Optimisation of Signal Timings in a Road Network

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Abstract. Road network simulation models and tools are increasingly being used for strategic and operational traffic management with the use of widely available online traffic data. The widespread use of such models raises the prospect of transport system optimisation, improving energy consumption, delays and carbon emissions. Although strategic interventions such as the building of new roads or infrastructure is costly and time-consuming, significant savings can be made through the modelling and optimisation of the operation of the network through signal timings.

Keywords: Infrastructure Networks · Algorithms · Road Networks.

1 Introduction

With rapid economic development, fast growing populations, and an increasing number of vehicles in the urban areas, transportation networks are becoming increasingly congested. This results in wasted energy, increased delays, poor urban air quality, and increased carbon emissions. Due to the high costs of extending current transportation infrastructure [3] and space limitations in cities, it is often not a feasible choice to increase the capacity of the network by constructing new roads and traffic equipment. Hence, researchers have been focused on improving the efficiency of the current transportation networks through intelligent traffic control strategies.

It is well known that the performance of a transportation network is highly sensitive to the traffic lights' settings in various ways including mobility [25], the safety of pedestrians and vehicles [21] and environmental pollution [16]. One practical way to make a given transportation network more efficient is to apply a suitable signal control strategy. As an efficient approach for enhancing the capacity of current transportation networks, optimisation of signal timing parameters of traffic lights, such as cycle time [10, 9, 18], green time [4, 16, 29], offset time [2, 18, 16], and phase sequence [22, 15, 17], has received a great deal of attention in studies of transportation networks. From an optimisation perspective, the problem of optimum signal timings of a transportation network is highly nonlinear and non-convex, in which the modification of a timing plan of a given traffic light can significantly affect the traffic flow in the other areas of the network. The Webster method is one of the most efficient classic signal optimisation method, in which the delay time of a single junction is optimised to find a optimum cycle time formula [27]. However, this method only optimises the delay of a single junction and it does not consider the interactions of the traffic lights of multiple junctions. The precise layout and configuration of the network will determine the extent to which a globally optimised solution can outperform a locally optimised one. The number of junctions, their geographic proximity, traffic demand and the number of signal cycles will all determine the potential for interaction between signals.

To consider the interaction phenomenon of the traffic lights within the whole network, the traffic signal control problem of a transportation network can be formulated as a global optimisation problem. Classical optimisation algorithms, in which the calculation of the gradients of the objective function and constraints is inevitable, are not suitable approaches for the signal optimisation of network with numerous signalized intersections. As alternative approach for classical optimisation methods, meta-heuristic optimisation algorithms, such Genetic Algorithm (GA) [11], Particle Swarm Optimisation (PSO) [6], Ant Colony Optimization (ACO) [5], Differential Evolution (DE) [24] algorithm, and Harmony Search (HS)[8] algorithm, have been successfully applied to solve a wide range of complex highly nonlinear engineering optimisation problems. They can be easily implemented to solve an optimisation problem without gradient information about the objective function and constraints. In this paper, a meta-heuristic approach is proposed to solve the signal optimisation problem of a real-world transportation network. To measure the performance of the network, a set of objective functions are considered, including waiting time, fuel consumption, and vehicular emissions. To demonstrate the efficiency of the proposed approach, the signal timing plans of the traffic lights of the transportation network of a UK city is optimised and the obtained results are compared to those obtained from the classical Webster method. The numerical results verify the efficiency of the proposed approach to solve the signal optimisation of a real-world transportation network.

The organization of the rest of the paper is as follows. In Section 2, the signal optimisation of a transportation network is formulated by considering various objective functions. The modelling of a real-world transportation network of a city in United Kingdom (UK) is investigated in Section 3. The proposed meta-heuristic optimisation approach is discussed in Section 4. Experimental results of the optimisation is presented in Section 5. Finally, Section 6 concludes the paper.

2 Signal Optimisation Problem

The signal optimisation problem is an optimisation problem looking for the best signal timing plans for the traffic lights within the network in order to improve the performance of the network in terms of the waiting time, fuel consumption, number of stops, vehicular emissions, etc. In the literature there are various objectives considered for signal optimisation such as minimisation of waiting times [25, 28, 14, 13, 19], fuel consumption [17, 23, 20, 2] and carbon emissions [2, 16, 29, 23]. These studies provide insights into how to improve the signal lights in a network based on the considered objective function. However, fewer studies have been carried out to understand the relative importance of different nodes of the network, different objectives and the effects from interactions between them in achieving overall network performance.

In the current study, a set of four objective functions are considered for the signal optimisation problem, which are the minimisation of carbon emissions, minimisation of total waiting times, minimisation of fuel consumption and the minimisation of the aggregated network performance. The signal optimisation problem for each of the mentioned objective functions can be formulated as follows:

– Waiting time minimisation:

$$Find : \mathbf{X} = [x_1, x_2, ..., x_n] \tag{1a}$$
$$Minimise : C_w(\mathbf{X}) = \Sigma_{j=0}^{m} W_{v_j} \tag{1b}$$

– Fuel consumption minimisation:

$$Find : \mathbf{X} = [x_1, x_2, ..., x_n] \tag{2a}$$
$$Minimise : C_f(\mathbf{X}) = \Sigma_{j=0}^{m} F_{v_j} \tag{2b}$$

– Emissions minimisation:

$$Find : \mathbf{X} = [x_1, x_2, ..., x_n] \tag{3a}$$
$$Minimise : C_e(\mathbf{X}) = \Sigma_{j=0}^{m} E_{v_j} \tag{3b}$$

– Performance optimisation:

$$Find : \mathbf{X} = [x_1, x_2, ..., x_n] \tag{4a}$$
$$Minimise : C_p(\mathbf{X}) = p\Sigma_{j=0}^{m} W_{v_j} + q\Sigma_{j=0}^{m} F_{v_j} + r\Sigma_{j=0}^{m} E_{v_j} \tag{4b}$$

In the above equations, $\mathbf{X}$ is a vector of decision variables containing the signal timing plans for the whole network, n is the number of signal parameters, $C_w(.)$, $C_f(.)$, and $C_e(.)$ represent the waiting time, fuel consumption, and emissions within the network, respectively, $C_p(.)$ indicates overall performance of the network, p, q and r represent the weighting coefficients for each of the objective functions, $\{v_1, v_2, ..., v_m\}$ represents the set of vehicles within the network and W_{v_j}, F_{v_j} and E_{v_j} represent waiting time, fuel consumption and emissions for vehicle v_j respectively. The weights for each objective can be adjusted based on user preference. The signal timing variables are the phase duration of traffic light states for each junction.

To consider the practical operation of traffic lights and safety regulations [1], the upper and lower bounds for the signal timing parameters are assumed as follows:

$$7s \leq x_i \leq 60s, i = 1, 2, ..., n \quad (5)$$

Other constraints based on the real-world conditions of the network could also be assumed, such as speed limits for vehicles, etc. However, in this study, we only assume the bounds of signal timing variables as the optimisation constraints.

3 Modelling a City Network with SUMO

In this study, the signal optimisation of a real-world transportation network of a city in the UK is investigated. (We call it "the benchmark city" and due to privacy regulations the actual name of the city is not mentioned in this study). The network is modeled by Simulation of Urban MObility (SUMO) software, which is a microscopic traffic simulation tool. Figure 1 shows the network configuration of the benchmark city. The open street map of the city is imported to the NETEDIT software, which is a graphical network editor for SUMO. The network has 9494 edges and 2207 nodes. In NETEDIT, the location of the traffic lights and their initial timings are defined.

For a weekday period 8:00AM-18:00PM, the realistic movements for cars, vans, lorries, and buses are used in the model, using the validated trip matrices. The Traffic Analysis Zones (TAZ) edges are used to describe sources (origins) and sinks (destinations) of trips. Pedestrian while not explicitly modelled are also considered as an all red traffic phase.

3.1 Inputs and Outputs of the model

As it displayed in Fig 1, the model includes 76 traffic lights with differing numbers of phases. The duration of each phase of traffic lights is treated as the inputs to the model. Hence, the number of decision variables of the optimisation model is 350. As it expressed by equation (5), the lower and upper bounds for these variables are set to 7s and 60s, respectively.

The outputs of the SUMO model are the waiting times, fuel consumption and carbon emissions for all the vehicles in the network as defined in Equation 1, Equation 2, Equation 3 respectively.

4 Evolutionary Optimisation Framework for a Road Network

The optimiser framework is built using the genetic algorithm library ParadisEO [12] which is available under an open source licence. For the Genetic Algorithm (GA) the population $P = \{X_1, X_2, ..., X_{j-1}, X_j, X_{j+1}, ..., X_\mu\}$ consists

Fig. 1: Network of a benchmark city

of individuals each representing a candidate solution. Such an individual is represented by a real valued vector $X_j = [x_1, x_2, ..., x_{i-1}, x_i, x_{i+1}, ..., x_n]$, where each GA gene [7] is represented by a real valued signal phase duration variable x_i."Fitness" or the quality is evaluated through a fitness function which captures the objectives and the constraints discussed in Section 2. Algorithm **??** outlines the evolutionary optimisation process in general.

Algorithm 1 $(\mu + \lambda)$-EA: Evolutionary Algorithm

1) Initialise the population $P = \{X_1, X_2, ..., X_{j-1}, X_j, X_{j+1}, ..., X_\mu\}$ with μ traffic light individuals $X_j = [x_1, x_2, ..., x_{i-1}, x_i, x_{i+1}, ..., x_n]$, i.e. a vector of potential traffic light phase durations x_i.
2) Select $C \subseteq P$ where $|C| = \lambda$.
3) For each $I_1, I_2 \in C$, produce offspring I_1' I_2' by crossover and mutation. Add offspring's to P.
4) Fitness evaluation of all $I \in P$
5) Select $D \subseteq P$ where $|D| = \mu$.
6)$P := D$
7) Repeat step 2 to 6 until termination criterion is reached.

In step 1, we generate a population P with μ traffic light individuals X_js within the feasibility region defined by the bound 5. In step 2, we employ random selection to select parents to apply genetic operators. We apply genetic operators, uniform crossover and uniform mutation in step 3. In step 4, the fitness function invokes the SUMO simulation with the traffic light assignment represented by the GA individual X_j as the input and, retrieves waiting time, fuel and emissions data as the outputs at the end of the SUMO simulation as described in Section 3.1. In the aggregated performance case, these outputs are aggregated to one formulae for fitness evaluation as described in Equation 4 in Section 2. In step 5, we use the fittest μ individuals as survivors.

5 Experiments

5.1 Impact from Signal Timings on Network Performance

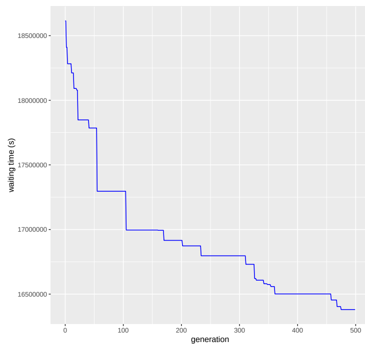
For this initial experiment we consider a rather simpler set up. The goal of this experiment is to understand the effect of traffic light timings on network performance in several different aspects.

We consider simple (1+1) EA with $\mu = 1$ and $\lambda = 1$. The initial population is generated from a uniform distribution within the feasibility region as defined in the constraint 5. The algorithm is run for 500 generations, separately for each objective, namely waiting time (Equation 1), fuel consumption (Equation 2), carbon emissions (Equation 3) and for the aggregated objectives with weighting of 1 (Equation 4).

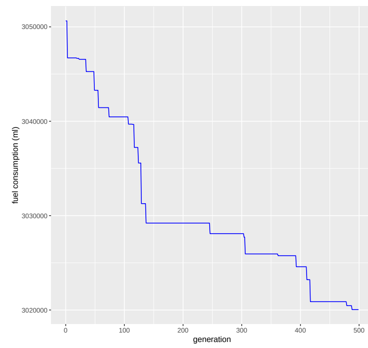
As shown in Figure 2 during only 500 generations with the simple EA, the waiting time, fuel consumption, carbon emissions and overall network performance has been improved by 12%, 1%, 2% and 2% respectively. It is evident from these results that the performance of the road network can be improved in several aspects (waiting times, fuel consumption, carbon emissions) by changing the signal timings.

5.2 Relative Importance of Nodes

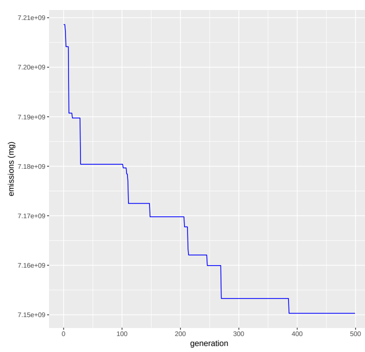
In order to identify the impact of each node (representing a junction) in the road network we conduct a set of experiments. In these experiments, we run the optimisation process changing the phase duration of each traffic light located at each junction separately and record the fitness achieved at the end of the process. Accordingly, in each algorithm run, the decision variables represent the phase durations of the traffic light for the specific junction defined by the id. The rest of the experimental set up is similar to Section 5.1. Figure 3 depicts these fitness values achieved by individual optimisation processes and Figure 4 depicts the locations of the signal lights in the map where the fitness difference is represented by the area of the circle denoting the fitness gain for the specific signal lights. Its observed that few signal lights such as 68, 66, 455, 298, 299, 191 and 148 have significantly higher fitness difference implying significantly higher impact on the optimisation process than the rest of the signal lights. The majority of the lights appear to have medium impact falling into the medium range while less than a quarter such as 67, 441, 18, 187 and 233 falls into the low impact



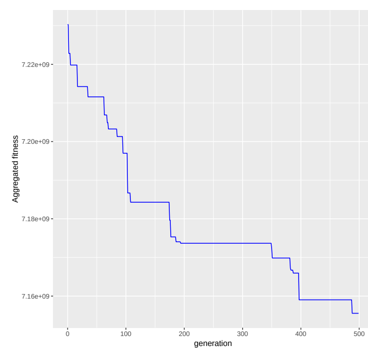
(a) Waiting time



(b) Fuel consumption



(c) Carbon emissions



(d) Overall network performance

Fig. 2: Fitness over generations

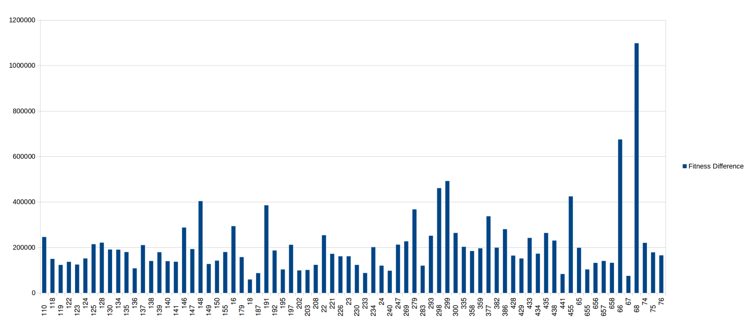


Fig. 3: fitness difference for the considered 76 lights

level. This figure illustrates two key aspects of the optimisation and problem, firstly it allows the user to highlight those areas of the network that would most benefit from changes to their signal timings which in this instance correspond with major junctions as expected, and secondly can be used as a mechanism for the evolutionary algorithm to focus its effort on those junctions that deliver most benefit e.g. through a differential mutation rate for these variables. This view 'under the hood' of the algorithm, provides an evolutionary algorithm's eye view of the optimisation problem and is useful in communicating algorithm decisions to the user.

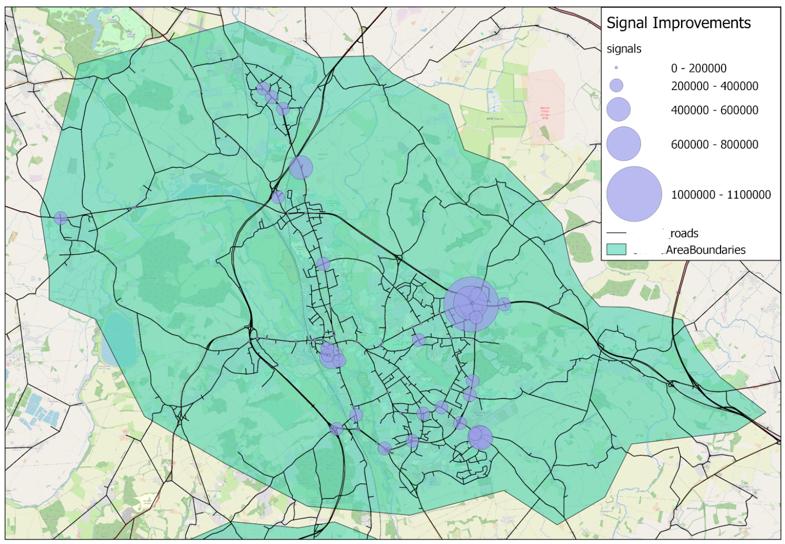


Fig. 4: fitness difference for the considered 76 lights

5.3 Bench-marking with Existing Controllers

The performance of the evolutionary algorithm is bench-marked against the Webster [27] and Green Wave methods, which are traditionally traffic signal optimisation techniques in the literature. For these experiments the GA settings are similar to Section 5.1 except we consider a larger population here, with a parent population size of $\mu = 10$ and offspring population size of $\lambda = 10$.

Webster The Webster method is a classic signal timing method, which is based on minimizing traffic delay to calculate the timing plan [27]. for a given intersection, the Webster method calculates the optimal cycle time from the following equation:

$$c_0 = \frac{1.5L + 5}{1 - Y}$$

where Y is the sum of the y values and refers to the intersection as a whole and L is the total lost time per cycle in seconds. The y values indicate the flow to saturation flow ratios for different lanes of the intersections.

Hybrid Greenwave-Webster Green wave control is another classical technique to regulate traffic signal of urban artery. The control effect is obvious, and the realization is simple. The core of control is to make vehicles successively come across intersections on the artery as many as possible, which can decrease the average number of stops and average delay time of vehicles. Based on the SUMO instructions, the green wave method can only be applicable to the traffic lights with the same cycle times. On the other hand, the researchers have reported that the network delay time is not significantly increased by changing the cycle times obtained by the Webster method within the interval $(0.75C_{opt}, 1.5C_{opt})$ [26], where C_{opt} is the optimum cycle length for a given traffic light. In order to apply the green wave method, we have changed the cycle times of all traffic lights yielded by the Webster method within the mentioned interval and it is assumed that the cycle time of all traffic lights are equal to 27s.

Results To initialise the GA we use some Webster solutions, where we use a subset of candidate solutions/individuals randomly generated from a uniform distribution within feasibility bounds similar to previous experiments and the rest of solutions optimised by Webster. It is observed that the GA optimises the solutions over the algorithm run and that the waiting time is improved by 11% with the GA compared to Webster (see Figure 6). With Webster, local optimisation of each single junction is conducted and this does not consider the interconnections of the nodes of the network. The results suggest that for optimisation of signal timings, the inter-connectivity of the nodes in road network seems to play an important role.

These results further highlight the importance of a good initial population. The suboptimal solutions of Webster provides a good starting point to GA. This is evident when comparing the fitness from the GA with random initialisation versus GA with heuristic initialisation from Webster in Figure 2a and Figure 6 respectively. It shows that during 500 generations, the GA with Webster initialisation could achieve fitness over 300% better than the GA with random initialisation. Nevertheless, its theoretically possible for a population based GA to achieve global optimum with high probability given a very large running time. Thus a good starting point can only help in reducing the time a GA takes to reach the optimum.

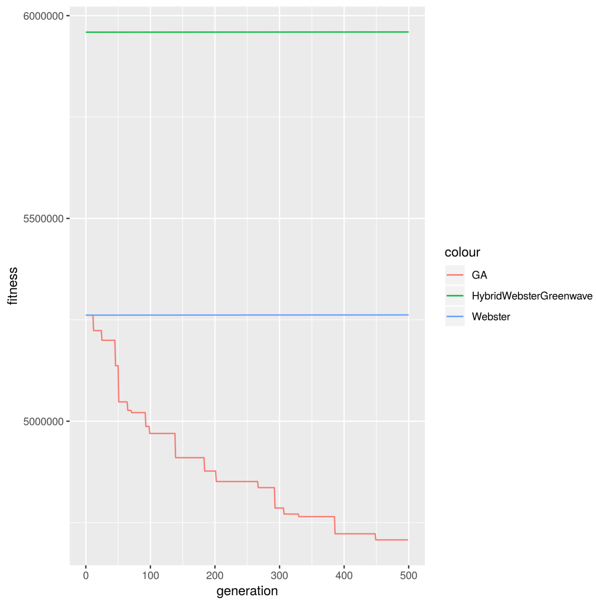


Fig. 5: Webster, Greenwave and GA

Fig. 6: waiting time over generations for Webster, Greenwave and GA

6 Conclusions and Future Work

The results of modelling and optimisation of a real world road/city network using a hybrid Webster-GA are presented. Several objectives related to the performance of a road network are considered individually and in combination. Experimental results show that there is an effect from signal timings on road network performance from several different aspects namely, waiting timings, fuel consumption and carbon emissions. Our approach based on GA was benchmarked with classical methods and results show that the GA improved performance by 11%. This is because of the global optimisation of GA considering the network as a whole compared to the other methods considering the nodes separately. The experimental results on relative importance of the nodes further show that certain areas within the road network are more crucial than the others when determining the overall performance of the network. Future work will concentrate on further investigations on the relative importance and inter-dependencies among the different nodes/node clusters of a road network as well as relative importance of the different objectives through multi-objective optimisation.

Another consideration is on how traffic reacts and reroutes according to the improvements made, behaviour changes of the vehicles have the potential to reduce the level of benefit seen. Traffic assignment is computationally costly, but co-evolving traffic routing alongside improvement of will yield solutions that account for changes to traffic routing.

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