm(28) is implemented in this study.

In the basic PSO algorithm, the location of each particle represents one possible solution and the position (x) and velocity (v) of each particle in the swarm is updated upon each iteration(25):

\[
x(t + 1) = x(t) + v(t + 1) \\
v(t + 1) = w v(t) + C_1 r_1(t) [g(t) - x(t)] + C_2 r_2(t) [p(t) - x(t)]
\]

Where \( w \) is the inertia weight, \( C_1 \) and \( C_2 \) are the social and cognitive accelerator constants, respectively, \( r_1 \) and \( r_2 \) are randomly generated numbers, \( g(t) \) is the best answer found by the population to that point, and \( p(t) \) is the best answer found by each particle. The location of the particles is updated through the optimization process until the particles converge to the optimal solution. Nevertheless, since in a binary problem the variables can be either 0 or 1, the generic version is unable to perform a global search and loses its efficacy (finding the optimal solution quickly) and accuracy (finding the global optimum solution). Thus, the binary version is introduced to eliminate these shortcomings(29).

In the BPSO, instead of updating the velocity of the particles, the probability of changing their location is updated. Consequently, the velocity equation (7) remains unchanged whereas equation (6) changes as below:

\[
if \left( r < S(v(t + 1)) \right) \rightarrow \quad x^i(t + 1) = 1 \\
else x^i(t + 1) = 0
\]

Where \( r \) is a generated random number in \((0, 1)\) interval and \( S(x) \) is the sigmoid logistic transformation function.

The mathematical formulation of the TSP locating problem was then linked to the BPSO algorithm. In this regard, for each intersection, a string of binary values was defined, representing
all the possible movements that can benefit from a TSP deployment. The problem variable is defined by concatenation of the binary strings:

\[
Y_1^1 Y_1^2 \ldots Y_M^1 Y_M^2 \ldots Y_{mS}^1 Y_{mS}^2 \ldots
\]

**FIGURE 2: Encoding of TSP locating problem for BPSO algorithm**

Once the evaluation module was linked to the optimization module, the search procedure can be performed. FIGURE 3 is a schematic view of the proposed search methodology. In this approach, after initialization of the search algorithm (optimization parameters), a set of candidate solutions are defined. For each scenario, signal setting parameters are updated in the simulation model and a set of microsimulation runs are performed. Results obtained from the simulation are then processed and the measure of performance for the candidate solution (Z value in Equation (1)) is calculated using the proposed model. This measure is then reported to the searching algorithm as the objective function, enabling the algorithm to proceed and generate new candidate solutions. This process is iterated until a defined stopping criterion is met.

**FIGURE 3 Flowchart of the Search Methodology**

**NUMERICAL EXAMPLE**

This section applies the proposed optimization framework to a numerical example. To fulfil this task, a code was developed in the .Net environment using C# programming language. All the runs were performed on a desktop computer with an Intel® Core™ i7 3.4-GHz processor and 16 GB of installed memory (RAM). The calculation of the objective function and the generation of initial answers were performed using a shared module to make the runs of the algorithms analogous. The stopping criterion was assigned to be met when no improvement was observed in 50 iterations. The maximum speed for microsimulation was assigned when the simulation resolution was set to 3 time steps per simulation second.

To examine the performance and capabilities of the proposed framework, it was applied to a grid network, consisting of 12 nodes, 24 links, and 9 intersections. Three bus routes were also defined such that TSP conflict may occur at two of the intersections. The links were defined as four-lane (two lanes per direction) segments of 400 meters. All the bus stops were defined to be at the far-side of the intersection. The network was modelled in VISSIM 6.0 microsimulation software (FIGURE 4).
FIGURE 4 Network Layout of the Example Study

**TSP Logic**

In this example, Green Extension (GE) and Red Truncation (RT), two of the most common preferential strategies (30), were utilized as the prioritization logic. The following assumptions were made in developing the TSP logic:

1. Pre-computed signal timing is utilized when no bus is approaching the intersection.
2. GE is granted when a bus is detected on an approach, the signal is green, and the bus can pass the stop-line with this extension. In this case, once the bus crosses the stop line, transition to the next phase is triggered.
3. RT is granted when a bus is detected on an approach and the signal is red.
4. Prioritizing is ignored if a bus is detected in the cycle \( n+1 \). In other words, only one of buses that arrive in two consecutive cycles can receive priority.
5. The effect of the opposing flow rate would be reflected in initial signal timing (i.e., allocated green time for each phase in base scenario) that is performed using the SIDRA Intersection package (23).
6. The impacts of pedestrians and cyclists are neglected.
7. First-come first-served logic is utilized to handle simultaneous TSP requests.
8. Communication of the transit vehicles and signals is formed using two vehicle detectors, one deployed at 100m from the intersections and the other immediately after the stopping lines.

In this example, the traffic state was introduced as an O-D array (a flat 10 veh/h for each O-D trip). Vehicle route-choice was modelled using the VISSIM Dynamic Traffic Assignment (DTA) model. A default headway of 5 minutes was considered for all transit services. The simulation time consisted of a 30 minute interval as a network warm-up followed by a 60 minute simulation and data collection. For each scenario, five different simulation runs with different random seeds were performed. Travel times of individual vehicles (both transit and auto) were derived as the output of each simulation run. These data were then exported to an evaluation function to calculate the reliability measures.
Encoding the model

To encode the problem for the optimization module, two intersections where no bus was approaching (S5, S8) were neglected, thus a total of seven intersections were defined as the search space. In addition, bus services were all running in the through direction, thus at most, two movements of each intersection may benefit from TSP deployment (i.e. East-West and South-North). Consequently, the optimum solution was selected from a search space comprising $2^7$ scenarios.

Optimization results

The proposed objective function of this study considered the impacts of TSP in terms of car and bus travel time value and variability. A set of auxiliary objective functions were defined to investigate the effect of this generalized cost function and compare it with the other approaches. Minimization of average bus travel time (objective 1), total travel time (both cars and buses-objective 2), bus variability (objective 3), bus travel time and variability (objective 4) along with Equation (1) were considered as the objective functions of the optimization problem. TABLE 1 shows the results of the optimization process and TSP impacts considering different objective functions. For each objective function, the optimum combination was obtained and the effect of deploying TSP was measured as the percentage of changing travel times and variability measures, compared with the base scenario. For the proposed objective function (objective 5), the optimum TSP combination for the given network consisted of seven TSP equipment in six intersections, as shown in the table. In addition, as a result of introducing a bus reliability index (objective 3-objective 5), the average bus travel time saving was slightly less to achieve a higher level of improvement (8% more) in the measure of reliability. Considering bus variability as the only measure of performance could make the transit service up to 26% more reliable than the base (no TSP) scenario, yet with more than 4% reduction in bus travel time. Regarding the impacts of TSP on the vehicular traffic stream, it was generally expected that once the traffic related elements were considered in the objective function, the optimization trend would lessen negative TSP impacts on the crossing movements. Nevertheless, the results showed that for this network and level of demand, the impacts of TSP on vehicular traffic were negligible (less than 0.03% on average travel time and less than 0.76% in variability) and introducing traffic related elements to the objective function did not change the optimum solution. A sensitivity analysis on the congestion level (next section) showed, however, that this is not always the case.

<table>
<thead>
<tr>
<th>TABLE 1 Optimization of TSP location problem with different objective functions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Objective Function</strong></td>
</tr>
<tr>
<td>------------------------</td>
</tr>
<tr>
<td>objective 1 (t_b)</td>
</tr>
<tr>
<td>objective 2 (t_p + t_b)</td>
</tr>
<tr>
<td>objective 3 (var_b)</td>
</tr>
<tr>
<td>objective 4 (t_b + var_b)</td>
</tr>
<tr>
<td>objective 5 (Equation 1)</td>
</tr>
</tbody>
</table>

* \(a\) means TSP is implemented in intersection a for bus route b
** impact is defined as \(x^a,x^b/x^a,x^b\) where \(x^a,x^b\) are optimum and base measures, respectively

Performance of the optimization algorithm

To measure the performance of the implemented heuristic algorithm in solving the TSP location problem, a greedy search of the whole search space was performed. Using an enumeration method, all the possible TSP combinations were first simulated and the results were exported to a database. Consequently, the exact solution (the global best TSP combination) was known and PSO convergence behaviour could be measured not only for efficiency (how fast the algorithm converged) but also for accuracy (how good the solution was).
FIGURE 5(a) shows the convergence behaviour of the optimization process in reaching the optimal answer for different social and cognitive (i.e., $C_1$, $C_2$, respectively) parameters. According to the figure, although different convergence behaviour was observed for different parameters, in all the optimization processes the optimal solution was successfully found. It was observed that in scenarios with a lower swarm size, having a higher $C_1$ value led to a broader search, thus a higher number of calling the objective function was required. Nevertheless, this was not the case in optimizations with a higher number of particles. In other words, although increasing the swarm size can impose an increase in the convergence time, less calling of the objective function may be required (FIGURE 5b). Since each evaluation requires performing a number of simulation runs, a well-tuned optimization module can decrease the total computational cost of the process. Tuning the parameter for the defined problem will be performed as an extension of this research.

![Convergence behaviour of the optimization algorithm (a) and the effect of swarm size on the performance of the algorithm (b)](image-url)
**Effect of changes in the network congestion**

In the numerical example, the traffic state was assumed to be 10 veh/h for each O-D pair and a headway value of 5 minutes was assumed for all bus routes. It was shown how different objective functions can change the optimum solution, and the importance of considering a generalized cost function was confirmed. In order to inspect the impacts of network parameters, sensitivity analyses on the level of congestion and bus frequencies were performed, and the changes in results were identified.

**Sensitivity Analysis on Congestion Levels,**

A sensitivity analysis was performed on the level of congestion to see its impact on different terms of the objective function. To perform this analysis, a scale factor for the defined O-D demand array was defined. The optimization process was then performed, seeking the minimum generalized objective function. As can be seen in **TABLE 2**, the number of prioritized sections in the optimum solution is the same for lower levels of congestion while different measures follow the same trend. However, once greater demand was imposed on the network, fewer TSP treatments were suggested as the optimum solution. In addition, the impacts on private cars were more crucial, thus the optimization module introduced solutions that accrued passenger cars. In other words, the bus prioritization task of TSP was sacrificed to mitigate passenger cars travel time and variability. The weighting parameters in Equation (1) as well as the car travel time threshold (σ in constraint (3)) can be used to manage the behaviour of the framework in terms of the strictness of bus prioritization.

<table>
<thead>
<tr>
<th>O-D Demand (veh/h)</th>
<th>Optimal combination</th>
<th>Car TT Impact (%)</th>
<th>Bus TT Impact (%)</th>
<th>Car Reliability Impact (%)</th>
<th>Bus Reliability Impact (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>{1,2,3,4,6,7,9}</td>
<td>0.03</td>
<td>-4.53</td>
<td>0.75</td>
<td>-23.62</td>
</tr>
<tr>
<td>20</td>
<td>{1,2,3,6,7,9}</td>
<td>0.12</td>
<td>-4.63</td>
<td>1.22</td>
<td>-25.79</td>
</tr>
<tr>
<td>30</td>
<td>{1,2,3,6,7,9}</td>
<td>0.13</td>
<td>-4.44</td>
<td>0.35</td>
<td>-22.80</td>
</tr>
<tr>
<td>40</td>
<td>{1,2,3,4,6,7,9}</td>
<td>0.20</td>
<td>-3.83</td>
<td>1.40</td>
<td>-27.97</td>
</tr>
<tr>
<td>50</td>
<td>{1,2,3,4,6}</td>
<td>-0.90</td>
<td>-3.59</td>
<td>-1.58</td>
<td>-18.69</td>
</tr>
<tr>
<td>60</td>
<td>{2,3,4,6}</td>
<td>-1.24</td>
<td>-2.93</td>
<td>-1.52</td>
<td>-10.45</td>
</tr>
</tbody>
</table>

**Sensitivity Analysis on bus frequencies**

To identify the impact of bus headway on TSP performance, a simulation model was developed for different levels of bus frequencies. The model was developed for four different headway values (2, 3, 5, and 10 minutes) and critical impacts of TSP on every element were captured (**TABLE 3**). It was observed that at a lower level of transit frequencies, a higher level of reliability was achievable. While the maximum improvement in the measure of reliability was around 12% in 2 minute headways, 30% improvement was achievable if the headway was 10 minutes, possibly due to less probability of having multiple TSP requests. This trend could not be seen in the measure of bus travel time saving where a slight decrease in this index was observed. Regarding the negative impacts of TSP on the traffic state, more frequent services imposed slightly higher impact on passenger cars (less than 0.4% and 1.4% for travel time value and reliability indexes, respectively).

<table>
<thead>
<tr>
<th>Headway (min)</th>
<th>Bus TT Saving (%)</th>
<th>Bus Var (%)</th>
<th>Car TT Impact (%)</th>
<th>Car Var Impact (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>-3.6</td>
<td>1.6</td>
<td>-12.3</td>
<td>6.6</td>
</tr>
<tr>
<td></td>
<td>Best</td>
<td>Worst</td>
<td>Best</td>
<td>Worst</td>
</tr>
<tr>
<td>3</td>
<td>-3.9</td>
<td>1.2</td>
<td>-22.1</td>
<td>2.1</td>
</tr>
<tr>
<td></td>
<td>Best</td>
<td>Worst</td>
<td>Best</td>
<td>Worst</td>
</tr>
<tr>
<td>5</td>
<td>-2</td>
<td>0.2</td>
<td>-26.4</td>
<td>5.1</td>
</tr>
<tr>
<td></td>
<td>Best</td>
<td>Worst</td>
<td>Best</td>
<td>Worst</td>
</tr>
<tr>
<td>10</td>
<td>-2.4</td>
<td>0.7</td>
<td>-30.3</td>
<td>8.5</td>
</tr>
<tr>
<td></td>
<td>Best</td>
<td>Worst</td>
<td>Best</td>
<td>Worst</td>
</tr>
</tbody>
</table>
CONCLUSION

This study has presented an optimization framework to assist decision-makers to select the best potential locations for deploying TSP treatments. Firstly, a mathematical formulation for the TSP locating problem was proposed. The objective of the function was minimization of the travel time and its variability for both buses and cars. This framework was found to be applicable to grid networks and can consider the possible interdependency of signal settings at neighbouring intersections. The framework can allow practitioners to implement different TSP logic or settings at a network level. A heuristic algorithm (BPSO) was implemented and linked to the model to perform the search process. The model was then utilized to solve a case study example. It was shown that ignoring the variability measures in the objective function can lead to a sub-optimal solution. In this regard, the impacts of TSP on vehicular traffic were shown to be crucial only at higher levels of congestion. In addition, it was shown how the impact of TSP on different parameters varies at different bus frequencies. The general conclusion of this paper shows the abilities of the proposed framework in helping decision-makers plan for TSP deployment from a network-wide perspective.

Future research will be directed at improving the performance of the framework. Firstly, the computational costs of the evaluation model could be improved by optimizing and tuning simulation parameters, and introducing heuristic and customized operators to mitigate the computational cost of the process. Finally, other preferential treatments as well as different TSP logic could be introduced as the variables of the problem, thereby pursuing maximum efficiency of TSP for the whole transportation system.

ACKNOWLEDGMENTS

The authors would like to acknowledge the Australian Research Council for supporting this project through a Discovery Early Career Researcher Award with grant number DE130100205.

REFERENCES


