Metaheuristic approach for designing robust traffic signal timings to effectively serve varying traffic demand

Chaitrali Shirke [a]*, Nasar Sabar [b], Edward Chung [1c], Ashish Bhaskar [a]

[a] *Civil Engineering and Built Environment, Queensland University of Technology, 2 George St., Brisbane, QLD 4000, Australia*

[b] *Department of Computer Science and Information Technology, La Trobe University, Melbourne, VIC 3083, Australia*

[c] *Department of Electrical Engineering, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong*

[1] Corresponding author. Tel.: +852 2766 4019; E-mail address: edward.cs.chung@polyu.edu.hk

Metaheuristic approach for designing robust traffic signal timings to effectively serve varying traffic demand

Abstract

Traffic demands at intersections vary across various periods of a day and from day to day. Generally, fixed time traffic signals are designed considering the average traffic flows across multiple days over a predetermined time interval. This approach overlooks the day to day variability in traffic demand, leading to inefficient and unreliable signal control performance. A signal plan should be robust such that it is less sensitive to demand variations and can maintain near-optimal performance during varying traffic demand. To address this need, the paper presents a new offline scenario-based framework, named *Metaheuristic Robust plan Approach* (MHRA), that identifies a robust plan for fixed time signals. MHRA includes a heuristic that considers optimum signal plan for various demand scenarios and corresponding costs to find a robust solution. The numerical experiments are performed using realistic traffic demand scenarios on an arterial corridor to verify the MHRA framework. The outcomes concluded that the framework produces a robust signal plan that outperforms a nominal signal plan based on average traffic demand and maintains stable performance under varying demand. Benchmarking MHRA with other scenario-based approaches proposed in the literature such as *mean-variance optimisation* and *conditional value at risk minimisation* confirms better efficiency for MHRA.

Keywords: robust traffic signal; fixed time traffic signals; varying traffic demand; day to day variation; metaheuristic approach

1. Introduction

Traffic signals are an integral part of arterial roads. Thus, optimised traffic signals play a critical role in managing recurrent congestion. The efficiency of arterial signal control relies mainly on the signal plans designing technique and how that technique addresses two-dimensional variation in traffic. Traffic flows on arterial roads vary significantly within different periods of a day (referred to as period to period) and from day to day, which may cause unstable signal control performance. Field observations have shown that day to day traffic demand on arterial roads can vary from 10% to 40% (Kieu et al., 2015).

There exist various techniques to produce signal plans such as fixed time signal plans, plan selection techniques, real-time or adaptive techniques etc. State-of-the-practices in many developing countries are fixed time, due to the associated high costs of real-time adaptive signal control systems. Moreover, fixed time signal timings are default failsafe options for advanced traffic signal controllers.

Fixed time signals are also referred to as time-of-day (TOD) signals because a day is segmented into a few time intervals called TOD intervals, and a signal plan is predetermined for each time interval. To effectively address the period to period traffic flow variation, it is essential to identify optimal TOD breakpoints. The basic principle for determining the intervals is that the traffic pattern within each interval is relatively consistent. Thus, the predetermined signal plan is best suited for the condition of this particular TOD. Several studies (Smith et al., 2002; Guo & Zhang, 2014; Chen et al., 2019) focus on the determination of optimal TOD breakpoints to define TOD intervals. For each TOD interval, the signal timing plan is obtained by either applying Webster's formula (Webster, 1958) or using optimisation tools such as TRANSYT (Vincent et al., 1980), TRANSYT-7F (Wallace et al., 1984), and SIDRA (Akcelik et al., 1984) with the average values of traffic flows as the inputs.

Traffic demand significantly fluctuates within a TOD interval, especially during peak period TOD interval. To consider this variation, traditionally observed traffic volume during peak hour is multiplied by peak hour factor (PHF) to conservatively define the design flow rate for peak period. However, due to day to day variability, the PHF also varies from day to day (Tarko & Perez-Cartagena, 2005).

Researchers (Heydecker, 1987; Hellinga & Abdy, 2008) have identified that if the degree of day to day variability of traffic demand is significant then optimising signal timing for the average flows may incur a considerable additional delay. To take into account the worst case, researchers (Smith et al., 2002; Park & Kamarajugadda, 2007) have suggested considering 90th percentile of traffic demand. However, the resulting timing plan may be over-conservative, leading to inferior average performance. Based on the simulation of field traffic conditions, Stevanovic et al. (2011) also reported that the signal timings optimised for average (i.e. median, mean or mode) traffic flows perform better when subjected to day to day varying traffic compared to those optimised for higher-than-average (e.g. 75th and 85th percentile) traffic demand.

On the contrary to TOD signals, some systems use a plan selection method to adapt to the period to period varying traffic demand. Such systems predetermine signal plans for different possible traffic conditions along the day, out of which, one is selected to serve observed traffic demand. STREAMS arterial management (Transmax, 2015) – implemented in Queensland, Australia – is an example of a plan selection based control system. Similarly, Lin et al. (2011) proposed a plan selection method to balance the queue lengths varying due to variations in vehicle arrival queue lengths on different approaches of an intersection. STREAMS and Lin et al. (2011) categorise traffic conditions into different groups based on road occupancy and queue length, respectively. Further, a signal plan is designed for each group using the average traffic demand of the group. However, for such a plan selection approach, a signal plan is designed for each traffic condition group using the average traffic demand of the group. The demand variation within each group is not considered, and it is essential to design a signal plan such that it provides an optimal solution to all possible traffic variations in each group. For example, say a signal plan is intended to serve the traffic when the occupancy is within 15% to 30%. Such a signal plan should maintain an average optimal performance under different demand profiles expected within a given range of occupancy. Thus, it is essential to consider a day to day variation in traffic demand while designing a signal plan for TOD signals as well as a plan selection method.

Under the day to day traffic demand variation, the performance of the signal plan can be judged by two measures, namely, efficiency and robustness. The signal plan producing the optimal value of the objective functions such as total delay, total throughput etc. is known as an efficient signal plan for a given demand. On the other hand, robustness is a measure of deviation in the performance of a signal plan across various traffic demands. Given the conflicting nature of efficiency and robustness of signal control, a trade-off between them is inevitable to achieve satisfactory performance of signal plan under varying demand. The signal plan that minimises the cost associated with different demand scenarios and whose performance is reasonably stable under different realisations of traffic volumes is known as a robust signal plan. In other words, the signal plan is robust if, under certain demand variations, the signal plan behaves reasonably good with respect to its quality, feasibility, or optimality.

To design a robust plan for fixed time signals that can maintain stable performance under day to day demand variation, this paper proposes an offline scenario-based framework called *MetaHeuristic Robust plan Approach* (MHRA). The 'scenario-based' term refers to the discrete number of historical traffic flow scenarios with certain occurrence probability such that the different scenarios capture day to day variation of traffic demand. Here, the occurrence probability of the demand scenario refers to the probability of observing a similar demand scenario on different days. MHRA includes a heuristic that considers optimum signal plan for various demand scenarios and corresponding costs to find a robust solution. MHRA also addresses the following research gaps in the literature primarily in Yin (2008)'s work (details in section 2):

- Existing frameworks for designing robust signal plans depend on human judgement to achieve a proper balance between robustness and efficiency. This can lead to an inferior robust signal plan.
- There is room to improve the efficiency and complexity of existing frameworks.

MHRA can be implemented using any standard offline optimisation tool and simulation model.

The remainder of the paper is organised as: section 2 presents the literature review and discusses research gaps in detail. Section 3 introduces the proposed MHRA. Section 4 evaluates the proposed MHRA by comparing its performance with the traditional approach and other approaches in the literature. Conclusions and recommendations for further research are offered in section 5.

2. Literature review

This section discusses the approaches used in practice and literature to address two-dimensional traffic variation while designing a control plan. Firstly, methods for optimal TOD breakpoint determination – which is mainly useful to manage period to period traffic variation – are reviewed. Thereafter, approaches proposed in the literature to address the day to day demand variation and their limitations are discussed.

To effectively deal with period to period traffic variation, optimal TOD breakpoints are determined by using archived traffic data and heuristic statistical methods. For example, Smith et al. (2002) and Wang et al. (2005) used respectively, hierarchical clustering and K-means method to determined TOD breakpoints. These clustering techniques sometimes result in infeasible clusters (with few data points) because they do not consider the time variable. To address this limitation, researchers such as Guo and Zhang (2014) and Chen et al. (2019) developed an advanced clustering technique that considers the time of traffic occurring as a dimension. Furthermore, clustering methods need empirical adjustments like merging short periods into adjacent longer ones which can make the previous optimal number of clusters selection suboptimal (Song et al., 2018). Ma et al. (2018) formulated time series data partitioning problem to obtain homogeneous partitions that do not require empirical adjustments. A few researchers like Park et al. (2003); Park et al. (2004); Abbas and Sharma (2005) proposed to use Genetic Algorithm (GA) based optimisation with delay as a fitness function to determine TOD breakpoints instead of using a statistical technique like clustering.

Though several studies address the need for optimal TOD breakpoints to deal with period to period traffic variation, only a few studies address the need for robust signal timings under day to day flow variation. Yin (2008) investigated methods of signal optimisation for fixed time control under day to day demand variations and presented three models to determine robust optimal signal timings. These three models are briefly described below:

1) Scenario-based mean-variance optimisation (MSD approach)

MSD approach aims to minimise the weighted average of mean delay (D) and the standard deviation (SD) of the delay across various demand scenarios (refer to equation 1). The weights vary from zero (minimising the mean only) to one (minimising the SD only).

$$\min z = (1-\gamma) * D + \gamma * SD \quad (1)$$

Where γ is a weighting parameter, $0 \leq \gamma \leq 1$.

2) Scenario-based conditional value-at-risk minimisation (MCVAR approach)

This approach uses conditional value-at-risk (CVAR) as a measure for robustness. CVAR is defined as a loss or regret incurred by those high-consequence scenarios whose collective probability of occurrence is $1-\alpha$, where α is a specified confidence level (say, 90%). Refer to Rockafellar and Uryasev (2002); Yin (2008) for more details on the concept of CVAR. Firstly, for each demand scenario, the optimisation problem is solved to find minimum delay per vehicle with respect to that scenario. Subsequently, the loss or regret is defined for any timing plan that may not be optimal for a scenario. Finally, CVAR is minimised to obtain a robust signal plan.

3) Min-max optimisation (MNMX)

A min-max approach only needs some prior knowledge about traffic conditions such as minimum and maximum demand observations at an intersection. The objective function of the MNMX approach is to minimise the maximum delay per vehicle possibly incurred within the likelihood region. The critical point of the MNMX approach is uncertain traffic flows are assumed to be bounded by a likelihood region which is defined by the traffic engineers by using estimates of maximum and minimum likely flows for each lane group. The geometry of the flow likelihood region reflects preference or trade-off between efficiency and robustness.

Yin (2008) demonstrated that all the abovementioned approaches produce signal timings whose performance is less sensitive to traffic flows variations and perform better for worst-case scenarios. Many researchers have applied one of the three approaches to design robust solutions for different traffic control problems. Summary of such research studies is presented in Table 1. Besides designing signal timings, the robust optimisation methods (especially MNMX approach) are also widely analysed in bus priority control (Ibarra-Rojas et al., 2015; He et al., 2016) and network-level traffic control (Han et al., 2016; Ampountolas et al., 2017; Zhong et al., 2018).

Table 1: Summary of research studies that applied robust approaches to various traffic control problems

Study	The problem addressed or application of a robust approach	The approach adopted to find a robust solution
Zhang and Yin (2008)	Proposed robust coordination of actuated signals on arterials to address the issue of uncertain starts and ends of coordinated, green phases.	MCVAR
Zhang et al. (2010)	Developed a model for optimising cycle length, green splits, phase sequences, and offsets in an integrated manner for pre-timed signals along urban arterials.	MCVAR
Ukkusuri et al. (2010)	Proposed a robust signal control strategy where future demand is assumed to be uncertain. The primary source of uncertainty in the model is represented in the O–D demand.	MSD
Li (2011)	Pointed out the difficulties working with nonlinear programming methods and reaching global optimum under traffic flow uncertainty. Proposed a discretisation modelling approach, where the cycle, green time, and traffic volume are divided into a finite number of discrete values.	MNMX
Tettamanti et al. (2014)	Designed a robust signal split for the proactive online system. The uncertainty in traffic demand is considered by introducing an arbitrary, unknown but bounded uncertainty vector over the future prediction horizon.	MNMX
Liu et al. (2015)	Proposed a two-stage, online signal control strategy for dynamic networks using a linear decision rule (LDR) approach and a robust distributional optimisation (DRO) technique where the signal plan is optimised for worst-case demand scenario.	MNMX
Hao et al. (2018)	Proposed to use Tabu search-artificial bee colony algorithm to solve the signal optimisation problem.	MSD
Chen et al. (2020)	The robust signal approach has been used to plan signal timings for an intersection that has tidal flow lanes. The concept of tidal flow lanes, also known as exit lanes for left-turning (EFL) is recently introduced to improve throughput at an intersection.	MSD

Studies presented in Table 1 analyse the performance of resulting robust signal timings using the mean of delays for various demand scenarios (efficiency) but do not evaluate the impact of robust signal timings on the delay for individual demand (robustness). Moreover, the three approaches, i.e. MDS, MCVAR, and MNMX have the following limitations:

- MSD approach is sensitive to the choice of weighing parameter for two measures, namely, mean and SD. Depending on the variability among the input demand scenarios, one of the measures can dominate the solution and thus will not result in a fair, robust solution.

- MCVAR approach needs additional step, i.e. optimising a delay for individual demand scenario before solving a model for the robust signal plan. This leads to higher computation time and complexities when a number of demand scenarios are high.
- Performance of MNMX approach is sensitive to the geometry of the flow likelihood region, which depends on the judgment of traffic engineer and choice of likelihood region affects the optimality and robustness of the resultant timing plan. It can result in an overly conservative signal plan if extreme demands are used to define the likelihood region.

Hence, a simpler and more efficient approach called MHRA is developed in this paper to design robust signal plans for fixed time signals.

3. Metaheuristic Robust signal plan Approach (MHRA)

The objective of the proposed MHRA is to identify the signal plan that is robust to different demand profiles in the given TOD interval. The TOD intervals can be obtained using any standard process, as discussed in section 2. The MHRA uses a scenario-based approach. Hence, the input for the framework is a discrete number of historical demand scenarios observed in the given TOD interval. Here, the demand scenario is defined in terms of traffic flow rate observed at the entry point of all external links of an arterial corridor/ study area.

Say we have a set of demand scenarios $[TD] = \{TD_1, TD_2..TD_K\}$ and respective optimal signal plans [S]= $\{S_1, S_2..S_K\}$, where S_k is the optimal signal plan for the corresponding demand TD_k. The optimal signal plan, S_k may include cycle length (C) phase sequence (PS), phase durations (G) and offset (O) for each intersection along the study corridor. In MHRA, we propose to simulate each demand scenario from [TD] using a signal plan from [S] and generate a K x K estimated delay matrix (D) (see Figure 1). The columns in Figure 1 represent various demands from the set $[TD]$ and rows represent different signal plans from the set [S]. Here, the values of the cell D(j,k) represents the delay estimated by simulating demand TD_k from $[TD]$ using signal timing S_j from [S]. Here, the diagonal values are the delay for a demand TD_k using its optimal signal S_j.

The last column (Figure 1) represents the total delay for each signal plan, $TotalD(k)$. It is obtained by adding the delay values across the row i.e. $\sum_{k=1}^{K} D\ (j,\ k)$. The signal plan that gives the minimum value of $TotalD$ is selected as the robust signal plan for a given set of demands. The signal plan corresponding to minimum $TotalD$ gives either lower delay for the demand scenario compared to the delay obtained from other signal plans or slightly higher delay than its optimum delay value. However, overall it performs better for all the demand scenarios as compared to other signal plans.

S_j \ TD_k	TD_1	TD_2	....	TD_K	$TotalD(j) = \sum_{k=1}^{K} D\ (j,k)$
S_1	$D(1,1)$	$D(I,2)$	....	$D(1,I)$	$TotalD(1)$
S_2	$D(2,1)$	$D(2,2)$	....	$D(2,I)$	$TotalD(2)$
:	:	:	:	:	:
S_K	$D(I,1)$	$D(I,2)$	....	$D(K,K)$	$TotalD(K)$

Figure 1: Illustration of the MHRA delay matrix to obtain a robust signal plan

Figure 2 summarises the MHRA, which involves two major parts. In the first part (left side of Figure 2), the signal optimisation problem is solved for each demand scenario from $[TD]$ with a step presented by dotted box in Figure 2. To define and solve this problem, user can use any standard formulation such as minimisation of delay or queue length or their combination and tool such as SIDRA, TRANSYT-7f and MAXBAND. Decision variables can include all or selective signal parameters (cycle length, phase sequence, phase times and offsets). This first step will generate an optimal signal plan, S_k for each traffic demand scenario creating a set of signal plans [S]. The second part (right side of Figure 2) of the framework involves simulating each demand scenario using multiple signal plans generated in previous steps and recording the delay value for each simulation. For simulation at this step, i.e. a step shown by the dashed box in Figure 2, user can use the same model used for performance evaluation in step one.

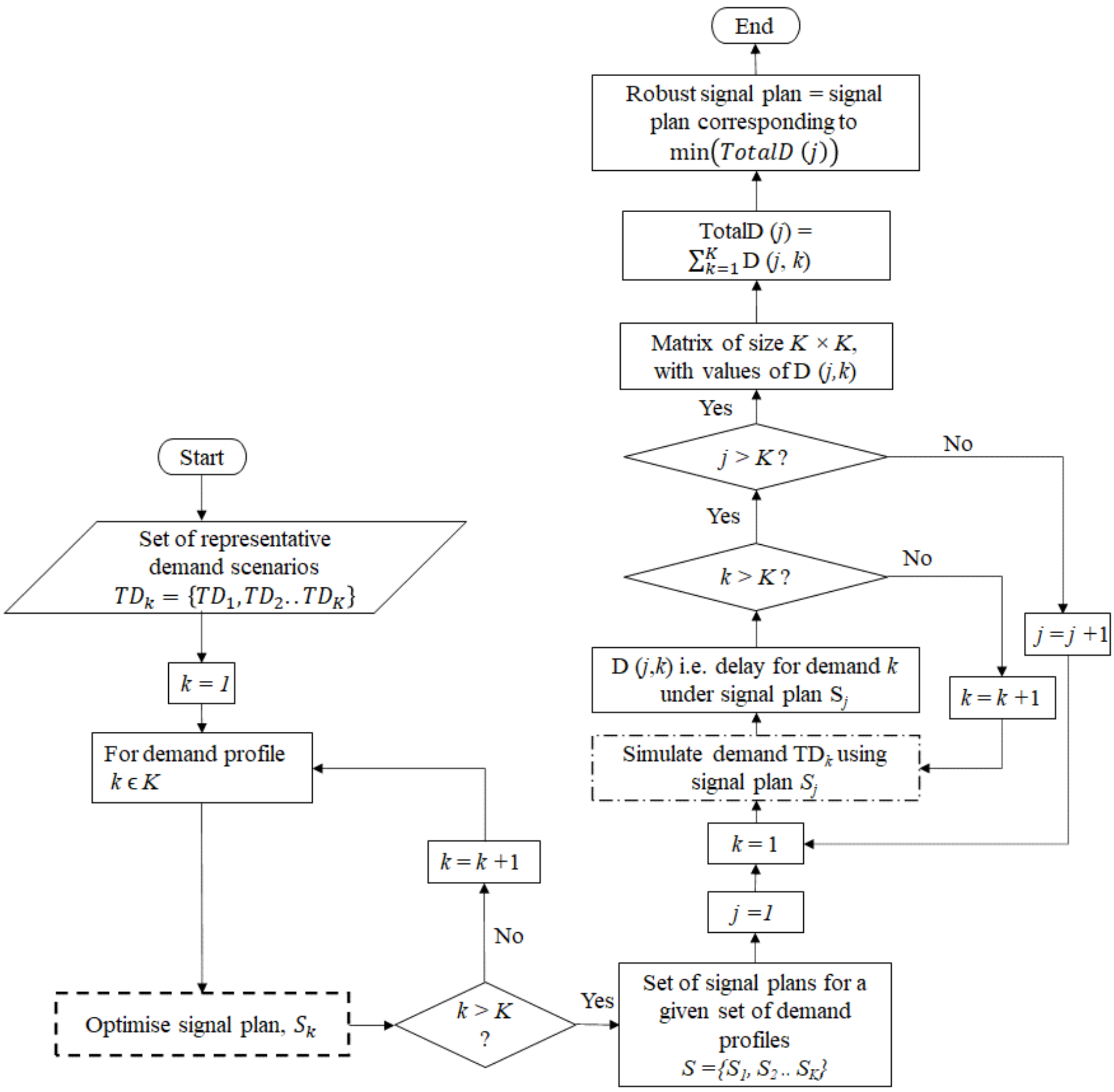

Figure 2: MHRA for robust signal plan design

4. Evaluation of MHRA

This section presents the experiment and its outcome designed to compare the performance of the robust signal plans obtained from the MHRA with a nominal signal plan designed using average traffic demand (refer to section 4.2). Also, the performance of MHRA is compared with other scenario-based approaches of robust signal timings design, i.e. MSD and MCVAR (refer to section 4.3). MNMX approach is not scenario-based and addresses uncertainty in traffic flow by using only maximum and minimum likely flows. Hence, for a fair comparison, MNMX is not included.

4.1 Experiment inputs

One of the major arterial corridors along Gympie Road in Brisbane, Queensland, is modelled for this experiment. The configuration of the corridor consisting of four major intersections is shown in Figure 3. Traffic demand is collected during the morning peak, i.e. 7:00 to 8:00 AM using stop line loop detectors installed on each link of the corridor. Observed demand is in terms of a number of vehicles travelling in each direction at each approach of an intersection. The demand is observed for all working days of September 2018. Figure 4 shows the average observed demands per hour per day along with the corresponding SD in the bracket.

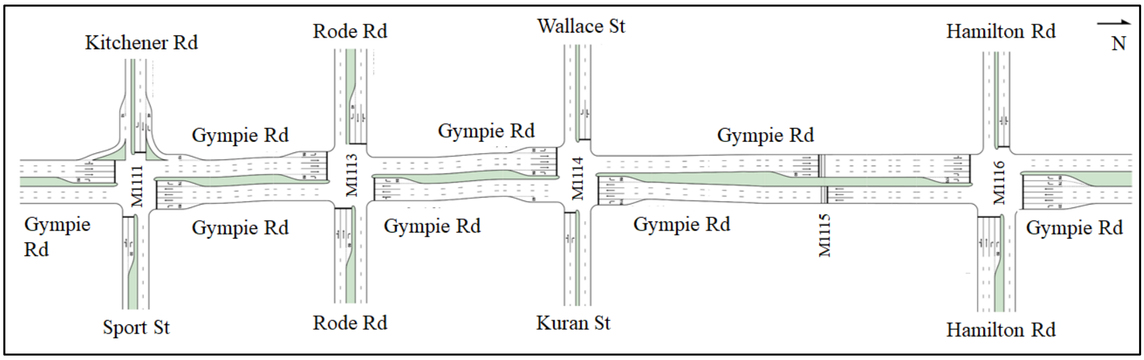

Figure 3: Configuration of arterial corridor used to evaluate the proposed MHRA

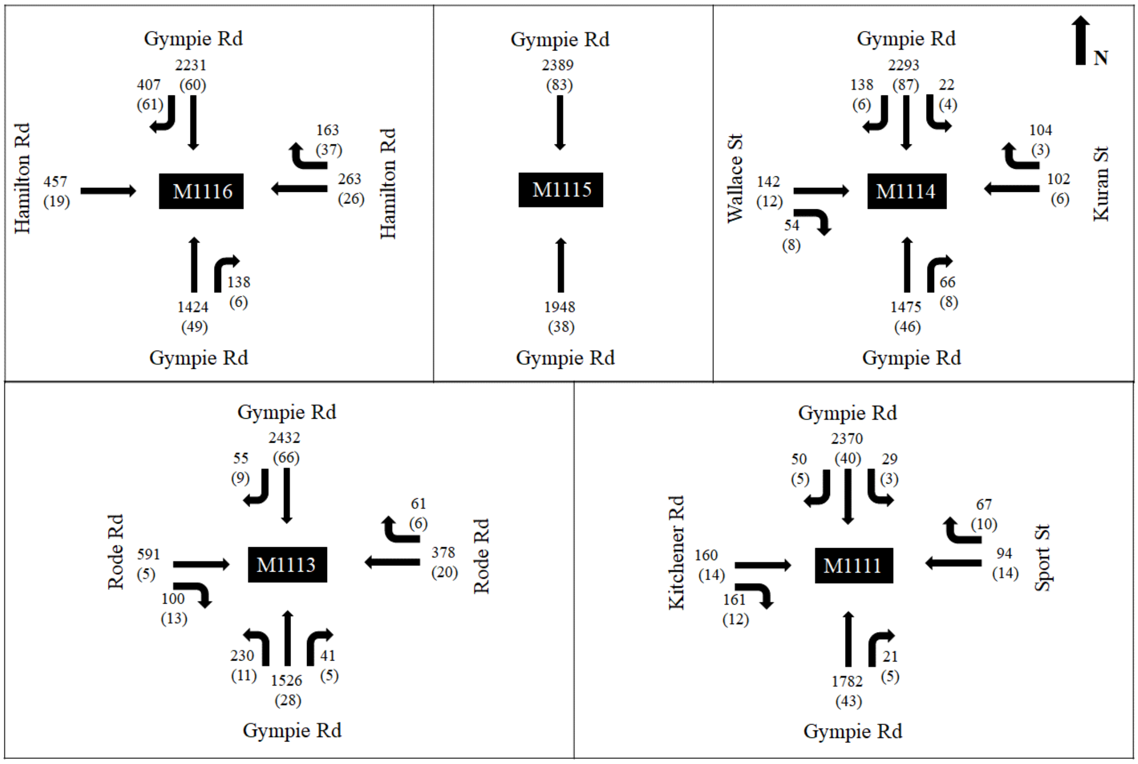

Figure 4: Mean traffic demand in vehicles/hr and standard deviation (values in brackets) on arterial traffic corridor

For scenario-based designing methods, i.e. MHRA, MSD and MCVAR, 15 demand scenarios are randomly generated using the mean demand and SD shown in Figure 4 to represent day to day variability in observed traffic demand. Each demand scenario consists of vehicles per hour travelling in each direction at each approach of each intersection. The occurrence probability of each demand scenario is not considered for this experiment because each demand scenario is treated uniquely. Hence, the total delay will not be calculated with expectation. Out of these 15 demand scenarios, five are used for designing signal plans, and remaining scenarios are used to validate the robustness of those signal plans. Day to day variability in 15 demand scenarios – calculated as (SD in demand/mean demand) × 100 – was found to be 10%. The detailed discussion on sample size to follow in section 4.4.

For the experiment, a signal plan that needs to be optimised is defined as a set of phase durations (G_k) and offsets (O_k) for each intersection. Note that, for intersection

M1115, i.e. pedestrian crossing, phase durations were not optimised because simulating pedestrian demand is not in the scope of this research. Instead, those phase durations are predetermined using field observations and kept constant for all designing methods. The offset is used to coordinate phases serving SB through movement along Gympie road because SB through traffic flow was observed to be critical. The cycle length and phase sequence implemented in practice are used for this experiment. Cycle length was observed to be 120 sec for all intersections from 7:00 to 8:00 AM, and the observed phase sequence is shown in Figure 5. Here, solid arrow and dotted arrow represent vehicular movement and pedestrian movement, respectively.

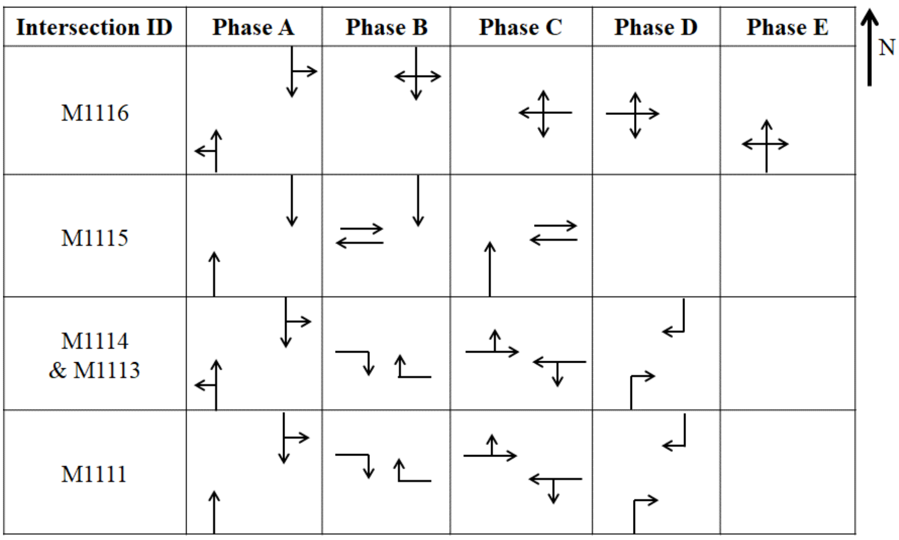

Figure 5: Sample phase sequence

Decision variables and tools used for experiments in section 4.2 and 4.3 are summarised in Table 2. The simulation and optimisation tool selection process is discussed in corresponding sections.

Table 2: Summary of decision variables and tools used for experiments

Experiment in	**Model to estimate the delay**	**Optimisation tool**	**Decision variables**	**Predetermined variables**
Section 4.2	SIDRA	SIDRA	Phase times and offset	Cycle length and phase sequence
Section 4.3	ACTM	Genetic Algorithm (GA)		

4.2 Robust plan Vs Nominal plan

To compare MHRA with a standard design approach i.e. signal plan designed for average traffic demand, the performance of signal plan obtained from MHRA is compared with SIDRA, which is widely used and well-accepted industry standard for offline signal optimisation. For this comparison, the arterial corridor shown in Figure 3 is modelled in SIDRA. The mean demand shown in Figure 4 is directly used as an input to generate a signal plan using SIDRA. For a fair comparison, SIDRA is also used for MHRA application as the tool to complete steps shown by the dotted box and the dash-dotted box in Figure 2. Using SIDRA to implement MHRA also demonstrates that any standard offline signal optimisation tool can be used to implement the MHRA. Here, SIDRA can be replaced by a standard tool such as TRANSYT-7f or MAXBAND.

The phase timings obtained from SIDRA and MHRA are presented in Figure 6. All the values are expressed in seconds. The offset values were the same for SIDRA and MHRA solution because SIDRA evaluates offset as the time required to cover the distance between consecutive intersection in free-flow condition. However, the phase durations obtained from SIDRA and MHRA are different.

To evaluate the performance of these signal plans, ten demand scenarios kept aside for validation are simulated in SIDRA software using the optimised SIDRA and MHRA signal plans. Corresponding total delay for each demand scenario is estimated from SIDRA simulation. Mean (SD) of total delays from all ten demand scenarios was 398 veh-hr (SD = 139) and 369 veh-hr (SD =104), for SIDRA and MHRA, respectively. The proposed MHRA gives a signal plan that results in a 7% lower delay as compared to the signal plan obtained from the traditional approach represented by the SIDRA signal plan here. The results of the t-test at 95% confidence level show that total delay values from SIDRA method are significantly different from total delay values from MHRA.

These results are consistent with Yin (2008); Zhang et al. (2010) who also found that the robust plans outperform the corresponding traditional nominal plan designed using average demand. Similar results are expected when SIDRA is replaced by TRANSYT-7f or MAXBAND in the above experiment.

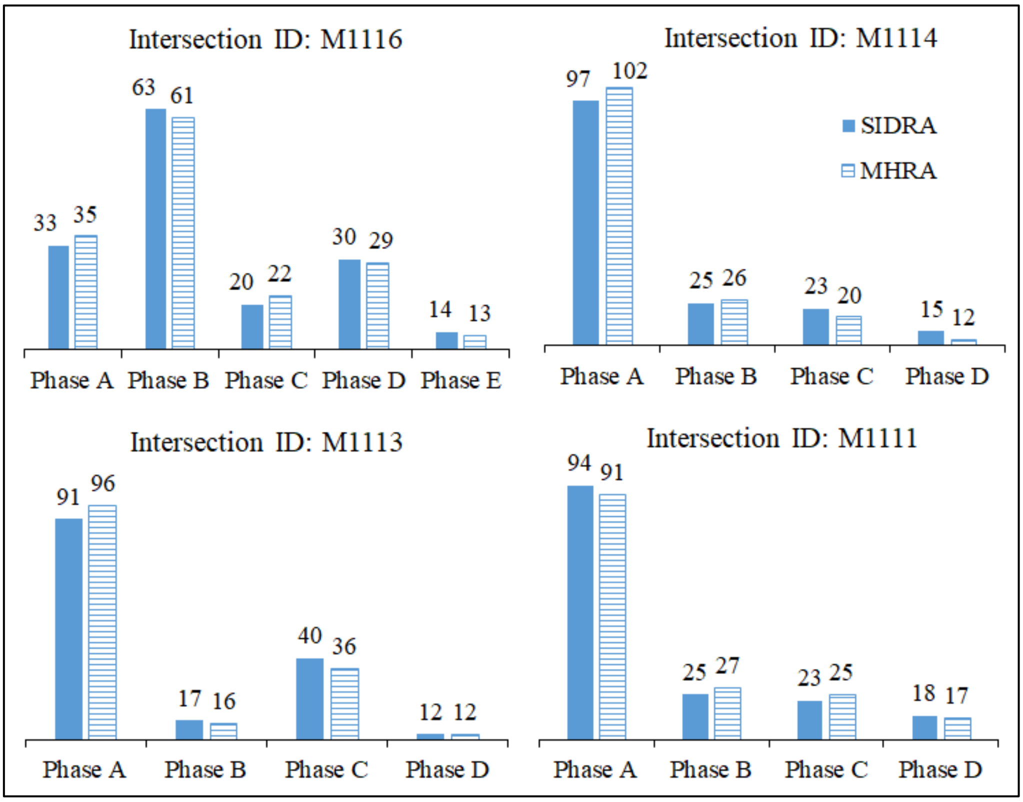

Figure 6: Phase timings from SIDRA and MHRA (values are in seconds)

4.3 Comparison of MHRA with MSD and MCVAR

Signal plans are designed using MHRA, MSD and MCVAR approach for the demand and corridor presented in section 4.1 to compare their performances.

4.3.1 Optimisation and simulation tools

The standard signal designing tool such as SIDRA, TRANSYT-7F etc. cannot be used for MSD and MCVAR approaches due to the inherent differences in their optimisation objectives. Thus, MSD and MCVAR approaches are implemented using the Genetic Algorithm (GA) shown in Figure 7. For a fair comparison, we use GA in MHRA as well to obtain an optimal signal plan for a given demand scenario (i.e. step presented by dotted box in Figure 2).

MCVAR and MSD approaches minimise fitness functions, namely, 'CVAR' and 'sum of mean delay and SD'. Refer to Yin (2008) for the detailed formation of these fitness functions. MHRA minimises the total delay for each demand in the given set of scenarios. Fitness functions are calculated using Arterial Cell Transmission Model (ACTM) proposed by Shirke et al. (2019) that can model arterial traffic dynamics such as shockwave, queue formation and dissipation close to reality. GA with Cell Transmission Model-based traffic simulation has been widely used for signal optimisation (Lo, 2001; Zhang et al., 2010).

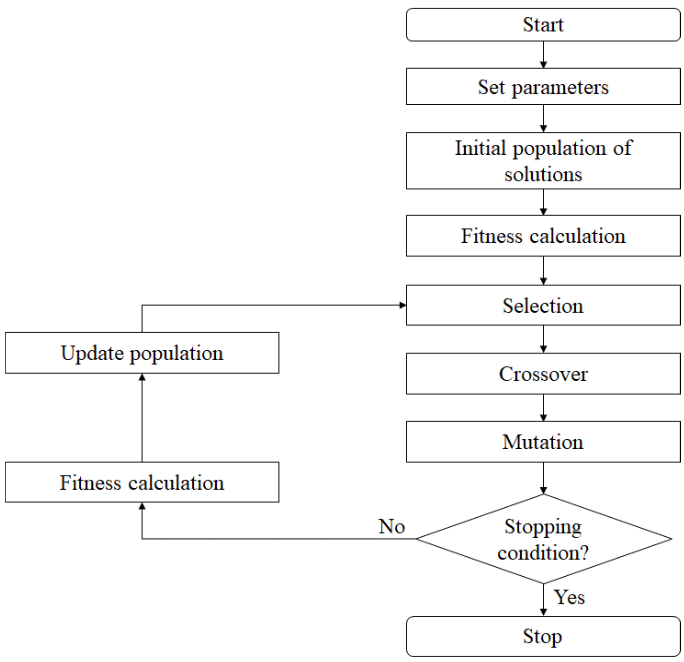

Figure 7: Genetic algorithm

As mentioned in section 4.1, cycle length and phase sequence are predetermined. Also, for intersection M1115, i.e. pedestrian crossing, phase durations were not optimised because simulating pedestrian demand is not in the scope of this research. Instead, those phase durations are predetermined using field observations and kept constant for all designing methods. For other intersections, optimised phase durations are obtained from all approaches, i.e. MSD, MCVAR and MHRA. For all approaches, the offset is calculated by subtraction the queue discharging time from free-flow travel time between two consecutive intersections. For each approach, the average queue length is obtained from the ACTM simulation using optimal phase durations.

4.3.2 Results

The signal plans consisting of phase durations and offset at each intersection obtained from MSD, MCVAR and MHRA are presented in Figure 8. All the values are expressed in seconds. As all the methods of obtaining signal plans compared in this experiment are different in terms of their objective functions, the resulting signal plans are also significantly different. This can be confirmed from the signal plans presented in Figure 8. To evaluate the performance of signal plans, ten demand scenarios that were not used in the designing process are simulated using these signal plans in ACTM, and the corresponding total delay for each demand scenario is estimated. The total delay under the signal plan generated by MSD (solid line with a triangle), MCVAR (dashed line with a cross) and MHRA (dotted line with circles) for ten demand scenarios are plotted in Figure 9. The total delay expressed in veh-hr is plotted on y-axis for demand scenario shown on the x-axis.

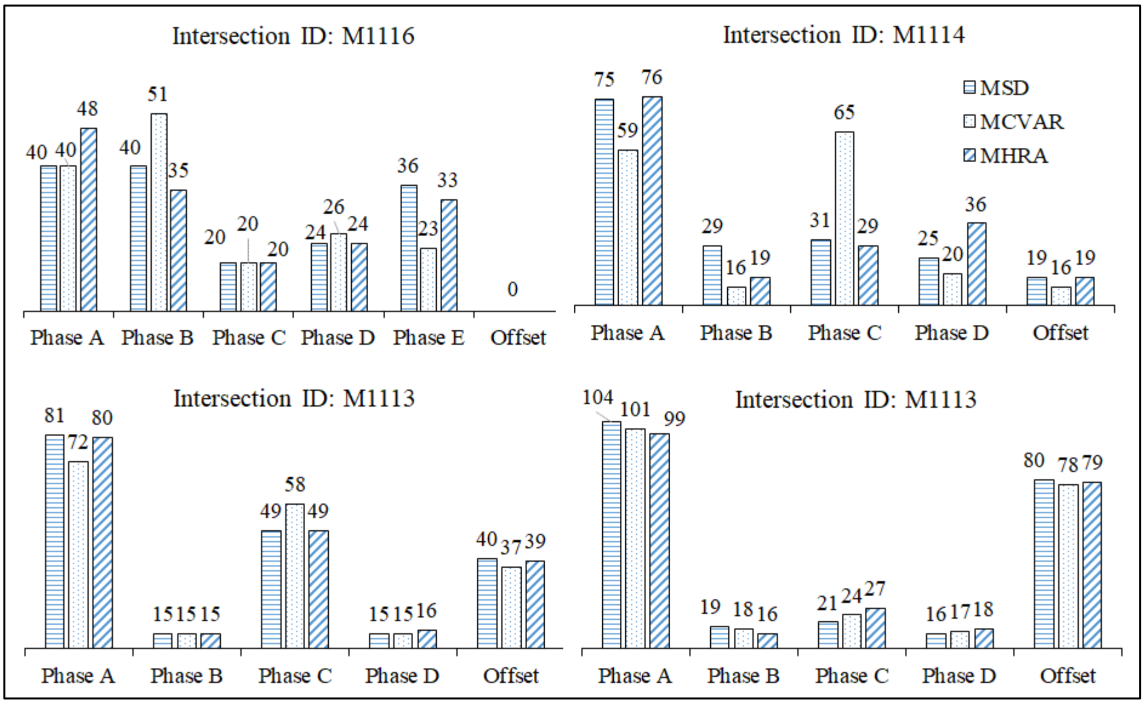

Figure 8: Signal plans from different designing methods (values are in seconds)

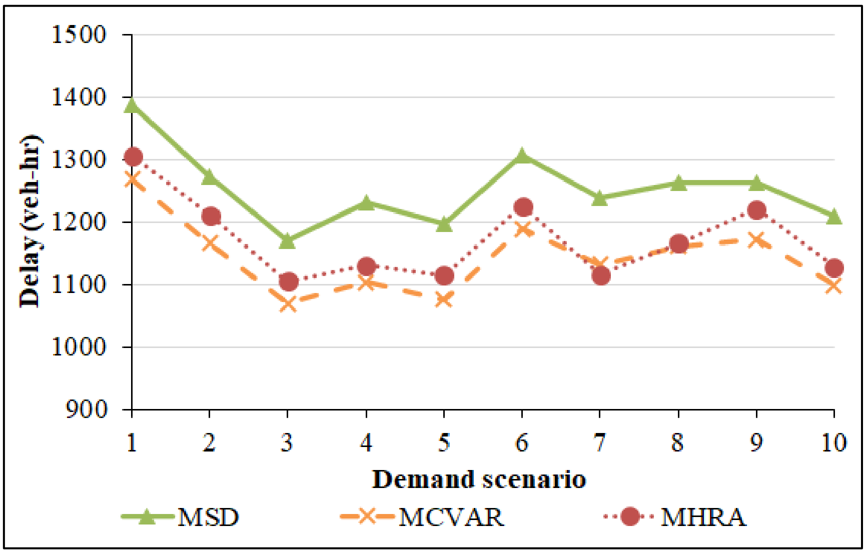

Figure 9: Evaluation of signal plans obtained from different methods

Mean (SD) of total delays from all 10 demand scenarios was found to be 1254 veh-hr (SD = 62), 1143 veh-hr (SD = 61), and 1172 veh-hr (SD = 63) for MSD, MCVAR and MHRA, respectively. The method proposed in this research to design a robust signal plan i.e. MHRA gives a signal plan that results in a 3% lower delay as compared to the signal plan obtained from the MSD approach. The results of the t-test at a 95% confidence level show that total delay values from MSD approach are significantly different than the total delay values from MHRA. On the other hand, there is no significant difference in total delay values from MCVAR and MHRA. However, the computation time of the MHRA method is half that of the MCVAR because MCVAR needs to perform optimisation twice, first for obtaining optimum delays for each of the demand scenarios and then to minimise the CVAR.

Thus, it can be concluded that the MHRA proposed in this research is either more effective and/or more efficient as compared to other approaches available in the literature for obtaining robust signal plans such as MSD and MCVAR.

4.4 Discussion on the selection of sample demand scenarios

All three approaches, i.e. MHRA, MCVAR, and MSD, use demand scenarios, i.e. one possible set of realisations of the varying traffic flows to come up with a robust solution. Yin (2008) confirmed that a relatively small number of scenarios would be able to produce near-optimal policies. Furthermore, though Yin (2008) suggested that sampling can be applied to generate the representative scenarios if the distributions are known, one question remains unanswered, i.e. will random sampling affect the resulting robust solution?

To answer this question, we designed five different robust signal plans using MHRA. For designing each signal plan, randomly five demand scenarios were generated using mean demand and SD shown in Figure 4. Thereafter, the performance of each of these signal plans is compared with each other by simulating ten demand scenarios that were used for evaluation in section 4.3.2. The ACTM was used for simulation. Figure 10 depicts the total delay estimated for each demand scenario under five different robust signal plans designed using MHRA.

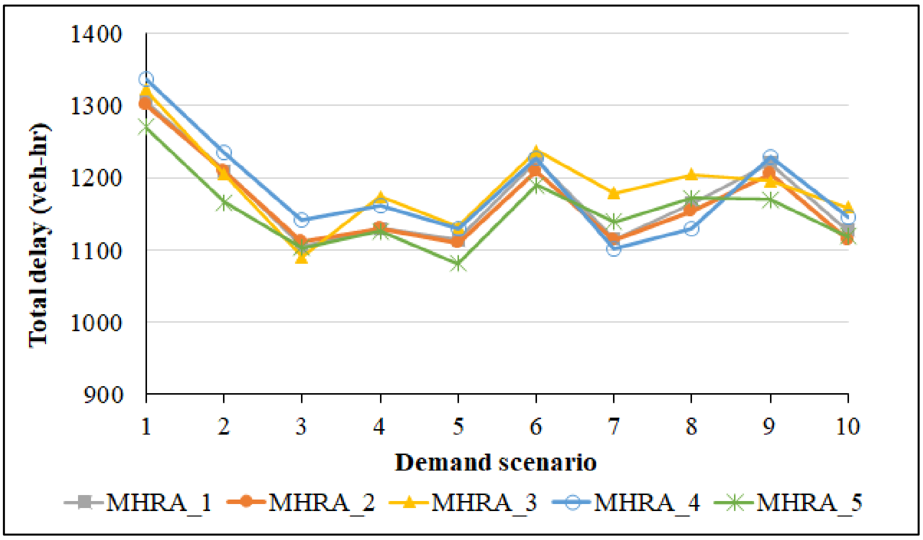

Figure 10: Sensitivity of a robust solution to sampling

As seen in Figure 10, the total delay values obtained from five different robust signal plans are not significantly different, which is also confirmed by performing a statistical t-test at the 95% confidence level. Thus, it can be concluded that a random selection of sample demand scenarios does not affect the performance of a robust solution. The above results also confirm that the sample size of five demand scenarios was enough for this experiment. We would have required larger sample size if variation in delay values shown in Figure 10 was significant.

4.5 Sensitivity analysis

The more scenarios we include, the more robust solution we are likely to obtain; however, it will also increase computation time. This has also been acknowledged in the previous research studies (Mulvey et al., 1995; Laguna, 1998; Yin, 2008) that used a scenario-based approach. Based on computation experiments, these studies have also shown that a relatively small number of scenarios will be able to produce near-optimal policies. For real-world applications, these studies suggest selecting 20–200 flow scenarios from the field data for the same time-of-day interval.

To support the abovementioned discussion, sensitivity analysis on the number of demand scenarios and the trade-off between performance and computation time was performed. We compared robust signal plans generated from MHRA using 5, 10, 15 and 20 demand scenarios. These demand scenarios were randomly generated using mean demand and SD shown in Figure 4. The resulting signal plans were used to simulate five demand scenarios other than those used for signal plan generation. The average delay for those five demand scenarios under robust signal plans obtained from 5,10,15 and 20 demand scenarios are shown in Figure 11 (refer to line with dots). Figure 11 also shows a computation time for signal plans (refer to line with triangles) where 'X' represents computation time for the robust signal plan generated using five demand scenarios. With the increase in the number of demand scenarios, the performance of resulting signal plans did not improve. However, the computation time increased linearly (i.e. computation time = five × number of demand scenarios used to develop robust solution). Hence, for the experiment presented in this section, we concluded that five demand scenarios were sufficient.

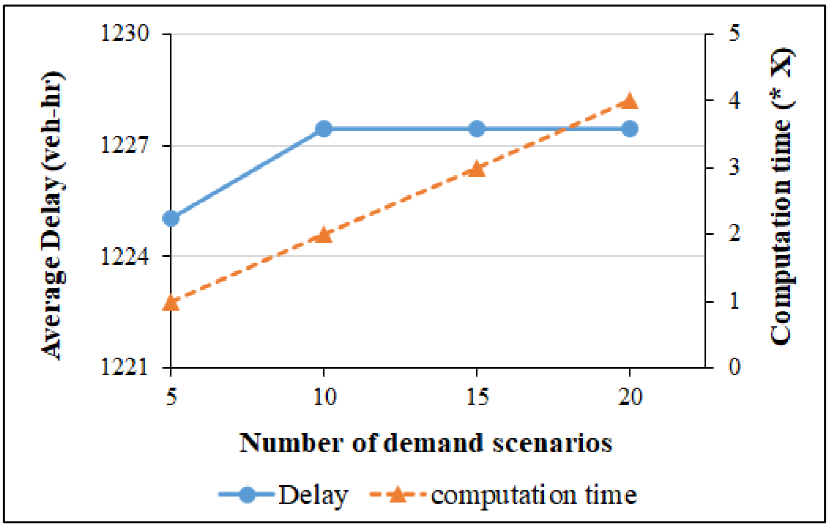

Figure 11: Sensitivity to the number of demand scenarios and computation time

5. Concluding remarks and future research

The performance of a signal plan fluctuates with day to day variation in traffic demand. Therefore, it is of utmost importance to determine robust signal timings that can address such variations. To this end, this paper presents an offline scenario-based framework called *MetaHeuristic Robust plan Approach* (MHRA) for the design of a robust signal plan that is less sensitive to two-dimensional demand variations. Numerical experiments confirm that proposed MHRA maintains better and more stable performance than the traditional approach that uses mean demand (e.g. SIDRA) because MHRA results in lower delays as well as the lower standard deviation in delays under various traffic demands. Additionally, when compared to scenarios-based methods available in the literature, i.e. mean-variance optimisation (MSD) and conditional value-at-risk minimisation (MCVAR), MHRA can generate an effective (lower delay values) and efficient (lesser computation time) robust signal plan, respectively.

We acknowledge that any scenario-based approach will have higher computation time as compared to the signal design method based on single (i.e. average or 85th percentile etc.) demand profile. However, studies such as Zhang and Yin (2008); Zhang et al. (2010) have demonstrated the applicability of scenario-based MCVAR approach – that has higher computation time than MHRA – to an arterial corridor and grid network. Experiments performed in this paper also show the applicability of MHRA to an arterial corridor. Hence, it is safe to say that the proposed MHRA method could be applied to large scale problems subjected to the trade-off between performance and computation time.

MHRA is flexible in choosing the simulation tools to estimate delay or other objective function, and signal decision variables to optimise. Thus, it can be implemented using standard offline optimisation tools such as SIDRA, TRANSYT-7f, MAXBAND etc. This paper demonstrates the use of SIDRA for implementing MHRA. Similarly, the research can be extended to include other tools and benchmarking of different approaches should be performed.

Furthermore, this research uses a GA for the optimisation process without evaluating the suitability of any other optimisation algorithm. Thus, for future research, the applicability of new algorithms such as Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm (Spall & Chin, 1994; Spall & Chin, 1997), Particle Swam Algorithm (PSA) (Chen & Xu, 2006) should be explored to enhance its efficiency of the proposed robust signal designing framework.

Though in this research the MHRA is verified to design robust signal plans only for an offline, fixed time signal control, the performance of reactive and proactive real-time signal control systems is also expected to improve by introducing such robust signal plan approach as below:

- Real-time reactive systems such as SCATS (Gross, 2000), SCOOT (Hunt et al., 1981) etc. observe changes in traffic conditions for a few cycles and then take actions to manage these changed traffic conditions. The traffic state observed in a cycle is, however, subjected to change in the next cycle and such variations need to be considered through MHRA for planning effective reactive control actions. For example, Tong et al. (2015); Li et al. (2018) proposed a stochastic programming approach to consider the uncertainties in traffic demand while scheduling real-time traffic signals.
- Conversely, proactive real-time systems such as OPAC (Pooran & Farradyne, 2000), UTOPIA (Stevanovic, 2010) etc., need predictions of traffic states to select a suitable control plan. However, any prediction error can deteriorate the performance of traffic control (Pohlmann & Friedrich, 2010). To minimise the

prediction error, uncertainties (e.g. SD) in demand can be predicted instead of predicting a single (e.g. mean) value. Based on mean and SD various demand scenarios can be defined, and using MHRA, robust signal plan can be designed, which minimises the cost associated with these different demand scenarios.

Thus, in the future, the applicability of MHRA should be explored to consider traffic demand variation in real-time control systems and enhance their performance.

References

Abbas, M. M., & Sharma, A. (2005). Optimization of time of day plan scheduling using a multi-objective evolutionary algorithm. *Civil Engineering Faculty Publications*, 20.

Akcelik, Associates, & ltd., p. (1984). SIDRA INTERSECTION. Retrieved from http://www.sidrasolutions.com

Ampountolas, K., Zheng, N., & Geroliminis, N. (2017). Macroscopic modelling and robust control of bi-modal multi-region urban road networks. *Transportation Research Part B: Methodological, 104*, 616-637. doi:https://doi.org/10.1016/j.trb.2017.05.007

Chen, J., & Xu, L. (2006, 5-8 Dec. 2006). *Road-Junction Traffic Signal Timing Optimization by an adaptive Particle Swarm Algorithm.* Paper presented at the 2006 9th International Conference on Control, Automation, Robotics and Vision.

Chen, K., Zhao, J., Knoop, V. L., & Gao, X. (2020). Robust Signal Control of Exit Lanes for Left-Turn Intersections With the Consideration of Traffic Fluctuation. *IEEE Access, 8*, 42071-42081. doi:10.1109/ACCESS.2020.2977134

Chen, P., Zheng, N., Sun, W., & Wang, Y. (2019). Fine-tuning time-of-day partitions for signal timing plan development: revisiting clustering approaches. *Transportmetrica A: Transport Science, 15*(2), 1195-1213. doi:10.1080/23249935.2019.1571536

Gross, N. R. (2000). *SCATS adaptive traffic system.* Paper presented at the TRB Adaptive Traffic Control Workshop.

Guo, R., & Zhang, Y. (2014). Identifying Time-of-Day Breakpoints Based on Nonintrusive Data Collection Platforms. *Journal of Intelligent Transportation Systems, 18*(2), 164-174. doi:10.1080/15472450.2013.802151

Han, K., Liu, H., Gayah, V. V., Friesz, T. L., & Yao, T. (2016). A robust optimization approach for dynamic traffic signal control with emission considerations. *Transportation Research Part C: Emerging Technologies, 70*, 3-26. doi:https://doi.org/10.1016/j.trc.2015.04.001

Hao, W., Ma, C., Moghimi, B., Fan, Y., & Gao, Z. (2018). Robust Optimization of Signal Control Parameters for Unsaturated Intersection Based on Tabu Search-Artificial Bee Colony Algorithm. *IEEE Access, 6*, 32015-32022. doi:10.1109/ACCESS.2018.2845673

He, H., Guler, S. I., & Menendez, M. (2016). Adaptive control algorithm to provide bus priority with a pre-signal. *Transportation Research Part C: Emerging Technologies, 64*, 28-44. doi:https://doi.org/10.1016/j.trc.2016.01.009
Hellinga, B., & Abdy, Z. (2008). Signalized intersection analysis and design: implications of day-to-day variability in peak-hour volumes on delay. *Journal of Transportation Engineering, 134*(7), 307-318.
Heydecker, B. (1987). Uncertainty and variability in traffic signal calculations. *Transportation Research Part B: Methodological, 21*(1), 79-85.
Hunt, P., Robertson, D., Bretherton, R., & Winton, R. (1981). *SCOOT-a traffic responsive method of coordinating signals* (LR 1014 Monograph).
Ibarra-Rojas, O. J., Delgado, F., Giesen, R., & Muñoz, J. C. (2015). Planning, operation, and control of bus transport systems: A literature review. *Transportation Research Part B: Methodological, 77*, 38-75. doi:https://doi.org/10.1016/j.trb.2015.03.002
Kieu, L.-M., Bhaskar, A., & Chung, E. (2015). Public Transport Travel-Time Variability Definitions and Monitoring. *Journal of Transportation Engineering, 141*(1), 04014068. doi:10.1061/(ASCE)TE.1943-5436.0000724
Laguna, M. (1998). Applying Robust Optimization to Capacity Expansion of One Location in Telecommunications with Demand Uncertainty. *Management Science, 44*(11-part-2), S101-S110. doi:10.1287/mnsc.44.11.S101
Li, J.-Q. (2011). Discretization modeling, integer programming formulations and dynamic programming algorithms for robust traffic signal timing. *Transportation Research Part C: Emerging Technologies, 19*(4), 708-719. doi:https://doi.org/10.1016/j.trc.2010.12.009
Li, L., Huang, W., & Lo, H. K. (2018). Adaptive coordinated traffic control for stochastic demand. *Transportation Research Part C: Emerging Technologies, 88*, 31-51. doi:https://doi.org/10.1016/j.trc.2018.01.007
Lin, W.-H., Lo, H. K., & Xiao, L. (2011). A quasi-dynamic robust control scheme for signalized intersections. *Journal of Intelligent Transportation Systems, 15*(4), 223-233.
Liu, H., Han, K., Gayah, V. V., Friesz, T. L., & Yao, T. (2015). Data-driven linear decision rule approach for distributionally robust optimization of on-line signal control. *Transportation Research Part C: Emerging Technologies, 59*, 260-277.
Lo, H. K. (2001). A cell-based traffic control formulation: strategies and benefits of dynamic timing plans. *Transportation Science, 35*(2), 148-164.
Ma, D., Li, W., Song, X., Wang, Y., & Zhang, W. (2018). Time-of-day breakpoints optimisation through recursive time series partitioning. *IET Intelligent Transport Systems, 13*(4), 683-692.
Mulvey, J. M., Vanderbei, R. J., & Zenios, S. A. (1995). Robust Optimization of Large-Scale Systems. *Operations research, 43*(2), 264-281. doi:10.1287/opre.43.2.264
Park, B., & Kamarajugadda, A. (2007). Development and Evaluation of a Stochastic Traffic Signal Optimization Method. *International Journal of Sustainable Transportation, 1*(3), 193-207. doi:10.1080/15568310600737568
Park, B., Lee, D.-H., & Yun, I. (2003, 8-8 Oct. 2003). *Enhancement of time of day based traffic signal control.* Paper presented at the SMC'03 Conference Proceedings. 2003 IEEE International Conference on Systems, Man and Cybernetics. Conference Theme - System Security and Assurance (Cat. No.03CH37483).

Park, B., Santra, P., Yun, I., & Lee, D.-H. (2004). Optimization of Time-of-Day Breakpoints for Better Traffic Signal Control. *Transportation Research Record, 1867*(1), 217-223. doi:10.3141/1867-25
Pohlmann, T., & Friedrich, B. (2010). *Online control of signalized networks using the cell transmission model.* Paper presented at the Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on.
Pooran, F., & Farradyne, P. (2000). *Optimized Policies for Adaptive Control (OPAC).* Paper presented at the Workshop on Adaptive Traffic Signal Control Systems, 79th Annual Meeting of the Transportation Research Board, Washington, DC.
Rockafellar, R. T., & Uryasev, S. (2002). Conditional value-at-risk for general loss distributions. *Journal of Banking & Finance, 26*(7), 1443-1471. doi:https://doi.org/10.1016/S0378-4266(02)00271-6
Shirke, C., Bhaskar, A., & Chung, E. (2019). Macroscopic modelling of arterial traffic: An extension to the cell transmission model. *Transportation Research Part C: Emerging Technologies, 105*, 54-80. doi:https://doi.org/10.1016/j.trc.2019.05.033
Smith, B. L., Scherer, W. T., Hauser, T. A., & Park, B. B. (2002). Data–Driven Methodology for Signal Timing Plan Development: A Computational Approach. *Computer-Aided Civil and Infrastructure Engineering, 17*(6), 387-395. doi:10.1111/1467-8667.00285
Song, X., Li, W., Ma, D., Wu, Y., & Ji, D. (2018). An Enhanced Clustering-Based Method for Determining Time-of-Day Breakpoints Through Process Optimization. *IEEE Access, 6*, 29241-29253. doi:10.1109/ACCESS.2018.2843564
Spall, J. C., & Chin, D. C. (1994, 14-16 Dec. 1994). *A model-free approach to optimal signal light timing for system-wide traffic control.* Paper presented at the Proceedings of 1994 33rd IEEE Conference on Decision and Control.
Spall, J. C., & Chin, D. C. (1997). Traffic-responsive signal timing for system-wide traffic control. *Transportation Research Part C: Emerging Technologies, 5*(3), 153-163. doi:https://doi.org/10.1016/S0968-090X(97)00012-0
Stevanovic, A. (2010). *Adaptive traffic control systems: domestic and foreign state of practice* (Project No. 20-5 (Topic 40-03)).
Stevanovic, A., Kergaye, C., & Stevanovic, J. (2011). Evaluating Robustness of Signal Timings for Varying Traffic Flows. *Transportation Research Record, 2259*(1), 141-150. doi:10.3141/2259-13
Tarko, A. P., & Perez-Cartagena, R. I. (2005). Variability of Peak Hour Factor at Intersections. *Transportation Research Record, 1920*(1), 125-130. doi:10.1177/0361198105192000115
Tettamanti, T., Luspay, T., Kulcsár, B., Péni, T., & Varga, I. (2014). Robust control for urban road traffic networks. *IEEE Transactions on Intelligent Transportation Systems, 15*(1), 385-398.
Tong, Y., Zhao, L., Li, L., & Zhang, Y. (2015). Stochastic programming model for oversaturated intersection signal timing. *Transportation Research Part C, 58*, 474-486. doi:10.1016/j.trc.2015.01.019
Transmax. (2015). STREAMS ITS. Retrieved from https://www.transmax.com.au/cms/
Ukkusuri, S. V., Ramadurai, G., & Patil, G. (2010). A robust transportation signal control problem accounting for traffic dynamics. *Computers & Operations Research, 37*(5), 869-879.
Vincent, R., Mitchell, A., & Robertson, D. (1980). *User guide to TRANSYT version 8.*

Wallace, C. E., Courage, K., Reaves, D., Schoene, G., & Euler, G. (1984). *TRANSYT-7F user's manual*.
Wang, X., Cottrell, W., & Mu, S. (2005). *Using k-means clustering to identify time-of-day break points for traffic signal timing plans.* Paper presented at the Proceedings. 2005 IEEE Intelligent Transportation Systems, 2005.
Webster, F. V. (1958). *Traffic signal settings* (Report No. 39).
Yin, Y. (2008). Robust optimal traffic signal timing. *Transportation Research Part B: Methodological, 42*(10), 911-924.
Zhang, L., & Yin, Y. (2008). Robust synchronization of actuated signals on arterials. *Transportation Research Record: Journal of the Transportation Research Board*(2080), 111-119.
Zhang, L., Yin, Y., & Lou, Y. (2010). Robust signal timing for arterials under day-to-day demand variations. *Transportation Research Record: Journal of the Transportation Research Board*(2192), 156-166.
Zhong, R. X., Chen, C., Huang, Y. P., Sumalee, A., Lam, W. H. K., & Xu, D. B. (2018). Robust perimeter control for two urban regions with macroscopic fundamental diagrams: A control-Lyapunov function approach. *Transportation Research Part B: Methodological, 117*, 687-707. doi:https://doi.org/10.1016/j.trb.2017.09.008