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Optimization of mixed cycle length traffic signals

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SUMMARY

Mixed cycle length operation has been recommended for networks where individual intersections process considerably different traffic volumes. The signals to operate at lower or higher cycle lengths are determined heuristically. This paper demonstrates that the use of mixed cycle lengths as given by the heuristic is inferior to operation under a common cycle length. This contradicts findings in earlier studies, and the difference in conclusion is due to the use of updated optimization methodology. A procedure for incorporating the allocation of mixed cycle lengths into the global optimization of all signal timing variables by a genetic algorithm is proposed. The mixed cycle length timing plans obtained from this procedure are an improvement over those determined heuristically. Mixed cycle length operation is found to be of a more limited application than indicated in previous studies. Copyright © 2012 John Wiley & Sons, Ltd.

KEY WORDS: traffic systems; transportation networks; transportation systems transit; highway and traffic engineering; travel time; headway; flow; gap

1. INTRODUCTION

In a network of pre-timed traffic signals, it is common practice to assign the same cycle length to all signals. This ensures that the relative timing, or offsets, of signals is repeated each cycle, thus maintaining a fixed synchronization. Synchronization can also be achieved by the selection of cycle lengths that have a common multiple. For example, we could have one signal operating at a cycle length of 30 seconds and another at a cycle length of 60 seconds. The relative timing of the signals is still repeated every 60 seconds. In this case, we have a 60-second cycle time, and the signal operating on a 30-second cycle time is said to operate with double cycling as it completes two cycles in 60 seconds. If we have signals operating at cycle times of 90 and 60 seconds, the relative timing of signals will be repeated every 180 seconds. Here, the cycle time is 180 seconds, and the signals operating at 90 and 60 seconds are said to operate with double and triple cycling, respectively.

Mixed cycle operation is thought to be appropriate for networks where there is a large differential in the volume of traffic processed by individual signals. Assuming two possible cycle lengths at each signal, there are 2^m possible cycling scenarios for a network of m signals. An exhaustive consideration of all cycling scenarios is thus not feasible. Traffic engineers must rely on heuristic techniques for identifying which signals to operate on shorter and longer cycle lengths. However, these heuristics do not guarantee a globally optimum signal-timing solution.

In this paper, a method for incorporating the allocation of mixed cycle lengths into the signal-timing optimization procedure is proposed. Optimization by genetic algorithms will be considered. This will allow for the global optimization of the cycle length of each signal simultaneously with other signal-timing variables such as green time allocation, offsets, and signal phasing. The method is evaluated on

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several test networks. Furthermore, there are no studies demonstrating the advantage of mixed cycle length operation using contemporary methodology. Thus, a secondary objective is to quantify the advantage of mixed cycle operation where timings are optimized by genetic algorithms and the quality of signal timing schemes are estimated by a microscopic stochastic traffic simulator.

This paper is organized as follows: A review of the relevant literature is given first. The methodology is discussed next. The results from the experiments follow. Finally, a summary of the findings and recommendations on mixed cycle length operation is given in the conclusion.

2. BACKGROUND AND LITERATURE REVIEW

We first discuss cycle length optimization for a single intersection. Arguments for and against the use of mixed cycle lengths in signalized networks are presented next. Empirical findings on mixed cycle length operation are also discussed. Genetic algorithms and their application in traffic signal optimization are covered. All signalized junctions considered in this section and through the remainder of this paper consist of four approaches labeled north (N), east (E), south (S), and west (W).

2.1. *Optimal cycle length for a single intersection*

The time between vehicle arrivals, also known as vehicle headways, at an isolated intersection is generally acknowledged to follow an exponential distribution [1]. At the onset of green, the departure of a queue of vehicles occurs at an approximately constant rate called the saturation flow rate [2]. Vehicles arriving at a green signal when no queue is present are not delayed. For this traffic model, Webster [2] obtained an approximate formula for the steady-state vehicle delay. This is the average delay experienced assuming the signal has been operating for an infinite length of time. He also obtained the following approximate formula for the delay minimizing cycle length:

$$C = \frac{1.5L + 5}{1 - Y} \tag{1}$$

where L is the total loss time for the intersection including amber and all-red period (seconds), q_i is the arrival flow on approach i (vehicles/hour), s_i is the saturation flow for vehicles on approach i (vehicles/hour), and

$$Y = \max\left(\frac{q_N}{s_N}, \frac{q_S}{s_S}\right) + \max\left(\frac{q_E}{s_E}, \frac{q_W}{s_W}\right) \tag{2}$$

2.2. *Theoretical argument in favor of mixed cycle lengths*

We present a motivation for the use of mixed cycle lengths as given by Chaudhary *et al.* [3] with the aid of a numerical example. Suppose we have a two-signal network with only through movements as described in Figure 1.

Applying Webster's optimal cycle length formula (1) separately for each signal, we obtain optimal cycle lengths of $C_1 = 58$ and $C_2 = 116$ seconds for signals 1 and 2, respectively. We find that the "busier" intersection requires a longer cycle length. If we coordinate the signals with a common cycle length, one or both signals must make a compromise with respect to its optimal cycle length. This concession can be eliminated by operating signal 1 at a cycle length of C_1 and signal 2 at a cycle length of C_2. That is, use mixed cycle lengths with a 116-second cycle length and operate signals 1 and 2 on double and single cycling, respectively.

This example also illustrates the heuristic procedure that is used to identify opportunities for mixed cycle length timing and to determine the signals to operate at lower and higher cycle lengths. We will refer to it as Webster's heuristic. A more advanced procedure for determining mixed cycle allocation has been developed [4], but the method is still heuristic.

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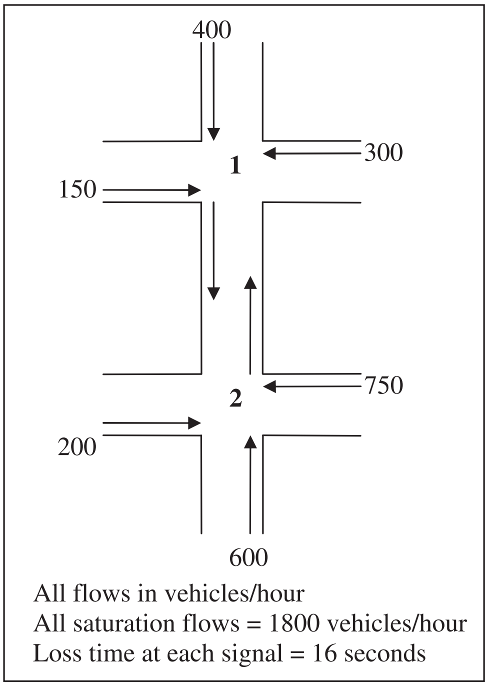

Figure 1. Hypothetical two-signal network.

2.3. Disadvantages of mixed cycle lengths

Because of the on/off nature of signals, the headways of vehicles traveling between intersections will have a more regular pattern and will no longer be exponentially distributed. The arrival of pattern of vehicles at downstream intersections is influenced by the relative offsets of adjacent signals. Offsets can have a profound impact on progression between signals. Thus, the application of Webster's results to individual signals in a network as demonstrated by the previous example is an approximation. Kreer [5] showed that mixed cycle lengths usually result in narrower progression bands than those obtainable under a common cycle length. He also demonstrated how mixed cycle lengths disrupt platoon structure and has recommended that the number of transitions between different cycle lengths be kept to a minimum.

2.4. Empirical findings on mixed cycle lengths

Empirical studies demonstrating the advantage of mixed cycle lengths over a common cycle length have been performed ([6–8] and [5]). More recent studies have not been reported in the literature. We discuss the study of Kreer [5] in some detail as

- It is the most convincing and rigorous study demonstrating the improvement of mixed cycle operation over a common cycle length setup.
- The test network considered by Kreer is re-examined in this study.

Kreer considered signal setting for the hypothetical arterial network with no turning movements illustrated in Figure 2. Values of $y \in \{ 1500, 2500, 3000 \}$ were considered to construct a network with a single signal with a higher cycle time requirement due to heavy cross-street traffic. The commercial signal-timing package TRANSYT [9] was used. TRANSYT uses a deterministic macroscopic traffic simulation model and obtains optimal signal timings by minimizing a linear combination of delay and stops called the performance index with a hill-climbing search algorithm. Three optimization scenarios were considered:

- Common cycle length for all signals.
- Single cycle at signal 3 and double cycling at all other signals.
- Double cycle at signal 3 and triple cycling at all other signals.

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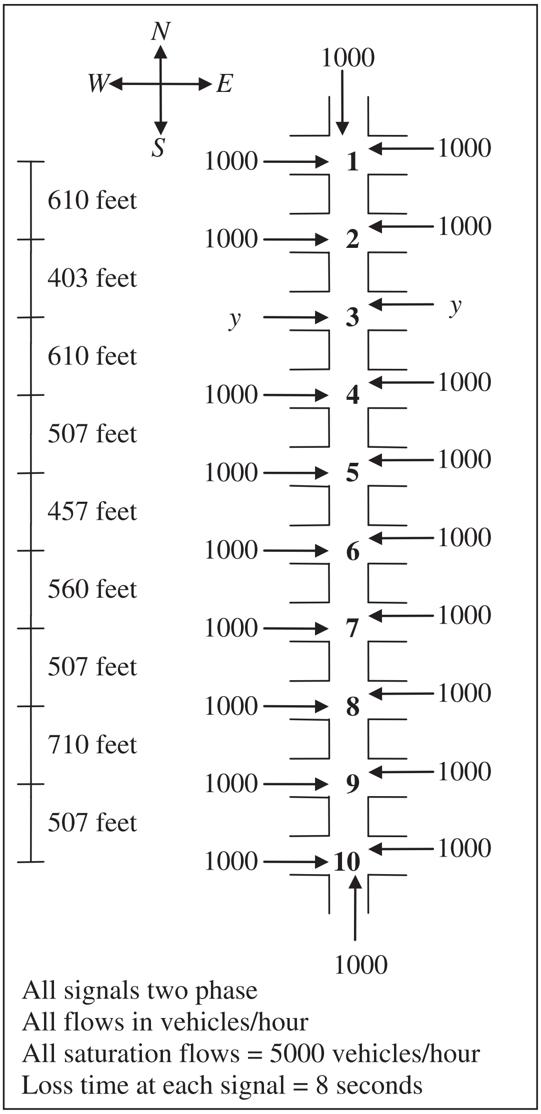

Figure 2. Test network considered by Kreer.

The two mixed cycle length scenarios enforce a longer cycle length at the busier intersection as recommended by Webster's heuristic. Reductions in the performance index of between 7% and 10% were obtained for the mixed cycle length scenarios relative to the common cycle length scenario.

2.5. Genetic algorithms

Genetic algorithms are global optimization algorithms based on the mechanisms of natural selection and evolutionary theory [10]. Optimization is performed using a population of individuals. Each individual represents a point in the search space. Associated with each individual is the computed objective function value. The set of decision variables of each individual is encoded into a real or binary representation that is acted upon by genetic operators. Optimization is performed by manipulating the population of individuals by using the following procedures:

- *Initialization*: Individuals in the initial population are assigned to random points in the search domain. These individuals constitute the first generation.
- *Selection*: Individuals in the population are selected for reproduction. For minimization problems, individuals with a smaller objective function value are favored for selection.

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- *Crossover*: Once individuals have been selected for reproduction, these "parents" are paired and one or more "children" are created using a crossover operator. Crossover creates children by combining or blending the genetic material of the two parents.
- *Mutation*: The mutation operator performs random alterations to the genetic material of an individual.
- *Replacement*: A fixed finite population size is usually applied, and a replacement scheme is defined to determine which individuals from the parent and child populations survive to form the next generation.

After initialization, the remaining steps are repeated until a stopping criterion is met, such as the completion of a specified number of objective function evaluations. The individual with the best objective function value in the final generation is taken as the optimal solution produced by the algorithm.

Genetic algorithms have been found to be superior to hill climbing, random search, quasi-Newton search, and simulated annealing on traffic signal optimization problems ([11–13] and [14]). Another advantage with genetic algorithms is that signal-phase structure and sequence can be included in the global optimization. Commercial packages for determining signal timings such as TRANSYT-7F [15], VISSIM [16], and PASSER V [3] have introduced optimization by genetic algorithms.

3. METHODOLOGY

The proposed method for incorporating allocation of mixed cycle lengths into the genetic algorithm optimization is given first. MSTRANS, the traffic simulation model used, is discussed next. Implementation details of the genetic algorithm are also covered. The test networks are described at the end.

3.1. Genetic encoding

The encoding scheme developed by the author [17] for optimization of signal timings under a common cycle length is extended to accommodate mixed cycle lengths. The encoding scheme is a combination of real and binary encodings.

Let

$C_{\min}$ = minimum cycle length (seconds)
$C_{\max}$ = maximum cycle length (seconds)
A = duration of an amber interval (seconds)
R = duration of an all-red interval (seconds) and
$g_{\min,\,\mathrm{phase}}$ = minimum duration of green phase including signal change period (seconds)

Now, for a particular individual in the genetic algorithm population, let

C = network cycle time (seconds)
N_i = number of cycles completed by signal i in the network cycle time ($N_i = 1$ for single cycling $N_i = 2$ for double cycling and $N_i = 3$ for triple cycling)
C_i = cycle time of signal i(seconds)

$$= \frac{C}{N_i} \tag{3}$$

φ_i = offset of traffic signal i with respect to beginning of its *N/S* green phase relative to the start of the *N/S* green phase at signal 1 (seconds)
$\rho_{i,\,N/S}$ = duration of *N/S* green phase at traffic signal i including amber and all − red transition period (seconds) and
$\rho_{i,\,E/W}$ = duration of *E/W* green phase at traffic signal i including amber and all − red transition period (seconds)

$$= C_i - \rho_{i,N/S}. \tag{4}$$

With common cycle operation or with a pre-specified mixed cycle allocation, $\{N_i\}$ are pre-specified and need not be included in the optimization. Alternatively, we consider combining either

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single/double mixed cycling or double/triple cycling. In these cases, each N_i is encoded using a single binary variable. All other decision variables use a real encoding where each decision variable x is represented by a fractional value $D(x)$ in the range [0, 1]. These fractional values are transformed into usable signal-timing plans using Equations (5)–(7) in the succeeding paragraphs:

$$C = C_{\min} + \lfloor (C_{\max} - C_{\min}) D(C) \rfloor \tag{5}$$

$$\varphi_i = \begin{cases} 0 & \text{for } i = 1 \\ \lfloor (C-1) D(\varphi_i) \rfloor & \text{for } i \neq 1 \end{cases} \tag{6}$$

$$\rho_{i,N/S} = g_{\min,\text{phase}} + \left\lfloor \left(C_i - 2g_{\min,\text{phase}}\right) D\left(\rho_{i,N/S}\right) \right\rfloor \tag{7}$$

The encoding scheme also has allowance for the optimization of signal phasing, but this remains unaltered by the allowance for mixed cycles.

3.2. MSTRANS

MSTRANS is a stochastic microscopic traffic simulation model developed by the author. Vehicle entry headways, turning movements, and certain driver behavioral decisions are generated stochastically using a pseudo random number generator. The model applies a fixed increment time step to advance the simulation. Vehicle status and kinematics are updated each second. Modeling logic and parameters are based on findings from the literature on driver behavior and vehicle characteristics. MSTRANS has been found to produce results comparable with CORSIM [18], a widely used commercial stochastic microscopic traffic simulator [19]. A thorough account of the functional details of the model, a review of the literature justifying the model logic, and a complete code listing are given by Kesur [19].

3.3. Genetic algorithm implementation

A delay minimization strategy is considered. A delay measure called extended network delay is used, which removes a certain shortcoming of the more traditional delay measures associated with traffic simulation models [17].

The cross-generational elitist selection, heterogeneous recombination, and cataclysmic mutation genetic algorithm [20] with a population size of 50 is used. This genetic algorithm includes an incest prevention mechanism, a population elitist replacement mechanism and reproduction by crossover alone with cataclysmic mutation to reintroduce diversity. The blend crossover and real mutation operators are used [21]. Mean delay is estimated by a single run of the MSTRANS stochastic simulation model. The same random number seed is used in MSTRANS when evaluating each individual in a particular run of a genetic algorithm, thus subjecting all signal-timing policies to identical experimental conditions. This reduces the variability in estimated delay and allows the genetic algorithm to identify improved solutions with higher accuracy. This particular design of the genetic algorithm has been found to have the best performance on the traffic signal optimization problem [17].

An additional 20 independent replications of the best solution found by the genetic algorithm are performed in MSTRANS to obtain an unbiased measure of mean delay. Furthermore, to account for the stochastic nature of the genetic algorithm search mechanism, we performed 20 independent runs of the genetic algorithm optimization procedure and averaged the delay over these runs. That is, we quote and compare $X_F = \frac{1}{400}\sum_{i=1}^{20}\sum_{j=1}^{20} X_{F,i,j}$, where $X_{F,i,j}$ = delay (seconds/vehicle) on the jth independent replication of the best individual found after F function evaluations on the ith independent run of the genetic algorithm.

Separate optimization runs are performed for each of the cycling scenarios in Table I. Comparisons between the different scenarios are made on the basis of X_F. Tests for statistically significant differences in the population mean of solution quality are performed using the statistical model developed by the author [19]. All comparisons are made at the 5% significance level.

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Table I. Optimization scenarios.

Name	Description
Common cycle length	Common cycle length operation
Webster single/double	Single/double cycling with N_i based on Webster's heuristic
Webster double/triple	Double/triple cycling with N_i based on Webster's heuristic
Auto single/double	Single/double cycling with N_i optimized by the genetic algorithm
Auto double/triple	Double/triple cycling with N_i optimized by the genetic algorithm

3.4. *Test networks*

The network constructed by Kreer [5] in Figure 2 and several large real-world networks are considered. All test networks use fixed time signal controllers.

3.4.1. *Kreer's network*

Cross-street flow levels of $y \in \{1500, 2500, 3000\}$ at intersection 3 are considered. A total of $F = 10\,000$ function evaluations are allowed for each optimization run.

3.4.2. *Real-world networks*

A 9-signal arterial network and a 14-signal grid network are considered. Although Kreer's network has been specifically designed with mixed cycling operation in mind, the allocation of cycle lengths in these real-world examples is less obvious, as we will demonstrate later. Furthermore, turning movements are present, and phase optimization is applied. The arterial network was constructed by combing two data sets. Signal spacing was taken from a network in New Orleans, Louisiana [22], and the traffic flows were obtained from a network in Lawrence, Kansas [23]. The grid network was based on a data set for downtown Ann Arbor, Michigan [24]. Low traffic flow (undersaturated) and high traffic flow (oversaturated) scenarios are considered for each. Full network specifications are given in Kesur [19]. A total of $F = 15\,000$ function evaluations are allowed for each optimization run.

The domains of cycle times examined for each network and cycling scenario are given in Table II. The values of $C_{\min}$ and $C_{\max}$ for the mixed cycle scenarios were chosen to ensure that the minimum and maximum implemented cycle lengths $\{C_i\}$ correspond to the minimum and maximum cycle lengths under the common cycle length scenario (Equation (3)).

4. RESULTS

4.1. *Kreer's network*

We start by comparing results from the first three optimization scenarios in Table I to test whether we obtain the same findings as Kreer by using a more updated evaluation and optimization methodology. The resulting values for $X_{10\,000}$ (seconds/vehicle) are given in columns 2, 3, and 4 in Table III.

A startling finding is that the delays for the common cycle length strategies are smaller than those from the mixed cycle length timing plans enforcing a longer cycle length at signal 3. For $y = 1500$ and $y = 3000$, the differences are statistically significant.

Table II. Cycle times examined in test networks.

	Kreer's network		Real-world networks	
Cycling scenario	$C_{\min}$	$C_{\max}$	$C_{\min}$	$C_{\max}$
Common cycle	30	120	36	144
Single/double cycling	60	120	72	144
Double/triple cycling	90	240	108	288

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Table III. Delay of best solutions found by optimization algorithms on Kreer's network.

	Optimizer							
	Genetic algorithm					Hill climber		
y	Common cycle length	Webster single/ double	Webster double/ triple	Auto single/ double	Auto double/ triple	Common cycle length	Webster single/ double	Webster double/ triple
1500	19.95	20.70	20.47	20.44	20.92	21.61	21.90	21.26
2500	26.62	26.11	28.13	25.77	28.13	29.99	27.43	29.19
3000	42.56	44.25	47.74	40.28	46.21	48.22	45.62	48.62

The signal-timing plan with the smallest delay from the 20 optimization runs under a common cycle length for $y = 3000$ was identified. Similarly, the best solution from the optimization runs under single/double mixed cycling for $y = 3000$ was also identified. For each of these signal timing plans, the total vehicle delay (vehicle minutes) was computed separately for each direction of travel. The sample means from 100 independent replications of MSTRANS are given in Table IV.

The objective of the mixed cycle length strategy is partially achieved in that the delay to cross-street movements is reduced as signals are assigned more appropriate cycle lengths. However, this is performed at the cost of disrupting progression along the arterial, resulting in an increased delay to vehicles traveling on the arterial. The overall net effect is an increase in delay using mixed cycle lengths.

Thus, mixed cycle length operation appears to offer no benefits. This is in contradiction to Kreer's results. The reason for the difference in conclusion can be identified by analyzing the evolution of the best solution obtained for the different numbers of function evaluations. That is, an examination of X_F (seconds/vehicle) for $F \in \{1000, 2000, 3000, \ldots, 10\,000\}$. This is given in Table V for $y = 3000$.

We find that for a less extensive search, (i.e., smaller F), one would conclude that mixed cycle length scenarios do better. A possible explanation for this may be that although the global optimum solution under a common cycle operation is an improvement over that from mixed cycle control, local optima under mixed cycle control are superior to those from a common cycle operation. Less capable optimization algorithms such as the TRANSYT hill-climbing procedure used by Kreer, or a genetic algorithm with limit scope, may converge to these local optima and fail to identify the globally optimal solutions.

Table IV. Comparison of total delay (vehicle minutes) for each direction of travel.

Direction of travel	Common cycle length	Webster single/double
E	1639	1590
W	1636	1617
N	822	875
S	658	760
Total	4755	4842

Table V. Evolution of best solutions in Kreer's network for $y = 3000$.

Number of function evaluations (F)	Common cycle length	Webster single/double	Webster double/triple
1000	52.51	47.07	50.63
2000	49.93	45.58	50.34
3000	47.68	45.33	49.56
4000	46.71	44.96	49.78
5000	46.13	44.93	49.07
6000	44.51	44.75	48.38
7000	44.03	44.15	47.65
8000	43.34	44.25	47.91
9000	42.52	44.07	47.98
10 000	42.56	44.25	47.74

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To test the validity of this hypothesis, a computer code to duplicate the TRANSYT hill-climbing algorithm was written and applied using MSTRANS as the evaluator. The same random number seed was used in MSTRANS to evaluate each signal-timing plan, effectively transforming the delay value produced by the stochastic simulator into a deterministic function. Twenty independent replications of the best solution from the hill-climbing algorithm were performed in MSTRANS to obtain an unbiased measure of delay. The final solution obtained by the hill-climbing algorithm is dependent on the random number seed used. To account for this, we repeated the entire hill-climbing optimization exercise 20 times using a different random number seed in each case. The results quoted in columns 7, 8, and 9 of Table III are the mean values from these 20 optimization runs. The hill climber is unable to locate the solutions with the same quality as those found by the genetic algorithm and results in the incorrect conclusion obtained by Kreer that the mixed cycle length solutions are superior.

To investigate whether better mixed cycling options exist, we consider the last two optimization scenarios in Table I where the allocation of cycle lengths is performed by the genetic algorithm. The resulting values of $X_{10\,000}$ (seconds/vehicle) are given in columns 5 and 6 of Table III. Comparing these results with the mixed cycle allocations from Webster's heuristic,

- For $y = 1500$, the best mixed cycling strategy is the single/double mixed cycling obtained by the automated procedure, which is a statistically insignificant improvement over those obtained using Webster's heuristic.
- For $y = 2500$, the improvements using the automated procedure are statistically insignificant.
- For $y = 3000$, the automated procedure provides statistically significant improvements for both single/double and double/triple mixed cycling.

Thus, we find that mixed cycle length optimization via the automated procedure is as good as, or better than, mixed cycle length optimization using Webster's heuristic.

With the automated mixed cycle length allocation procedure, the performance of single/double mixed cycle length optimization is a statistically significant improvement over double/triple mixed cycle length optimization in all cases. Comparing single/double mixed cycle length optimization using the automated procedure with common cycle length optimization,

- A statistically significant degradation in performance is observed with mixed cycle optimization for $y = 1500$.
- A statistically significant 3% reduction in delay is obtained with mixed cycle optimization for $y = 2500$.
- For $y = 3000$, a statistically significant reduction in delay of 5% is obtained using mixed cycle optimization.

We find that mixed cycle operation has the potential to outperform common cycle length operation when the allocation of mixed cycle lengths is included in the optimization process.

From the multiple runs of the single/double mixed cycle genetic algorithm, we obtain 20 optimal cycling allocations. By considering the degree of agreement between the solutions, we can measure the reliability of the automated mixed cycle allocation procedure and discover how the cycle allocation from the automated procedure differs from the allocation using Webster's heuristic. The proportion of solutions with single cycling at each signal is given in Table VI.

For $y = 1500$, 90% of all solutions involve double cycling of all signals, which is effectively a common cycle length solution. This is an indication that the additional cross-street flow at signal 3 is not high enough to warrant a longer cycle time. This allocation is obtained even though a common cycle length strategy corresponds to only $\frac{2}{2^{10}} = 0.2\%$ of the search space. Consequently, we find no improvement using mixed cycle operation in this scenario.

For $y = 2500$, signal 3 is always allocated a single cycle. Nearby intersections are occasionally allocated single cycles. However, because the difference in performance between the various allocations is small, the genetic algorithm has trouble reliably identify any single allocation as best.

For $y = 3000$, signal 3 is always allocated a single cycle. Adjacent signals 2 and 4 are usually allocated single cycles as well. Signals adjacent to these are occasionally allocated signal cycles. This clearly aids progression along the arterial, allowing for an overall reduction in network delay relative to common cycle length operation.

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Table VI. Proportion of solutions with single cycling for Kreer's network.

Signal index i	y 1500 (%)	2500 (%)	3000 (%)
1	0.00	15.00	5.00
2	0.00	45.00	90.00
3	10.00	100.00	100.00
4	0.00	0.00	70.00
5	0.00	15.00	25.00
6	0.00	0.00	5.00
7	0.00	0.00	0.00
8	0.00	0.00	0.00
9	0.00	0.00	0.00
10	0.00	0.00	0.00

4.2. Real-world networks

The optimal cycle lengths of individual signals as given by Webster's optimal cycle length formula (1) are illustrated in Figure 3 where the cycle length (seconds) of each signal is marked on the *x* axis. From the figure, we can see that when applying Webster's heuristic, it is not always immediately obvious which signals to group and operate with lower and higher cycle lengths. A *K*-means cluster analysis [25] was performed to separate signals into two groups with similar cycle length requirements (i.e., $K=2$). On this basis, the signals with Webster cycle lengths given by the gray markers were assigned a lower cycle length, and the signals with the black markers were assigned a higher cycle length. The resulting values of $X_{15\ 000}$ (seconds/vehicle) for the various optimization scenarios are given in Table VII.

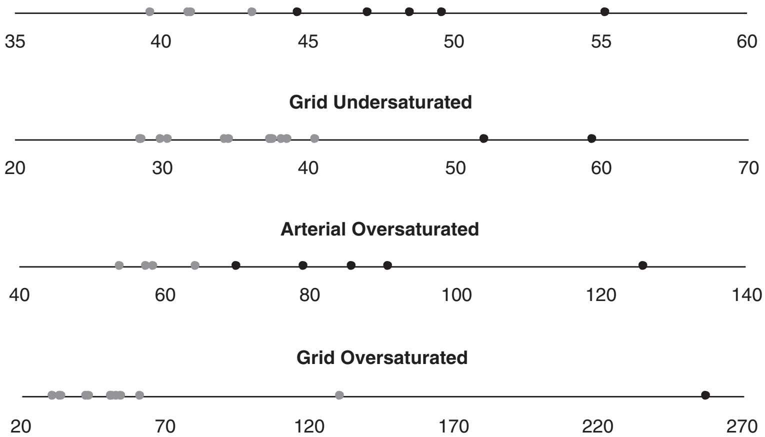

Figure 3. Optimal Webster cycle lengths of individual signals in real-world networks.

Table VII. Delay of best solutions found by genetic algorithm for real-world networks.

Network	Common cycle length	Webster single/ double	Webster double/ triple	Auto single/ double	Auto double/ triple
Arterial undersaturated	48.73	53.53	53.40	50.79	50.45
Arterial oversaturated	131.12	142.86	144.81	141.12	142.47
Grid undersaturated	35.90	40.14	42.18	37.19	37.15
Grid oversaturated	74.36	84.43	92.36	77.11	76.64

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For the case of single/double mixed cycling (columns 3 and 5), we find that automated cycle allocation by the genetic algorithm produces smaller delay than those allocations given by Webster's heuristic for all networks. These improvements are significant in all cases except for the arterial oversaturated network. This is true for the double/triple mixed cycling as well (columns 4 and 6). Comparing columns 5 and 6, we find the differences in delay between single/double and double/triple mixed cycling under the automated procedure to be rather small. These differences are statistically insignificant.

Although the mixed cycle timing plans obtained by the automated procedure are an improvement over those obtained from Webster's heuristic, common cycle optimization (column 2) produces statistically significant improvements in delay in all cases. Common cycle operation is better even though Webster's heuristic (Figure 3) indicates a potential for mixed cycle control.

5. SUMMARY AND CONCLUSION

A common held belief among traffic engineers is that mixed cycle length operation can substantially improve performance in traffic networks where there is a large differential in the volume of traffic processed by individual signals. Webster's cycle length formula is generally used as a heuristic to determine which signals to operate at lower and higher cycle lengths. Using state-of-the-art signal -timing optimization technology, we compared mixed cycle length strategies with a common cycle length strategy on a hypothetical arterial network with a design favorable for mixed cycle operation. A contradictory finding to a previous study was obtained in that the mixed cycle length strategies as given by the heuristic result in inferior network performance. The difference is due to the use of an improved optimization methodology.

A method for incorporating the allocation of mixed cycle lengths into the global optimization of all signal timing variables via genetic algorithms is proposed. This is shown to produce improved mixed cycle length strategies compared with those obtained using the heuristic. The mixed cycle length timing plans obtained are fairly consistent. The automated procedure can also identify situations where mixed cycling offers no advantage, as common cycle length solutions are a subset of the cycle allocations considered. Where mixed cycling is appropriate, the timing plans obtained usually involve operating groups of adjacent signals under the same cycle length. Single/double mixed cycling is better than double/triple mixed cycling in some cases.

On the hypothetical arterial network, the mixed cycle length strategy obtained from the automated procedure outperformed common cycle length operation by a small margin. The application of mixed cycle length operation in real-world test networks resulted in an increased delay. Thus, mixed cycle length operation is of a more limited application than indicated in previous studies.

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