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Comparative Performance Analysis of Multi-Objective Transit-Priority Systems

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Abstract - This paper demonstrates how can the Response Surface Methodology (RSM) simulation-based optimization be used in calibrating the transit priority based advanced traffic control systems. Three types of control types are considered; split, protected, dual phasing signal control. The proposed methodology is applied to some integrated heuristic based control that accounts for various triggers such as downstream signal congestion and identification of priority transit vehicle in traffic streams. The RSM accounts for multiple objectives related to the various network measures of effectiveness simultaneously by estimating the so-called composite desirability. Multiple objective functions were used; namely, maximizing the transit throughput and minimizing the mean travel time simultaneously. The three control types were analyzed under various network loading levels reflecting congested and highly congested scenarios. The RSM methodology proved to be efficient in optimizing the various control types, increasing the transit throughput and decreasing the mean travel time in almost all studied cases. Comparative analysis was conducted to assess the effectiveness of the various controllers in terms of transit throughput and mean travel time. A simplified multi-criteria ranking indicated the best performance in the case of dual, followed by the split, and finally the protected control.

Keywords: Traffic Control, Transit Signal Priority, Response Surface Methodology, Calibration, Multi-Objective Functions.

1. Introduction

Transit Signal Priority (TSP) is commonly categorized as a passive or active priority, adaptive/real-time priority with or without optimization. Passive priority uses a pre-timed signal plan to favor bus operation without explicitly recognizing actual bus presence. In the case of active priority, detectors are used, and the signal plan is altered in response to the presence of a transit vehicle. Depending on the location and capabilities of the transit detectors, active priority can also be classified as unconditional and conditional. Based on real-time flow profiles of transit and general vehicles, adaptive priority develops signal timing plans to provide priority for transit vehicles while incurring the least delay to the transit passenger or total person [1]. Some adaptive priority also entails optimization models like genetic algorithms and artificial neural network based control algorithm [2].

TSP can be applied at an isolated intersection, on an arterial, or over a network of intersections. Only very few papers have reported the performance of TSP in a complex urban traffic network with many overlapping or conflicting bus routes [3]. For a network-based application, sophisticated and advanced transit detection systems are essential (such as the automatic vehicle location and automatic passenger count, connected vehicle), and should be coupled with the non-transit vehicle queue detectors [4]. The real-time detection system monitors the transit vehicles continuously, and the signal controller integrates the monitored vehicle's information with the non-transit flow data to provide priority to the transit vehicles. At this level, various priority strategies and different optimization models can be applied to optimize the network performance.

The evaluation of TSP strategies can be categorized into three types: analytical evaluation, simulation test, and field test [1]. In the majority of the literature, the TSP evaluation has been commonly reported with an improvement in transit performance (i.e., travel time, delay). However, the improvement gained regarding transit performance is typically accompanied by deterioration in the performance of the cross-street traffic.

Ahmed and Hawas [3] developed an integrated traffic control system with TSP using a GPS based real-time transit detector system. The transit vehicle is considered as non-priority if it is bound to stop at some intermediate bus stop along the approach link. If the bus has already stopped or no bus stop along the approach link and its expected time to reach the stop line at the downstream end of the link is less than the green extension, then the bus is treated as a high priority bus. If the transit vehicle cannot reach the stop line within the green extension, the bus is regarded as a normal priority. This provides treatment to the issue of near or far side bus stops, as the TSP should additionally account for the dwelling time at the bus stop for nearside bus stop. Ahmed and Hawas [3] also introduced med block detectors to overcome the problem of short or large detection range, such as short detection range implies late priority calls having limited lead time for treatment and long detection ranges can result in less predictability or inaccuracy of the transit vehicle's arrival at the intersection. However, the impact of these detectors is not evaluated. Furthermore, despite the fact that the TSP system was tested with various signal controllers (split, protected, dual), there is no adequate discussion of the implications (pros and cons) of integrating the TSP with the different controllers.

The majority of the TSP systems in the literature lack some fundamental aspects that this research is attempting to address. First, the TSP s in literature have limited applicability to network operation (with overlapping and intersecting transit routes). Second, there is also another limitation because of the assumption that one point of transit vehicle's detection is sufficient for the system to operate. Nearly all the presented TSP's cannot be generalized to conditions beyond which the conditions they are calibrated for and tested. A TSP efficiently working for a specific traffic situation may not be as effective for another condition. The TSP system parameters are commonly selected to fit specific traffic conditions. It is natural as such that such systems should be re-calibrated each time they are deployed to different conditions (that the system was not optimized for). What makes it more challenging is the dynamics of traffic and the evolution of the traffic demand over the day. A TSP may operate efficiently during specific hours but then fails to run at other times because its parameters are adjusted for only some specific conditions (but not all). Furthermore, TSP systems commonly include multiple parameters that affect the performance, and as such the recalibration is undoubtedly a challenging, demanding multi-dimensional task. It is not clear from the literature how were most of the TSP systems calibrated and how parameters were estimated. Apparently, it seems like a trial and error calibration approach. It is probably unclear also how general ATMS systems (and specifically complex TSPs) are calibrated for the real-time operation to function efficiently at various demand levels and network configurations.

The necessity of traffic models calibration has been reported in the literature for various purposes. Micro-simulation models mimic events, such as gap-acceptance, speed adjustment, lane changing, and car-following. Each model has various parameters to describe the individual driver behavior and vehicle dynamics [5]. The calibration of these parameters is essential to replicate real-life events accurately for minimizing the discrepancy between the observed and simulated traffic conditions [6]. Earlier research also indicated the importance of calibration and validation of traffic simulation models for various ATMS functions [7, 8]. Control systems as well must be calibrated appropriately to regulate traffic efficiently by improving the overall network productivity [3].

In brief, there is a need to devise a methodology that can be used to assess the effectiveness of complex TSP based systems, calibrate its parameters to provide optimal (or at least close to optimal) control. The challenge of the devising such methodology is the complexity of the objective functions and the nonlinearity nature of it. Some of the TSP's found in the literature are even integrated with other advanced ATMS components such as incident detection and management [3], which makes the calibration of parameters even more challenging. Some of the TSP's may have few parameters to calibrate, and some may have many. As such, no matter what methodology is used to calibrate these parameters, it should be functional with various TSP systems and parameters.

This paper aims to present a simulation-based Response Surface Methodology (RSM) that can be used to calibrate and improve the effectiveness of the solutions of advanced complex traffic control systems in general. To demonstrate the application of RSM for parameter setting, the integrated traffic signal control system by Ahmed and Hawas [3] is used (as the case study controller to optimize). Any other controllers can also be optimized using the same methodology.

2. Integrated Traffic Signal Control System Parameters

Ahmed and Hawas [3] developed the integrated traffic signal control system that undertakes decisions of a currently running green phase to determine the next best phase to operate and when by considering some rule-based boundary conditions. These boundary conditions if met, they flag specific penalty parameters in the objective function to deploy, which in turn affect the value of the objective function for each phase. There are four modules to check these boundary conditions. First, the traffic regime state module responsible for estimating the congestion status of the upstream link to a signalized intersection. Second, the incident status module responsible for the likelihood of an incident on the link. Third, the transit priority module responsible for flagging specific links for transit priority based on the transit vehicle location and type. Fourth, the downstream blockage module responsible for scanning all downstream links of the intersection to account for their recurrent blockage (spill-back) conditions. Another actuation module is then deployed afterward to estimate the so-called actuation index for each phase, and identify the next candidate phase set based on the signal control type (e.g., dual, protected, split).

The mathematical model of the Integrated Traffic Control System is presented and explained briefly hereafter. The base congestion indicator of the upstream approach of an individual phase $\emptyset_j$ denoted by $J^{/,t}_{i,\phi_j}$ refers to the virtual queue of passengers on the upstream approach of that individual phase $\emptyset_j$ at time t, and could be estimated from Eq. (1). This base congestion indicator ($J^{/,t}_{i,\phi_j}$) is estimated without any adjustment for the incident status on the upstream approach of that individual phase $\emptyset_j$ at time t. That is, Eq. (1) applies only to normal recurrent conditions; that is if no incident is detected on the upstream approach of phase $\emptyset_j$.

$$J^{/,t}_{i,\phi_j} = \left[\begin{array}{c}\left(C^{c,t}_{i,\phi_j,u^/} \times O^{c}_{i,\phi_j,u^/} \times 1\right) + \left(C^{b,t}_{i,\phi_j,u^/} \times O^{b}_{i,\phi_j,u^/} \times \beta^{b}_{i,\phi_j,u^/}\right) + \left(C^{p,t}_{i,\phi_j,u^/} \times O^{p}_{i,\phi_j,u^/} \times \beta^{p}_{i,\phi_j,u^/}\right) + \\ \left\{\left(C^{c,t}_{i,\phi_j,u^/} \times O^{c}_{i,\phi_j,u^/} + C^{b,t}_{i,\phi_j,u^/} \times O^{b}_{i,\phi_j,u^/} + C^{p,t}_{i,\phi_j,u^/} \times O^{p}_{i,\phi_j,u^/}\right) \times r^{V,t}_{i,\phi_j,u^/} \times \beta^{V}_{i,\phi_j,u^/}\right\}\end{array}\right] \quad (1)$$

Where $C^{c,t}_{i,\phi_j,u^/}$, $C^{b,t}_{i,\phi_j,u^/}$,and $C^{p,t}_{i,\phi_j,u^/}$ are the total vehicular counts of the cars, c, normal priority buses, b, and high priority buses, p, respectively, at time t on the upstream approach link, $u^/$, relevant to phase, ϕ_j , of intersection i. $O^{c}_{i,\phi_j,u^/}$, $O^{b}_{i,\phi_j,u^/}$and $O^{p}_{i,\phi_j,u^/}$ are the average passenger occupancies of cars, normal, and high priority buses, respectively. The parameters $\beta^{b}_{i,\phi_j,u^/}$ and $\beta^{p}_{i,\phi_j,u^/}$ are coefficients for transit priority for normal and high priority buses, respectively. $r^{V,t}_{i,\phi_j,u^/}$ is the ratio of the vehicular queue length to the physical capacity of the corresponding link length. $\beta^{V}_{i,\phi_j,u^/}$ is a coefficient for the virtual queue of vehicles. If an incident is detected, the value of the base congestion indicator, $J^{/,t}_{i,\phi_j}$ is adjusted (increased) by the incident penalty coefficient $\beta^{N}_{i,\phi_j,u^/}$ to account for the potential incident on the upstream approach, $u^/$, as shown in Eq. (2):

$$J^{t}_{i,\phi_j} = \left(1 + \beta^{N}_{i,\phi_j,u^/} \times I^{N,t}_{i,\phi_j,u^/}\right) \times J^{/,t}_{i,\phi_j} \quad (2)$$

The J^{t}_{i,ϕ_j} value (in Eq. 2) is further adjusted (decreased) as shown in Eq. (3) by applying a downstream blockage penalty coefficient $\beta^{B}_{i,\phi_j,d^/}$ to account for blockage on the downstream exit link of phase ϕ_j. The value of $A^{t}_{i,\phi_j}$is referred to as the actuation index of the individual phase ϕ_j.

$$A^{t}_{i,\phi_j} = \frac{J^{t}_{i,\phi_j}}{\left[\left(1 + I^{B,t}_{i,\phi_j,d^/}\right)^{\beta^{B}_{i,\phi_j,d^/}}\right]} \quad (3)$$

It is important to note that all links of the network have detectors. The congestion on the downstream link is estimated using the information extracted from the downstream (exit) link detectors. Eq. (3) is introduced to penalize the links that have full or partial blockage; if one link is entirely blocked, the upstream phases of this particular link will be "penalized" and as such lesser green times to these phases that feed vehicles to such blocked link. This will prevent any further blockage on the incident links, reduce the likelihood of full blockage and avoid spill backs from and along entirely blocked incident links.

Eqs. (1), (2) and (3) are all used to estimate the congestion indicator (base or adjusted), but their values will depend on the met identified boundary conditions. For instance, the transit priority parameters and terms in Eq. (1) accounts for priority buses. If a priority bus is detected, these terms will be processed and as such the base congestion indicator will give different results as compared to the case where no priority buses are detected. The downstream congestion (in Eq. 3) as well as a boundary condition that is flagged by a blockage on downstream links (if and only if downstream exit links are flagged with blockage).

The actuation index of a candidate phase set Z_{i,Φ_k}^{t} is the sum of the actuation indexes of the two concurrent individual phases of the candidate phase set, Φ_k , $\Phi_k = \{\phi^{k,1} \cup \phi^{k,2}\}$. The Z_{i,Φ_k}^{t} index represents the final adjusted virtual queue of passengers considering the estimated impact of all the relevant boundary conditions which are represented by respective modules. The most deserving candidate phase set is the one of the maximum Z_{i,Φ_k}^{t}value.

$$Z_{i,\Phi_k}^{t} = A_{i,\phi^{k,1}}^{t} + A_{i,\phi^{k,2}}^{t} \tag{4}$$

The parameters of the controller should be calibrated for optimal performance. There are three primary parameters of this controller. First, the coefficient for virtual queue of vehicles on the upstream approach link (β^{V}) of a phase at an intersection. Second, the coefficients for transit priority (β^{b}or β^{p}); β^{p} is for the high priority buses and $\beta^{b}$is for regular priority buses on the upstream approach of a phase at an intersection. Third, the downstream blockage penalty coefficient (β^{B}) on the downstream exit link of a phase at an intersection.

The values of the parameters β^{V}, β^{b}or β^{p}, and β^{B} are likely to affect the network performance because of different penalty values via the signal control. The performance of the traffic network is represented herein by three output variables or measures of effectiveness (MOEs); these are: total number of bus trips served during a specific analysis period (N_{bus}), total network travel time in hours (T_t), and the trip mean travel time in seconds (t_m).

The study adopts a simulation-based optimization approach to model the relationships between the control parameters and the resulting MOEs. In brief, this study aims at studying the impact of these control parameters on the network MOEs by developing models for explaining the relationships between these parameters and the resulting each MOE under the actuated split, protected, dual signal control and congestion conditions. For simplicity, in this study both high and normal bus priority parameters, $\beta^{b}$and β^{p}, are assumed equal.

3. Response Surface Methodology and Calibration Framework

In this research, Response Surface Methodology (RSM) is used to get the best parameter configurations, as RSM requires a smaller number of simulation experiments than that of the Gradient-based method [9]. The idea of RSM is to construct a surrogate mathematical model(s) to approximate the underlying function [10]. RSM can be divided into two general methods: Central Composite Design (CCD) and Box–Behnken Design [11]. In this study, Box–Behnken Design (BBD) is used to get the optimum solutions (of the parameters vis-à-vis the specified MOEs) as the BBD is slightly more efficient than the CCD [12], and BBD is more efficient and economical than the similar three-level full factorial designs [13]. Details of applying the RSM will be demonstrated through simulation-based experiments afterward.

The integrated traffic control system [3] is chosen in this paper as the case study. At first, the parameters to calibrate are selected (herein, β^{V}, $\beta^{b} or\, \beta^{p}$, and β^{B}). The regions of the parameters for the first (1st) model are initially chosen arbitrarily. The RSM (Box-Behnken Design, BBD) is applied to generate the input settings for the various parameter combinations. The control system is simulated using values of each combination, and the measures of effectiveness (MOEs) are extracted from simulation results. The MOEs used here are N_{bus}, T_t, and t_m.

The so-called desirability function approach, as outlined by Derringer and Suich [14], is used to account for the multi-objective simultaneous consideration of the responses. Initially, each response is converted into an individual desirability, which varies over the range from zero to one dimensionless scale. The individual desirabilities are, then, used to estimate the composite desirability (D) using the geometric mean formula. The estimated composite desirability value depends on the specific preset objective (lower, target, upper) of each individual desirability element (response), the weight (r) which defines the form shape of desirability function for each response, and the importance parameters (w) of the various desirability items that are combined into a single composite desirability. Given the aimed objectives (e.g., maximize N_{bus} and to simultaneously minimize both T_t and t_m), the individual desirabilities are stated, and the problem is transformed into maximizing the composite desirability. The composite desirability unifies the individual desirabilities of all the response variables into a single measure and emphasis is placed on the response variables with the importance parameter (w). The importance parameters reflect the relative importance of the individual desirability in estimating the composite one as shown in Eq. 5 (weighted geometric mean).

$$D = \left[\left(d_{\mathrm{N}_{bus}}\right)^{w_{N_{bus}}} \times \left(d_{T_t}\right)^{w_{T_t}} \times \left(d_{t_m}\right)^{w_{t_m}}\right]^{1/3} \tag{5}$$

Where, $d_{\mathrm{N}_{bus}}, d_{T_t}$, and d_{t_m} are the individual desirability of the total number of bus trips (N_{bus}), the network's total travel time (T_t), and the trip's mean travel time (t_m), respectively; $w_{\mathrm{N}_{bus}}, w_{\mathrm{T}_t}$, and w_{t_m} are the importance parameter of N_{bus}, T_t, and t_m, respectively. The importance parameter determines the influence of each response on the composite desirability. In the case of placing equal importance on the responses all the importance parameters are set equally. In this study, all importance parameters of the individual desirability are set equal to one, i.e., $w_{\mathrm{N}_{bus}} = w_{T_t} = w_{t_m} = 1$.

The objective is interpreted regarding the target parameter for the response. If the objective is minimizing a response, the desirability is one for all response values less than or equal to a specific lower bound target. Alternatively, if the objective is maximizing a response, then the desirability is one for all values equal to or above a specific upper bound target. As an example, if the objective for the response of the total bus trips ($y_{\mathrm{N}_{bus}}$) is a maximum value, the individual desirability function $d_{\mathrm{N}_{bus}}$ is defined as follows:

$$d_{\mathrm{N}_{bus}} = \begin{cases} 0 & y_{\mathrm{N}_{bus}} < L_{\mathrm{N}_{bus}} \\ \left(\dfrac{y_{\mathrm{N}_{bus}} - L_{\mathrm{N}_{bus}}}{T_{\mathrm{N}_{bus}} - L_{\mathrm{N}_{bus}}}\right)^r & L_{\mathrm{N}_{bus}} \leq y_{\mathrm{N}_{bus}} \leq T_{\mathrm{N}_{bus}} \\ 1 & y_{\mathrm{N}_{bus}} > T_{\mathrm{N}_{bus}} \end{cases} \tag{6}$$

Where r is the weight that defines the functional form of the desirability function, and $L_{\mathrm{N}_{bus}}$ and $T_{\mathrm{N}_{bus}}$ are the lower bound and target values of the response (N_{bus}), respectively. Also, if the objective for the response is a minimum value (e.g., network total travel time, y_{T_t}), the individual desirability for the response d_{T_t} is defined as follows:

$$d_{T_t} = \begin{cases} 1 & y_{T_t} < T_{T_t} \\ \left(\dfrac{U_{T_t} - y_{T_t}}{U_{T_t} - T_{T_t}}\right)^r & T_{T_t} \leq y_{T_t} \leq U_{T_t} \\ 0 & y_{T_t} > U_{T_t} \end{cases} \tag{7}$$

Where, U_{T_t} and T_{T_t} are the upper bound and target of the response (T_t), respectively. Likewise, the objective for the response can be to achieve a specific target value, which is not used in this study. The weights of the desirability function (r) define the shape of the individual desirability function. If "r" is greater than one, it places more emphasis on being close to the target value of the response, and if "r" is less than one and greater than zero, it makes this less important [15]. If "r" is equal to one, the desirability function is linear that is used in this study.

Considering the specified objective function(s), the RSM is analyzed to estimate the so-called composite desirability, and the optimal setting is identified (one with maximum composite desirability). In this study, three objective functions were considered first (maximizing of N_{bus}, while simultaneously minimizing both T_t and t_m). The calibration is also carried out considering only one objective function (maximizing the N_{bus}) as well as considering two objective functions (maximizing the N_{bus} and minimizing the t_m). The composite desirability is estimated using the individual desirability of each objective function.

4. Simulation-Based Experimental Traffic Network

A grid-type network of 49 intersections is used in this study. Each intersection has four approach links (from the East, West, North, and South) and four exit links with three continuous lanes and two additional left-turn pockets with 80 m storage length each. Due to the extensive set of simulation-based runs and the corresponding RSM optimization in this study, it is decided to focus the scope of this research on the networks exhibiting high (E) to very high (F) traffic demand levels. The network consists of one short link (300 m) and one long link (600 m) side by side, alternatively in both vertical and horizontal dimensions. This network has seven (7) horizontal and seven (7) vertical arterials, and the origin and destination are chosen from the Eastern, Western, Northern and Southern boundary link entrances and exits, respectively. The adopted "car" trip distribution is as follows: from any origin on the Eastern boundary, 60% of the total originated trips are split equally among the destinations on the Western boundary, 20% are among the destinations on the Northern boundary, the remaining 20% are on the Southern boundary. Similar directional distributions are followed for any origin on the Western, Northern, and Southern boundaries.

Two different levels of traffic demand are used. The demand cases of "E" and "F" correspond to the high and very high car traffic volume of 1000 and 1500 per hour, respectively. The demand cases "E" and "F" are tested with the mean headway along the bus routes is 10 minutes and 5 minutes, respectively. Both demand cases are tested with the maximum green time (of any individual phase or phase set) of 45 seconds. A fixed bus route network including 18 directional routes is used for all simulation cases. The integrated system allows bus priority in grid networks in any direction and bus routes operate with uniform headways. The origins and destinations on the Eastern and Western boundaries are considered for bus routes as well. Some of the bus routes overlap on some of the links, and some intersections have both left- and right-turning bus trips on their associated approach links.

5. Results

The performance of the optimal variable settings of various controllers under high ("E") traffic demand, is shown in Table 1 compared with the sample mean that is calculated considering all the constructed model's data. The sample mean reflects the average performance of the integrated control system in case it is not appropriately calibrated. The optimal variable settings of the various controllers give the better performance (the higher total bus trips and lower mean travel time) than the sample mean. Table 1 indicates that the split actuated control under "E" traffic demand scenario gives the best performance among the control types, as it increases the total bus trips (by nearly 4%) and decreases the mean travel time (by 11%). Other control types (protected actuated, dual actuated) also shows better performance than the corresponding sample mean, as the total bus trips, $\mathrm{N_{bus}}$, is more and mean travel time, $\mathrm{t_m}$, is less.

Similarly, the performance of the optimal variable of various controllers under very high ("F") traffic demand, is shown in Table 2 compared with the sample mean of all the attempted model's data. The split actuated control under "F" traffic demand scenario also shows the best performance, as it gives nearly 5% more total bus trips and 2.4 % lesser mean travel time. Other control types (protected actuated, dual actuated) also shows better performance than the sample mean, as the total bus trips, N_{bus}, is more and mean travel time, $\mathrm{t_m}$, is less. Only the dual actuated control resulted in very marginal average travel time increase (+0.4%).

Table 1: Performance of the selected optimal variable settings of β^V , β^bor β^p, and β^B of various controllers under “E” traffic demand.

Criteria	Split actuated		Protected actuated		Dual actuated	
	N_{bus} (Trips)	t_m (seconds)	N_{bus} (Trips)	t_m (seconds)	N_{bus} (Trips)	t_m (seconds)
Sample Mean	155.5	942.1	98.8	1034.9	155.2	691.6
Using optimal setting	161.0	838.3	100.1	1012.7	155.2	688.7
% diff. in Performance	+3.6%	-11.0%	+1.3%	-2.1%	0.0%	-0.4%

Table 2: Performance of the selected optimal variable settings of β^V , β^bor β^p, and β^B of various controllers under “F” traffic demand.

Criteria	Split actuated		Protected actuated		Dual actuated	
	N_{bus} (Trips)	t_m (seconds)	N_{bus} (Trips)	t_m (seconds)	N_{bus} (Trips)	t_m (seconds)
Sample Mean	166.9	1498.1	121.9	1411.7	200.7	1412.2
Using optimal setting	175.1	1462.2	124.8	1391.8	206.1	1418.4
% diff. in Performance	+4.9%	-2.4%	+ 2.4%	-1.4%	+2.7%	+0.4%

Table 3 summarizes the key findings of various controllers under high (E) and very high (F) traffic demand scenarios. The control types are ranked considering the measures of effectiveness under each traffic demand scenario. It is evident that the dual actuated control type is performing best under both traffic demand scenarios considering the MOEs of N_{bus} and t_m. But considering only the N_{bus}, split control type is best under the “E” traffic demand scenario and dual control type is best under the traffic demand “F”.

Table 3: Summary of findings of various controllers under “E” and “F” traffic demand.

Criteria	**Split Actuated**		**Protected Actuated**		**Dual Actuated**	
	“E”	“F”	“E”	“F”	“E”	“F”
Rank based on N_{bus}	1	2	3	3	2	1
Rank based on t_m	2	3	3	1	1	2

6. Concluding Remarks

This paper demonstrates how can the Response Surface Methodology (RSM) simulation-based optimization be used in calibrating the transit priority based advanced traffic control systems.The suggested method was assessed via extensive case study analyses. The suggested RSM calibrates the parameters of the integrated system by selecting the values that can produce the best measures of effectiveness. The challenging task is to satisfy the requirements of transit and non-transit vehicles, which are very often diverse and conflicting. As an example, if transit signal priority is active in one approach, then the opposite side street would encounter adverse impacts in the form of more delay travel time. RSM uses the desirability function approach as well as the simultaneous multi-objective desirability of the responses to handle this complexity issue. This methodology can be applied to any control system. The calibrated settings MOEs outperformed the sample mean’s MOEs and the dual actuated control type is performing best under both traffic demand scenarios considering the MOEs.

The application of RSM has some limitations; the process of calibration itself cannot also be applied online due to the requirement of some engineering judgment for the analysis and model building process. Future research should consider calibrating the parameters of the traffic signal control itself, such as the minimum green, the maximum green, the vehicular extension period. It should also be valuable to add some measures of performance that reflect the network environmental quality and vehicular emissions explicitly by adding an objective function of minimizing the adverse environmental impact.

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