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Traffic signal optimisation in disrupted networks using a semi-dynamic approach*

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1. Introduction

To ensure operational continuity of urban road networks, the resilience of a transportation system has become an important issue. Over the last two decades, there has been extensive discussion about the need for robust networks to minimise the economic and social impacts of disruptions. Detailed reviews of the literature related to degraded networks have been conducted, e.g. Berdica (2002) and Mattsson and Jenelius (2015). Koorey et al. (2015) explored the scope for dynamic traffic signal control to reduce the impact of disruptions associated with non-recurrent congestion (e.g. traffic incidents). It has been suggested that reducing these will have a great effect on network reliability as half the congestion delay is caused by non-recurring events (Pearce, 2000, Schrank et al., 2009). Several studies of infrastructure resilience have proposed a disruption profile to capture the phases of any significant disruption before, during and after the disruption (Asbjornslett, 1999, Sheffi, 2005, Bruneau et al., 2003). More recently, Taylor (2017) presented a representation to reflect the dynamic performance of an infrastructure system. This distinguishes between frequent minor variations in performance and infrequent major disruptions. One can improve the resilience by reducing the area of the resilience triangle by reducing its height (i.e. reducing the reduction in system performance when the incident occurs) and/or its base (i.e. the recovery time). There are various options to achieve this, including constructing or improving parallel routes between given pairs of nodes. Another option is to use traffic signal control, and the aim of this study is to reduce the impact of a disruptive event using traffic signal control, as previously investigated by Koorey et al. (2015).

Traffic signal control can be used to assist drivers to avoid blockages and to use other routes to minimise delays. Various optimisation algorithms have been implemented to find the optimal set of signal timings, taking into account the impact of re-routing. One of these optimisation methods is the Cross-Entropy (CE) method proposed by Rubinstein (1997). Maher (2008) introduced the CE algorithm to optimise the signal settings on a six-arm signalised roundabout. Ngoduy and Maher (2011) and Maher et al. (2013) further explored the CE method to optimise traffic signals in urban networks. The results of applying the CE method showed encouraging advantages for computational efficiency and convergence, with its more formal mathematical and statistical basis making it simple to apply (Maher, 2008).

The time slices approach, presented in this paper, was proposed by Van Vliet (1982) using the simulation and assignment procedures in SATURN software package. This approach is referred to as quasi-dynamic (Van Vliet, 1982) and semi-dynamic (Bliemer et al., 2017), and the latter will be used in this paper to refer to the time slices approach. This method involves dividing the simulated time horizon into short time slices, with the traffic conditions at the end of a time slice becoming the starting conditions for the subsequent time slice. The main objective of this paper is to investigate the time slices assignment to improve the resilience of urban road networks subject to short-term closures in comparison with the results of the static approach described in Abudayyeh et al. (2018). Transport researchers have subsequently modelled residual queues using link capacity constraints (Bell, 1995, Kheifits and Gur, 1997, Schmöcker et al., 2008, Fusco et al., 2012, Bliemer et al., 2014, Tajtehranifard, 2017). These studies showed that this approach is considered a reasonable 'midpoint' between the static and dynamic assignment models as it combines the computational efficiency of static assignment models and the realism of traffic flow in dynamic assignment models.

2. Method and implementation

To understand the impact of disruptions on traffic network performance under optimum signal control, a bi-level optimisation problem was formulated. The approach, which was introduced by Ngoduy and Maher (2011), was adopted and extended to account for urban network degradations. The process for optimising the signal settings involves iterating between the CE algorithm and SATURN. The CE algorithm searches for the combination of signal settings which minimises the Total Travel Time (TTT), calling SATURN to estimate the flows and travel times for specified combinations of signal settings, considering re-routing.

The upper level optimisation problem represents planners trying to minimise the average travel time immediately after the disruptive event, when equilibrium has not yet been reached among the road users. The upper level of the problem is formulated as:

$$Min\, PI(\boldsymbol{X},\boldsymbol{q_{UE}}(\boldsymbol{X})) = \sum_{a=1}^{L} q_a t_a(\boldsymbol{X},\boldsymbol{q_{UE}}(\boldsymbol{X})); \quad subject\, to: \boldsymbol{X}(\boldsymbol{\beta},\boldsymbol{\theta},\boldsymbol{C}) \in \Omega \tag{1}$$

where $PI(\boldsymbol{X},\boldsymbol{q_{UE}}(X))$ is the performance index function (i.e. the TTT in the network) which is the sum of the product of the link flows and link travel times over the whole network and it depends on the vector of link equilibrium flows $\boldsymbol{q_{UE}}$ and the vector of signal timings $\boldsymbol{X}$ consisting of the vector of offsets $\boldsymbol{\beta}$, the vector of green times $\boldsymbol{\theta}$ and the cycle length $\boldsymbol{C}$; L is the number of links; q_a is the flow on link a; t_a is the average travel time for the link flow a. Consistent units are assumed throughout the paper. Since changing the signal timings in a network will generally cause some re-routing of traffic, $\boldsymbol{q_{UE}} = \boldsymbol{q_{UE}}(X)$; Ω denotes the feasible space of X defined as:

$$C_{\min} \le C \le C_{\max}; \quad 0 \le \beta_n \le C-1; \quad \theta_{n,s}^{\min} \le \theta_{n,s} \le \theta_{n,s}^{\max}; \quad C = \sum_{s=1}^{S_n} \theta_{n,s} + \sum_{s=1}^{S_n} I_{n,s} \tag{2}$$

where C_{min} and C_{max} are the lower and upper bound of the cycle length, respectively; β_n is the offset at node n; $\theta_{n,s}$ is the green time at node n for stage s; $\theta_{n,s}^{\min}$ and $\theta_{n,s}^{\max}$ are the lower and upper bound of the green time at node n for stage s; S_n is the number of stages at node n; $I_{n,s}$ is the inter-green time at node n for stage s. We consider the signal settings to be discrete integer values. The lower level represents users following the user equilibrium principle under the given network condition. This can be formulated as:

$$\boldsymbol{t(X,q_{UE})}.\boldsymbol{(q - q_{UE})} \ge 0 \qquad \forall q \in \Theta \tag{3}$$

where $\boldsymbol{q}$ is the vector of link flows and q_{UE} is the vector of equilibrium link flows. In Equation (3), $\boldsymbol{t(X,q_{UE})}$ denotes the vector of link travel times, which is dependent on the vector of signal timings and the equilibrium link flows. Θ denotes the feasible space of the link flow vector and is explicitly defined as:

$$\begin{aligned} &\sum_{p \in P} f_{ijp} = OD_{ij} \qquad \forall i \in O, j \in D \quad ; \; f_{ijp} \geq 0 \qquad \forall i \in O, j \in D, p \in P \\ &q_a = \sum_{i \in O} \sum_{j \in D} \sum_{p \in P} f_{ijp} \delta_{aijp} \qquad \forall a \in L \quad ; \; q_a \leq q_a^0 \qquad \forall a \in L \end{aligned} \tag{4}$$

where q_a^0 is the link capacity; *O* and *D* are the sets of origins and destinations; *P* is the set of possible paths; *i*, *j* are the origin index and destination index; *p* is the path index; f_{ijp} is the path flow between origin *i* and destination *j* using path *p*; δ_{aijp} is an indicator variable which equals one if the link *a* is on path *p* between *i* and *j*, and zero otherwise.

The CE method was originally developed to estimate the probability of occurrence of rare events (e.g. the probability of failure of a particular network), then it was extended to solve combinatorial optimisation problems when the objective function is very complicated and it is necessary to do a lot of sampling. A full description of the method is given in Rubinstein and Kroese (2004). The CE involves three main steps: generating a random sample from a pre-specified probability distribution function, evaluating the selected sample based on a performance index, then updating the sample based on a smoothing parameter (α). Each observation in this sample is scored for its performance as the solution to the specified optimisation problem. A fixed percentage of the best performing observations are referred to as the elite sample. The elite sample helps to update the parameters in the next generated solutions to improve the quality of the solution. The process is repeated until convergence occurs and an optimal solution is found.

3. A study case to test the numerical model on a real network

The performance of the proposed approach was assessed by applying it to the Cambridge (UK) network, which comprises 141 zones, 1,091 links and 608 nodes, including 24 signalised junctions with 2-phase arrangements. The common cycle length was fixed at 60 seconds, and all inter-greens were set to 5 seconds. The total demand in this network reflects one peak hour, with a total number of 42,023 commenced vehicle trips. The objective was to find the set of values for the 47 variables (i.e. 24 phase A green times and 23 offsets) that minimises the travel time in the network in the case of disruption. These variables were constrained to be integers (i.e. round-up of seconds), with the minimum green times being set to 7 seconds, and the offsets ranging from zero up to 59 seconds, with the offset at node 2045 being zero. The traffic flow at the most congested intersection (node 2010) was degraded by applying several blockage scenarios; which involved various combinations of two factors (the duration and the % of capacity reduction of the blockage).

3.1. Simulation results of static assignment

The results of simulating different blockage scenarios (i.e. the green times and offsets) are summarized in Table 1 for node 2010 and the adjacent nodes 3089 and 2040. These results are for five levels of capacity reduction (0%, 25%, 50%, 75%, and 100%) at node 2010, for a period of one hour. The results indicate that the optimal signal settings for node 2010 appear to be sensitive to the severity of the disruption. For instance, there is a 54% increase in the optimal green time at node 2010 with a 75% reduction in its capacity. Moreover, the changes as the capacity reduction increases from 0% to 100% are far from linear (i.e. the optimal settings tend to fluctuate). For example, the offsets at 2010 are, respectively, 17s, 41s, 12s, 18s, and 10s and the phase (A) green times at 2040 are, respectively, 43s, 22s, 43s, 43s, and 43s.

Table 1. Phase (A) green times and offsets for nodes: 2010, 3089, and 2040 using the static approach

Capacity reduction at node 2010 for 60 min.	Node 2010		Node 3089		Node 2040	
	Green Times (s)	Offsets (s)	Green Times (s)	Offsets (s)	Green Times (s)	Offsets (s)
0%	28	17	19	37	43	57
25%	23	41	22	37	22	9
50%	43	12	23	15	43	9
75%	43	18	12	28	43	9
100%	22	10	35	4	43	11

3.2. Simulation results of semi-dynamic assignment

Using the semi-dynamic approach, the simulated hour was divided into 4-minute intervals (i.e. 15 time slices) to test different degradation durations (4, 20, 36, and 60 minutes) and severities (25% reduction in capacity up to a complete closure) to replicate blockages in real life scenarios. The results of 4-minute intervals showed that when node 2010 is completely closed for different time durations the green times gradually decreased at the blocked junction, and increased at the nearby junctions (Table 2). In addition, the results show that the green times at node 2040 are increased to the upper bound (i.e. 43 seconds) during different degradation durations. This implies that traffic is diverting around node 2010 to the nearest node 2040.

Table 2: Phase (A) green times and offsets for nodes: 2010, 3089, and 2040 using the semi-dynamic approach

A complete capacity reduction at node 2010	Node 2010		Node 3089		Node 2040	
	Green Times (s)	Offsets (s)	Green Times (s)	Offsets (s)	Green Times (s)	Offsets (s)
4 minutes	43	28	20	59	43	15
20 minutes	35	42	20	11	43	45
36 minutes	30	10	24	22	43	35
60 minutes	21	22	31	6	43	42

3.3. Comparison of results for the static and semi-dynamic assignments

Compared with the static results, the semi-dynamic results show better convergence (i.e. fewer iterations) for offsets and green times, especially for offset values at the blocked node (Fig. 1a and 2a). The results obtained for a 50% reduction for 60 minutes using both static and semi-dynamic approaches are presented in Figs. 1 and 2, respectively for several intersections (i.e. 2010, 3089, and 2040), those figures describe the standard deviation of the best solutions over the 30 iterations.

Comparing the phase (A) green times and offsets results from applying the static and semi-dynamic approach (i.e. cells in Table (1) and Table (2) highlighted in gray) shows that for a 60 minute complete closure at node 2010, the semi-dynamic approach gave slightly lower phase A green times (21s at node 2010, 31s at node 3089, and 43s at node 2040) compared to (22s at node 2010, 35s at node 3089, and 43 s at node 2040) for the static approach. This could be due to the fact that the semi-dynamic approach converged quicker (i.e. fewer iterations for both green times and offsets) to better solution than the static approach. In terms of offsets, interestingly, the offsets for both the static and semi-dynamic results fluctuate, with higher values obtained for the semi-dynamic approach.

Figure 1: The convergence using the <u>static</u> approach for (a) offsets, (b) green times (phase A)

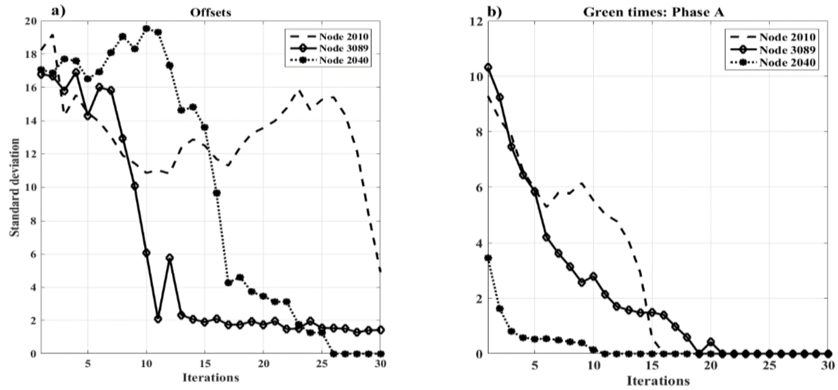
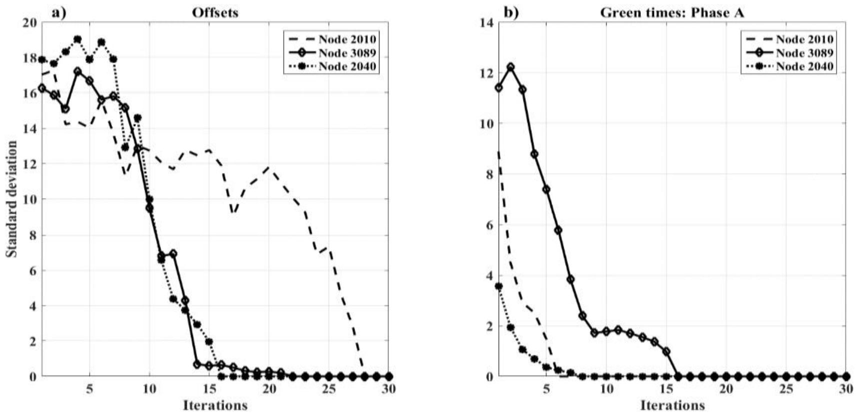


Figure 2: The convergence using the <u>semi-dynamic</u> approach for (a) offsets, (b) green times (phase A)



4. Discussion of results

Several points can be observed from the results. First, it was found that better convergence, in terms of iterations, has been achieved for green times and offsets using the semi-dynamic approach, especially for the blocked junction, as the offsets and phase (A) converged after 28 iterations for offsets and 16 iterations for green times compared to 30 iterations for offsets and 21 iterations for green times in the static approach for the same sample size 1,000. Second, it was noticed that both the level of reduction in capacity (i.e. 25% up to a complete closure) and duration (i.e. 4 minutes closure up to 60 minutes) have an impact on the convergence. For instance, the convergence was quicker for a 25% reduction in capacity (i.e. it takes less iterations) than for a complete reduction in capacity.

5. Concluding remarks and future research

In this paper, we have demonstrated that the CE optimisation method and the semi-dynamic approach can be used to find the optimal green times and offsets in disrupted networks to minimise the TTT. Furthermore, we have presented results for different blockage scenarios, using both the static and semi-dynamic approaches, to simulate different disruption severities and durations, allowing for changes in user route choice behaviour in the period immediately following a disruptive event (during the recovery period). The research results indicate that there is value in using the semi-dynamic approach (i.e. time slices) in modelling disrupted networks, as this approach gives better convergence, in terms of iterations. However, one should keep in mind that the running time for the semi-dynamic approach is higher than for the static approach. To reduce the running time for this network; the total number of iterations (i.e. 30 iterations) could be almost halved (i.e. to 16 iterations) as the semi-dynamic approach converged after 16 iterations.

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