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LOGAN's Run: Lane Optimisation using Genetic Algorithms based on NSGA-II

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Abstract— **Whilst bus lanes are an important tool to ensure bus time reliability their presence can be detrimental to urban traffic. In this paper a Non-dominated Sorting Genetic Algorithm (NSGA-II) has been adopted to study the effect of bus lanes on urban traffic in terms of location and time of operation. Due to the complex nature of this problem traditional search would not be feasible. An artificial arterial route has been modelled from real data to evaluate candidate solutions. The results confirm this methodology for the purpose of studying and identifying bus lane locations and times of operation. Additionally it is shown that bus lanes can exist on an arterial link without exclusively occupying a continuous lane for large periods of time. Furthermore results indicate a use for this methodology over a larger scale and potential near real-time operation.**

I. INTRODUCTION

Bus lanes are a commonly used solution to the growing problem of urban congestion and the increasing need for reliable public transport. As road use increases there is also an increase in journey travel time, unless infrastructure better suited to the new situation is built then the effect is that not only commuters but the environment and economy can suffer greatly. A common strategy to combat the increased need for populations to commute is the promotion of public transport to move people and goods about more efficiently, however public transport is only as good as the infrastructure upon which it is based and the likelihood of commuters considering it as an alternative. Keeping traffic moving is preferable to waves of traffic stopping and starting such as in congested scenarios with regards to air quality and pollution, as acceleration and deceleration typically consume far more fuel than normal [19]. Bus Lanes and similar High Occupancy Vehicle (HOV) lanes are commonly spotted on arterial links leading into cities and main circular roads in the United Kingdom and have been shown to have a positive impact in reducing travel times and improving journey time reliability. Bus lanes can often appear empty at peak times as whilst most motorists are moving slowly buses are not held up as much, presenting the lanes as potentially wasted space in the minds of some motorists (the Mayor of Liverpool, UK. recently suggested removing all bus lanes in the city [31]). The aim of this paper is to use a genetic algorithm (GA) alongside a simulation of an artificial urban artery to optimise the parameters of any present bus lanes, including time of operation and length. It is hypothesised that at critical traffic levels disabling or reducing the operation of bus lanes could help to ease the traffic condition without severe consequences for public transport reliability.

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II. BACKGROUND

This section presents some background information and related relevant literature on urban traffic management and control, traffic simulations, traffic condition forecasting, and HOV lanes as well as Genetic Algorithms.

A. Optimisation

Many strategies are proposed by Intelligent Transport Systems (ITSs) to solve the increasing problems of congestion within cities. The strategies that are defined are required to incorporate additional considerations for the promotion, and so needs, of reliable and consistent public transport. These two factors can be viewed as objectives that require optimisation.

Previous research has proposed the use of GA's to produce a near-optimal solution to congestion management. Park et al. [24] illustrated the use of GA in conjunction with the CORSIM (CORidor SIMulation) simulation program to attain near-optimal traffic signal timing plans during congested or over-saturated periods. Park et al. defined over-saturated as being conditions when a vehicle was prevented from moving freely, either due to other vehicles in an intersection or queuing in the exits of a link. For low and high demand volume cases, the GA-based algorithm was shown to outperform a representative delay-based model.

A similar approach was adopted by Teklu et al. [28]. A GA was again used to devise a near-optimal solution to traffic signal control to improve delays, safety and environmental measurements. To assist the optimisation process, they incorporated the use of driver re-routing in response to travel times. This was achieved through the addition of a network equilibrium model as a constraint to the optimisation process.

The existence of multiple objectives in a problem gives rise to a set of optimal solutions (which can be referred to as Pareto-optimal solutions), as opposed to a single optimal solution [14]. As with single-objective problems (which this paper previously discussed), the objectives can be both minimised and maximised. Differences occur in multi-objective optimisation as the objective functions constitute a multi-dimensional space. Multi-objective optimisation can be described as a

> "vector of decision variables which satisfies constraints and optimises a vector function whose elements represent the objective functions"[23].

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The optimal solutions can be defined as having *dominance* [13].

B. Non-dominated Sorting Genetic Algorithm-II: NSGA-II

NSGA-II [14] is a popular procedure which attempts to find multiple Pareto-optimal solutions in multi-objective optimisation problems. NSGA-II has three features:

- It uses an elitist principle.
- it uses an explicit diversity preserving mechanism
- it emphasises non-dominated solutions.

NSGA-II has the following structure (taken and adapted from [13] and [14]).

1) At any point the offspring population,Q_t is first created using the parent population P_t and the usual genetic operators.
2) The populations of both Q_t and P_t are combined to form a new population R_t.
3) Population R_t is filled by points of different non-dominated fronts. Those fronts that can not be accommodated are deleted.
4) Through the use of Crowding distance sorting, a perimeter cuboid formed from the nearest neighbour in the objective space, the top ordered list is chosen.

The multi-objective nature of reducing vehicle congestion whilst endeavouring to maintain bus flow lends itself to the use of NSGA-II algorithm. As a result, this research has focused on the use of this approach.

C. Traffic Models and Bus Lanes

Priority lanes (referred to here as bus lanes) are reserved for traffic of a particular type so as to improve travel times and travel time reliability for those users, such as buses, high-occupancy vehicles or as in 2012 in London, official Olympic traffic. Traditionally these lanes operate within either a fixed time during peak periods or continually depending on circumstance, however Zhu et al discover in[33] that Dedicated Bus Lanes (DBL) are only suitable for instances where traffic demand is considered to be low. Intermittent Bus Lanes (IBL) are therefore typically preferable when congestion is a significant factor in assigning a bus lane. Further to this, Currie et al [11] found that traffic volumes of over 1000 VPHPL (vehicles per hour per lane), or the rule-of-thumb “1KL threshold”, bus lanes were no longer useful in improving the condition of the network and offered more detriment than benefit.

Microsimulation of a road network can provide high-resolution metrics[29] on its current state at any given time step. By simulating individual driver behaviour and interactions across the network it is possible to obtain averaged metrics for each agent such as wait times, number of stops, speed, emissions and travel time. By modelling driver interactions at junctions and signals the effects of congestion can be observed in fine detail and signals can be optimised to keep stops and wait times to a minimum. Microsimulation is usually computationally taxing, requiring many thousands to hundreds of thousands of agents to be modelled simultaneously. This limitation has previously hampered microsimulation[26][27][32][10], however the cost of processing power has fallen significantly, making microsimulation cheaper and easier to achieve. Microsimulation as a result has become much more popular in recent times and is now widely used [20].

Traffic microsimulations have been widely used in many publications for a variety of purposes including air quality monitoring and prediction [22][3], the effects of traffic calming measures[17],Travel Time Prediction, the prediction of future traffic states[15][12][4][9] and for many other cases [2].

There are a number of microsimulation tools in existence, with products such as TSS’ Aimsun, PTV Group’s VISSIM/VISSUM and TRL’s TRANSYT. There are also many open-source alternatives such as SUMO (Simulation of Urban MObility)[1] and Matsim (Multi-Agent Transport Simulation). Each simulation tool employs different methodologies and models, presenting a wide choice for traffic prediction and modelling that allows the user to pick the best suite for their needs depending on the required level of detail, compatibility with infrastructure, planning abilities, signal control applications and efficiency, among other requirements.

SUMO has been chosen for the purposes of this paper due to it’s open-source, customisable nature which allowed integration with an external Genetic Algorithm. It has also been used previously in similar work [5], [21], [2].

III. OBJECTIVES

The objective of this paper is to study the use of genetic algorithms to demonstrate the effects bus lanes have on normal traffic and public transportation on a major arterial road. It is proposed that a genetic algorithm be used to evolve the positioning and timing of the bus lane along the artery to find more optimal settings. The results of this paper will be used in extension work both on the same scale as this paper and on a larger scale, such as a model of a city. Due to the diversity and heterogeneous nature of urban network infrastructure coupled with the changing behaviours of drivers it is expected to prove a feasible approach to the problem domain, significantly reducing the search time that would be necessary normally. It is envisioned that the work will highlight the complexity of the effects of bus lanes in urban networks. The long term scope for this is to provide a tool to advise local authorities on times of operation and positions for bus lanes on major urban arterial links. Success would provide a decrease in mean travel time for private road users without causing significant detriment to the public transport systems both in terms of travel time and user uptake.

IV. METHODOLOGY

A. The traffic model

To model the bus lane the open-source traffic microsimulation suite SUMO (Simulation of Urban MObility) was chosen due to the accessibility and customisability of the tools.

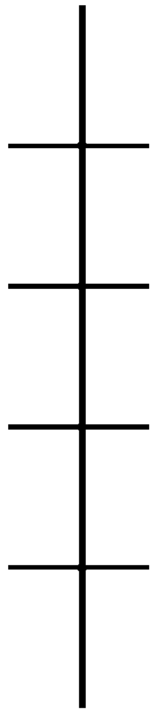

Fig. 1. Arterial network model as run in SUMO.

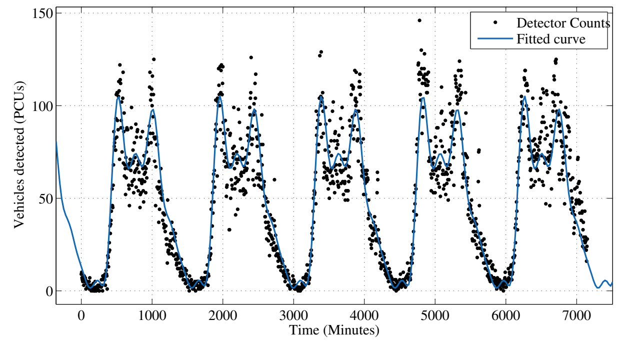

Fig. 2. Quantity of Vehicles Detected (PCU's) Against Time (Minutes)

SUMO provides a Python API which enables the solutions presented by the GA to be inserted into the simulation with ease, including adjusting the bus lane length and timings. The DEAP library[16] for Python was used to implement the GA.

A simple arterial network was defined using XML, consisting of a 1km long, 3 lane one way link, and 4 intersections, with the crossing links consisting of one-lane two way traffic (Fig. 1). The bus lane is on the right-most lane (as such, this network is right-hand, contrary to UK roads). The artificial arterial link is one-way as the models used in the simulation do not consider oncoming traffic[30], therefore adding oncoming traffic would add complexity that has little impact upon the result (excluding the additional turning phase at the cross roads). Additionally, it can be common for sections of arterial links in United Kingdom cities to be completely separated from their contra-flow, such as in Leicester.

Traffic lights are situated along the corridor, with offsets of *15s* applied to create a Green-Wave[8] effect. Traffic Assignment Zones (TAZs) are defined along the link which describe origins and destinations for the agents (to be used to create an Origin-Destination Matrix). The TAZs were A and B, which described the link origin and terminus respectively. Additionally C, D, E and F were defined which described the zones associated with the crossing links (Two links per zone).

To create the traffic demand for the simulation data was utilised from the City of Leicester, UK Urban Traffic Management and Control (UTMC) system, SCOOT. A week of data was collected from an inductive loop stationed along London Road just after a busy intersection, one of the final such intersections before the road joins the city circular.

The data was then fitted to a curve using a Fourier transform based curve fitting methodology, producing the signature AM/PM peak shape for Monday to Friday with the distinctive peaks and troughs, along with the single peak often seen on weekends (Fig. 2). The curve fitting is an important step to clean up the data and provide a generic yet realistic origin-destination matrix. It was decided for the purposes of this paper that a 5 minute time interval was suitable for describing the traffic demand. 8 hours of demand at a 5 minute resolution was produced for each of the TAZs along the link, 3.5 hours for each peak period with a 30 minute warm-up period for both peaks. This demand data describes the movement of vehicles from one TAZ to another and is used by the routing algorithm (A*[18]) to provide a list of links the agents will traverse. The majority of the traffic will travel from TAZ A to TAZ B.

An initial simulation of the network was performed with the full bus lane in operation during the time periods of interest, which are 07:00 to 10:30 for the AM-Peak and 15:00 to 18:30 for the PM-Peak. These times were based on previous literature, however there is no consensus on exact peak times as these are individual to different cities and roads [21][3].

B. The Genetic Algorithm

In order to investigate the bus lane timing and position optimisation, a genetic algorithm was used. The GA's candidate solutions are in a binary representation of bus lanes to be used and times these will be active. The space consists of the combination of bus lane timing and position parameters. The chromosome consists of 38 bits, as shown here:

Link 1	Link 2	...	Link n	Time 1	Time 2	...	Time m

The phenotype of an individual's genotype is the combination of bus lanes used on link 1 to n (10 links in this study) and time slots these are active (7 to 10.30 AM and 3 to 6.30 PM in 15 minute intervals; thus m = 28) in the simulated network. The total size of the search space of possible parameter combinations for the presented problem is 274,877,906,944.

NSGA-II has been chosen due to the multi-objective nature of the underlying problem, and due to it being a mature methodology that has been widely used in other works including Bus Network Optimization[6] and Traffic Signal Optimization[25][7].The GA has been implemented using the Python DEAP library. The VarAnd combination of crossover followed by mutation has been selected, with a 50% crossover rate and a 10% probability for mutation. Any other parameters were default DEAP settings. The fitness of each candidate solution has been evaluated by means of simulating the bus lanes and their timings in the SUMO simulator. The fitness of each objective has been calculated as follows:

$$O_v = \frac{\sum(v_k)}{max(k)} - itt$$

$$O_b = \frac{\sum(b_l)}{max(l)} - itt$$

where v_k is the travel time of vehicle k, b_l is the travel time of bus l, with a total of $max(k)$ other vehicles on the network and a total of $max(l)$ buses simulated in one full simulation run. itt is the rounded average ideal travel time for the network in seconds (75 seconds here).

In other words, the fitness for each objective is the change in mean travel time for the specific vehicle type over a simulation run towards the ideal free flow scenario. In this work, a population size of 50 and a termination after 51 generations has been selected due to the high computational strain in terms of processing time. The following section provides detailed results from multiple runs.

V. Experimental Results

A pair of control simulations were performed to establish two extreme baselines for the arterial link. In one case the bus lane operates continuously and is present along the entire length of the link, in the other there is no bus lane present. These controls were then evaluated on fitness in the same manners as the solutions presented by the GA, meaning an average travel time in seconds was measured for normal traffic and for bus traffic, which then had the rounded average ideal travel time for this arterial (75 seconds) subtracted to produce a difference from the free-flow condition speed (Table I). Whilst it is possible for vehicles to traverse the artery in a time close to free-flow (only a few seconds off), this will happen infrequently as they will need to arrive at a specific time in the signal phasing so as to catch the entirety of the Green-Wave.

	Normal	Bus
Bus lane	129.29s	20.56s
Unrestricted	27.22s	24.23s

TABLE I

Fitness adjusted travel times at 1 bus per 5 minutes

As expected the unrestricted case greatly improved the travel time of the normal traffic, however of interest is the fact that the bus average travel time only increased very slightly. The same experiments were repeated with an increased volume of buses (from one bus per five minutes to five buses per five minutes) and the results were more pronounced, showing an increase of over 10 seconds in travel time for buses when no bus lane was present (Table I and II). This shows that the bus lane has a noticeable positive effect on bus traffic along this link, which may grow when combined into a larger network (longer than 1km).

	Normal	Bus
Bus Lane	123.26s	24.70s
Unrestricted	31.10s	35.17s

TABLE II

Fitness adjusted travel times at 5 buses per 5 minutes

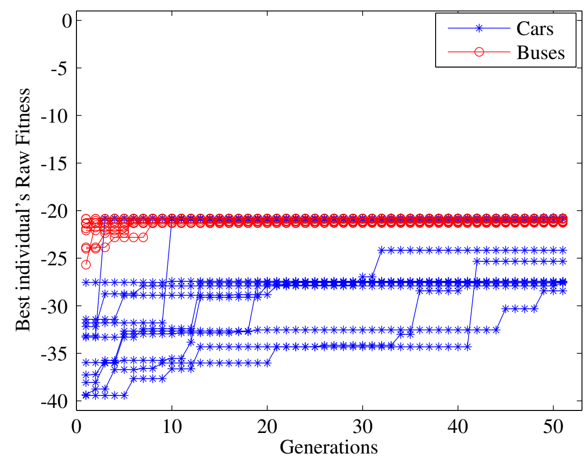

Fig. 3. Fitness for all GAs over all generations

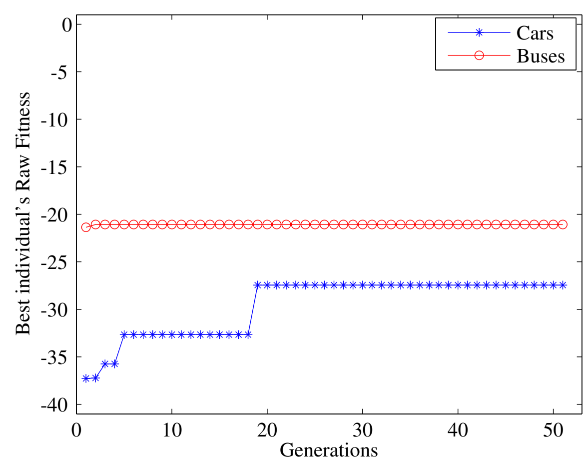

Fig. 4. Fitness for GA2 over all generations

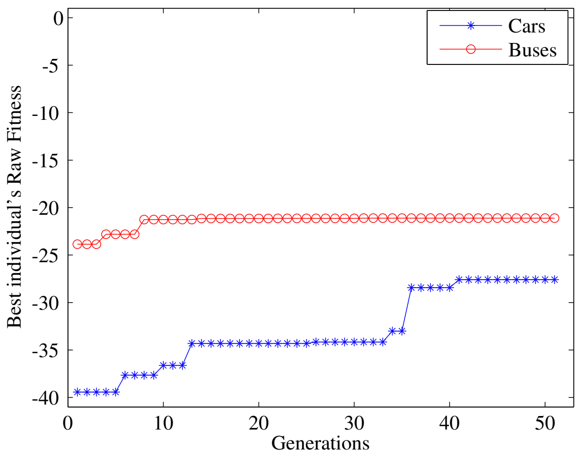

Fig. 5. Fitness for GA6 over all generations

As the experiments took a considerable amount of time to process due to a large search space it was not possible to repeat the experiments for different bus volumes. The experiments were performed at a rate of one bus every five minutes. The chromosomes produced from the GA often showed a similar trend in the positioning of the bus lane, with it starting further down the artery after the first set of signals. The solutions favoured non-contiguous periods of operation for the bus lane, often leaving 15-30 minute breaks. The change of positioning is likely due to the topology of the network, as the beginning of the artery has more vehicles joining than further on. This was somewhat expected as the structure of the network will have a significant impact on suitable locations for bus lanes.

The fitness of the solutions over time shows much improvement for the private car travel times, with the bus mean travel time improving slightly to a maximum in a short number of generations as shown in Fig. 3. Whilst some GAs evolve more quickly towards fitter solutions (Fig. 4) others require more generations closer to the terminal generation (see Fig. 5). This may indicate that the GAs have not yet converged fully. However, as expected all GAs converge towards 20-30 seconds from free-flow conditions. This is especially evident when comparing these to the control of 129.29 seconds for a dedicated bus lane.

The bus times are not improved as they very reach a mean traversal time that is close to optimal as shown in the controls. This is due to the low volume of buses (one every five minutes), however increasing the volume to five every five minutes (as mentioned previously) increases the mean travel time, creating more scope for optimisation.

VI. CONCLUSION

In this paper it has been shown that a genetic algorithm is a suitable methodology for investigating the impact bus lanes have on urban arterial links. It has been highlighted that the bus volumes in this experiment are low, meaning that we are not able see a significant range of improvements for the bus travel times. At higher volumes it is certain that the mean travel time would be more adversely affected than it has been in this paper, however there would still be a minimizing effect from the GA. The extremely large search space (2^{28}) for an entire network makes CI based methodologies the ideal candidates. The study of the GAs phenotypes throughout each generation has yielded useful and interesting information on the properties of priority lanes that are beneficial in terms of mean travel time. It was possible to reduce the mean travel time for private cars whilst avoiding a large detriment to the mean travel time for buses. Whilst the travel times are not too dissimilar to the no bus control solutions have been found that are close whilst still providing a priority lane for buses and taxis. As bus priority lanes are also implemented based policy and not just for the effects for the traffic condition the results show it is possible to provide the best of both worlds. Additionally it also means that if abnormal traffic conditions arise the impact on public transport would be reduced as there would be "refuges" available in the form of the intermittent bus lanes.

VII. FUTURE RESEARCH

As an extension this work will use a variety of bus volumes based on real bus timetables on the link for which the artificial network was based. Additionally there are alternatives to NSGA-II which should be further investigated along with alternatives to Genetic Algorithms, including Memetic Algorithms. An investigation using a model of the City of Leicester, UK is planned, using detailed link descriptions from Open Street Map combined with real demand data provided by Leicester City Council. A near real-time system is planned that will be investigated and tested in simulation to operate a real link, leading to a near real-time bus lane control system. A more detailed simulation experiment is also planned that will consider the effects of changing bus lane operation on the wider network, specifically focusing on the route re-planning agents may consider when a link is known to have improved or worsened in perceived travel time.

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