Multi-Segment Green Light Optimal Speed Advisory

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***Abstract*—The problem of how to adjust speed of vehicles so that they can arrive at the intersection when the light is green can be solved by means of Green Light Optimal Speed Advisory (GLOSA). The existing GLOSA approaches are single-segment, that is, they consider traffic lights independently by providing vehicles with the optimal speed for the segment ahead of the nearest traffic lights. In this article we introduce a new approach—a multi segment GLOSA—according to which several lights in sequence on a vehicle's route are taken into account. The speed optimisation process is performed using a genetic algorithm. We assume that a vehicle has access to all traffic light phase schedules that it will encounter on its route. The route is composed of segments divided by traffic lights. The proposed GLOSA provides a driver with speed advisory for each segment according to selected preferences like minimisation of total traveling time or fuel consumption. We demonstrate, that in free-flow conditions such multi-segment GLOSA results in much better results when compared with single-segment approach.**

Keywords—ITS; Traffic lights; GLOSA; Smart City; Optimisation; Genetic Algorithms.

I. INTRODUCTION

The aim of Intelligent Transportation Systems (ITS) is to optimise transportation efficiency and improve its safety through the use of technology. Such systems allow road users to be better informed and consequently make better trip-related decisions, leading to reduced travel time, fuel consumption and tailpipe emissions. Emissions of carbon dioxide (CO_2) (more than 99.8% of carbon in the fuel is emitted as CO_2) are linearly related to fuel consumption [1], [2], therefore, fuel economy improvement reduces the emissions. Minimising acceleration and braking significantly improves the economy. Slow-and-go driving pattern is always better than stop-and-go—about twenty percent more fuel will be used to accelerate from a full stop than from eight kilometres per hour [3]. In general, fuel-efficient driving strategy is to anticipate what is happening ahead, and drive in such a way so as to avoid stop-and-go movement pattern. Such a pattern is often caused by traffic lights, which have to distribute green time amongst the competing traffic flows. Hence, improving traffic signalisation so that traffic lights are synchronised with vehicle traffic and vice versa is also key issue from fuel-efficiency perspective. Conventional traffic light systems use pre-programmed timing schedules [4]. In areas were traffic volumes are unpredictable or rapidly changing smoother flows can be created by means of adaptive traffic lights [5]. Such lights adjust signal timing parameters in real-time, to adapt to traffic conditions, hence, they are ideally suited in areas were traffic volumes are unpredictable or rapidly changing. In the U.S. only a handful of adaptive systems were installed [6]. The other way around—traffic synchronisation to given timing schedules—can be achieved thanks to Green Light Optimal Speed Advisory (GLOSA) systems. Such systems—typically implemented as roadside message signs placed ahead from the signal—provide drivers with optimal speed advisory. Drivers can adjust their speed so that they arrive at the intersection when the light is green [7]. However, due to the significant costs and maintenance issues, only a small number of GLOSA systems was installed worldwide [8]. Countdown timers at traffic signals is an alternative approach allowing anticipated driving, however, their efficiency is limited [8].

Significance of the access to traffic light phase schedule by vehicles has been acknowledged by European and US transportation authorities [8]. Such information allows vehicles to calculate speed that will enable them to avoid stop-and-go driving patterns due to the lights, hence, is crucial for GLOSA systems. Recently, an infrastructure-less approach to access the schedules was proposed in [8]. The system called SignalGuru relies on a collection of windshield-mounted mobile phones, that allow to collaboratively learn the schedules. In the future this information will be available via Vehicular Ad Hoc Networks (VANETs) which will communicate with traffic lights equipped with wireless communications capabilities. Information about traffic light phase will most likely be included in VANETs-based cooperative traffic information systems (CTIS). In such systems traffic-related information is collected individually by vehicles and exchanged between themselves using wireless networks [9].

In this work we propose a new approach to GLOSA. Unlike in the literature, where traffic lights are considered independently (hereafter referred to as single-segment GLOSA) we assume that several lights in sequence on a vehicle's route are taken into account (hereafter referred to as multi-segment GLOSA). The route is composed of segments divided by traffic lights. In the single-segment approach speed advisory is given for the segment preceding the nearest lights (see Fig. 1a). In the multi-segment GLOSA the vehicle calculates a set of optimal speeds (one speed per each segment) before entering the first segment (see Fig. 1b).

We assume that vehicles have access to all traffic light schedules. Naturally, the proposed approach works best in free-flow traffic conditions with pre-timed traffic lights. Such conditions can be typically found in during off-peak hours or in restricted traffic lanes (e.g. bus-only lanes or high-occupancy vehicle lanes). In case of semi-actuated lights the system can still operate under moderate traffic. However, it might require

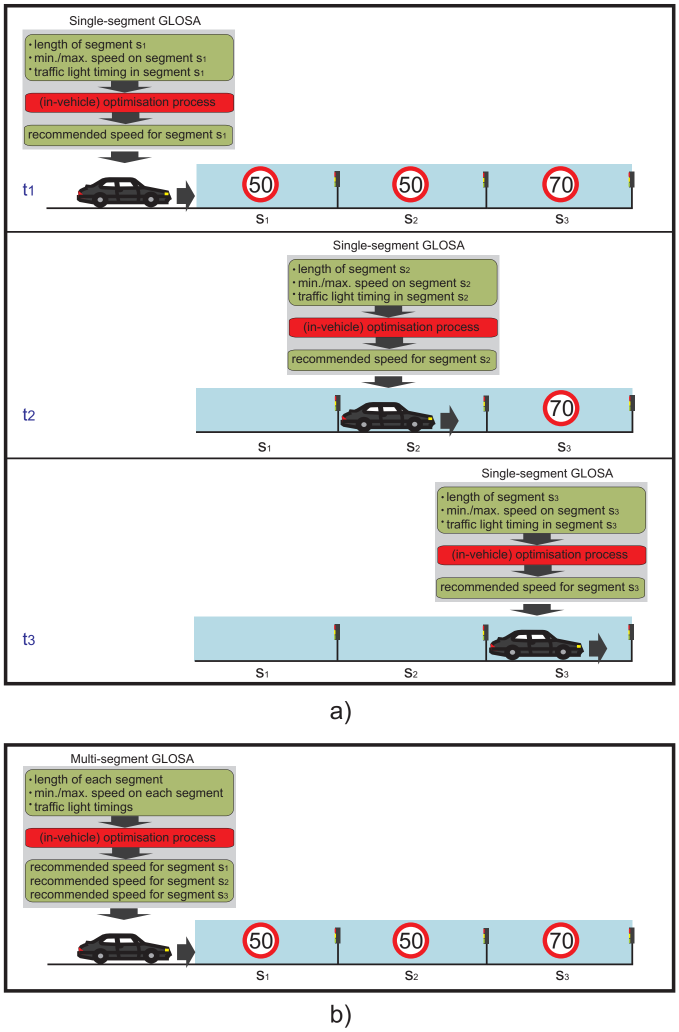

Fig. 1. GLOSA overview. In the single-segment approach (a) a vehicle calculates the optimal approaching speed to traffic lights placed at the end of current segment. In the multi-segment approach (b) a vehicle calculates a set of optimal speeds corresponding to all segments before entering the first segment.

additional re-calculations.

The main contribution of this article is as follows: (i) we introduce a novel infrastructure-less multi-segment GLOSA approach, (ii) we demonstrate how the optimisation problem of the approach can be solved using a genetic algorithm (GA), and (iii) we show, that in free-flow traffic conditions multi-segment GLOSA gives much better results than single-segment approach.

The paper is structured as follows. The next section discusses related work in the area. Section III introduces the multi-segment speed advisory. In particular, optimisation problem found in the multi-segment approach is given. Section IV explains how the problem can be solved using a GA. Section V contains specification of parameters and simulation results. The final section summarises the main conclusion.

II. Background and Related Work

Vehicle tailpipe emissions and its fuel utilisation are the single largest human-made source of carbon dioxide, methane and nitrous oxide [10]. According to [2] idle emission rates are low compared with acceleration and cruise emission rates—for instance, the average emissions during acceleration are ten times grater than during idle for carbon monoxide and nitric oxide, are five time greater for carbon dioxide and hydrocarbons. Hence, methods for reducing fuel consumption and tailpipe emissions should focus on smoothing stop-and-go driving pattern so that vehicles move with speed as constant as possible [2], [11]. This can be done by improving traffic signalisation so that traffic lights are synchronised with vehicle traffic and vice versa, that is vehicles can adapt by means of GLOSA systems their speed so that they arrive at the intersection when the light is green.

Traffic light control is typically in either pre-timed or actuated mode or some combination of the two [5]. In pre-timed control cycle length, phase plan, and phase times are predetermined and fixed. Pre-timed approach suites well closely spaced intersections with consistent traffic volumes and patterns [5]. In actuated control phase time is based on detection data. Actuation is typically achieved by vehicle detection devices (e.g. inductive loops) and pedestrian push buttons. However, signal timing is subject to a set of pre-defined parameters like maximum green duration, passage time, etc. [12]. Adaptive traffic lights belong to the latest generation of traffic control. They adjust signal timing parameters in real-time, to adapt to real-time traffic conditions, hence, their performance depends on the quality of detection systems [5]. Such systems can improve performance by five to thirty percent in areas with unpredictable or rapidly changing traffic volumes [5]. However, in the U.S. only a handful of adaptive systems were installed [6]. Commercially available adaptive controls include SCATS, SCOOT, RHODS and OPAC [4].

A. *Adaptive traffic lights*

Several approaches for optimisation of traffic light schedule have been proposed in the research literature. Good overview of existing work can be found in [13], [14]. The proposed methods are based on swarm intelligence (e.g. [15]), fuzzy logic ([16]), evolutionary computation ([17]), decision support systems ([18]), reinforced learning ([19]), and neural networks ([20]).

B. *GLOSA*

Traditional GLOSA systems implemented as roadside message signs placed ahead from the signal are not popular due to significant costs and maintenance issues [8]. The next-generation approaches assume integration of Dedicated Short Range Communications (DSRC) antennas into traffic lights. DSRC is a two-way short- to- medium-range wireless communication channel designed for VANETs [21]. The application of wireless technology to moving vehicles enables the creation of VANETs. Two particular transmission modes present in VANETs are suitable for GLOSA: *vehicle-to-vehicle* (V2V)—communication among nearby vehicles and *vehicle-to-infrastructure* (V2I)—communication between vehicles and roadway infrastructure. Several works have already investigated the use of V2V and V2I communication for GLOSA

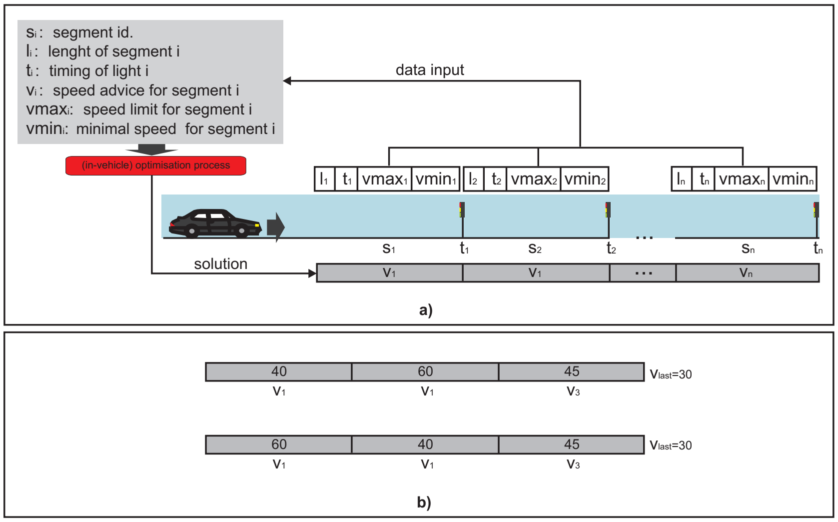

Fig. 2. Optimisation problem and solution encoding: calculation of speed advisory for three segments (a), example of solution encoding (b).

(e.g. [7], [22], [23]). Recently, and approach combining GLOSA and adaptive traffic light control was proposed in [24]. The authors propose electronic toll collection technology to communicate vehicles with traffic lights. To the best of our knowledge all GLOSA systems found in the literature advise speed to the nearest lights. In this work, we argue that multi-segment advisory (i.e. a set of adjacent lights is considered) gives better results.

III. Multi-segment GLOSA

We assume that traffic lights are pre-timed and traffic conditions allow vehicles to adapt their speed. In addition, vehicles have access to traffic light schedules. A simplified model of fuel consumption is used. The model takes into account speed differences between segments—fuel efficiency is maximised if speed is as constant as possible. That is, full stop at traffic lights and strong acceleration are avoided. The way the speed advise is implemented in vehicles is beyond the scope of this article, that is, we assume that each vehicle uses some system that allows following the advise (e.g. via an advanced cruise control system).

The problem is defined as follows: given a list of n segments $S = \{s_1, \ldots, s_n\}$, their length $l_i, 1 \leq i \leq n$, minimum and maximum speed allowed on the segments $[minSpeed_i, maxSpeed_i]$, and traffic signal schedules ts_i at the end of each segment i, defining the status of traffic light i at time t, $ts_i(t) = \{\text{GREEN}, \text{RED}\}$, the goal is to find the advisory speed for each segment $advSpeed = \{advSpeed_1, \ldots, advSpeed_n\}$ such that it will minimise certain objective $f(advSpeed)$ (e.g. fuel consumption or traveling time) of a trip that starts with the first segment s_1 and finishes at the end of the last segment s_n (see Fig. 2a):

$$\begin{aligned}
&\min \textstyle\sum_{i=1}^{n} f(advSpeed_i), && (1)\\
&\text{s.t.} \quad minSpeed_i \leq advSpeed_i \leq maxSpeed_i, && (2)\\
&\qquad ts_i(\textstyle\sum_{j=1}^{i} l_j * advSpeed_j) = \text{GREEN}, && (3)\\
&\qquad \forall i \in [1, n]. && (4)
\end{aligned}$$

The advisory for each segment is defined as the average speed that a vehicle should travel on the segment.

IV. GA for multi-segment GLOSA

In this section we start with the motivation for the application of evolutionary heuristic method for solving the optimisation problem related to the proposed multi-segment GLOSA. Next, we describe the method—a simple GA—used in this work. Finally, we explain our solution encoding and we define two fitness functions.

A. Motivation

The computational problem of finding the optimal set of speeds for our problem requires searching through a huge number of possibilities for solutions. Let us assume that n is the number of segments and sr is the speed range (the number of available speeds). Then, the number of possible solutions (nps) can be calculated as follows:

$$nps = sr^n. \tag{5}$$

For instance, if the maximum speed is fifty kilometres per hour, the minimum speed is thirty-five kilometres per hour and speed gradation is one kilometre per hour, than the number of possible solutions equals to 2^{24} for the problem with six segments and 2^{40} for the problem with ten segments. The search space is thus far too big to be searched exhaustively in reasonable time.

B. Method

In this work we apply a simple GA which has the following operators: selection, single point crossover, and mutation. The algorithm works as follows [25], [26]:

1) A population of candidate solutions to the problem (p n-bit chromosomes) is randomly generated.
2) Fitness $f(s)$ of each candidate solution s in the population is calculated (see Sec. IV-D for description of the function).

3) The following steps are repeated until p offspring have been created:
- A pair of parent chromosomes is selected from the current population. The probability of selection is an increasing function of fitness, the same chromosome can be selected more than once to become a parent.
- With probability p_c the pair is crossed over at a single randomly chosen point to form two offspring. In case when crossover does not take place, two offspring are copies of their parents.
- With probability p_m two offspring are mutated at each locus. The resulting chromosomes are placed in the new population. If p is odd, one new population member can be discarded at random.
4) The new population replaces the current population.
5) Go to step 2.

C. Solution encoding

In this work we use an integer representation, where each gene represents speed on a given segment. Hence, the number of genes equals to the number of road segments of a given problem instance (see Fig. 2a).

D. Fitness function

Fitness function assigns a score (fitness) to candidate solutions to a given problem. The score depends on how well that solution solves the problem at hand. In the problem defined in this paper the objective is to find a set of speeds such as fuel consumption is minimised. We assume, that this is achieved by keeping the speed as constant as possible and avoiding coming to a full stop at traffic lights. The fitness function (hereafter referred to as F-ECO) is defined as follows:

$$F_{ECO} = v_1 + \sum_{i=2}^{m} energyLoss_i, \tag{6}$$

where v_1 is the initial speed (i.e. speed on the first segment), m is the number of segments, and $energyLoss_i$ is based on the speed difference between the two consecutive segments (i and $i+1$) and the fact whether a vehicle came to a full stop or not. It is defined as follows: if at the end of segment i a vehicle makes a full stop before the light turns green again $energyLoss_i$ is calculated as follows:

$$energyLoss_i = v_{i+1} \tag{7}$$

Otherwise

$$energyLoss_i = \begin{cases} v_{i+1} - v_i & \text{if } v_{i+1} > v_i \\ 0 & \text{if } v_{i+1} <= v_i. \end{cases}$$

For $i = m$ the speed of the next segment v_{i+1} (not covered by the solution) is set to v_{last} parameter (artificial value).

As an example let us consider the two solutions shown in Fig. 2b. The first solution provides the following advice: $40km/h$ in segment s_1, $60km/h$ in s_2, and $50km/h$ in s_3. The second solution advices: $60km/h$ in segment s_1, $40km/h$ in s_2, and $45km/h$ in s_3. The parameter v_{last} is set to 40. Let us assume that such a light schedule is given that if a vehicle followed the advice given by the first solution it would stop at lights placed at the end of the second segment. If a vehicle followed the advice given by the second solution it would stop at the end of the third segment. In the first case the value of F_{ECO} would be equal to 110, while in the second one it would be 105.

TABLE I. SPECIFICATION OF PARAMETERS FOR GA AND SIMULATIONS.

	Parameter	Value
GA	Population size (p)	100
	Termination condition	700 generations
	Number of independent runs	100
	Selection	binary tournament
	Crossover operator	one-point, p_c=0.9
	Mutation operator	uniform, p_m = 0.01
	Elitism	2 individuals
Simulations	Number of segments	3–15
	Speed limit	50km/h or 70 km/h (equal prob.)
	Minimum speed	35 km/h if speed limit is 50 km/h
	Minimum speed	40 km/h if speed limit is 70 km/h
	Segment length	500m
	Min. duration of green light	20s
	Max. duration of green light	40s
	Min. duration of red light	15s
	Max. duration of red light	25s
	Speed gradation	1km/h
	v_{last}	40km/h
	# of roads (k)	1, 100

For purposes of comparison second fitness function (hereafter referred to as F-TT) evaluating the solution under the criterion of traveling time was defined:

$$F_{TT} = \sum_{i=1}^{m} (tt_i + wt_i), \tag{8}$$

where tt_i is traveling time in segment i and wt_i is waiting time at traffic lights placed at the end of segment i.

V. COMPUTATIONAL EXPERIMENTS

In this section we report the evaluation of GA-based multi-segment GLOSA. In particular, we compare our approach with single-segment GLOSA.

A. GLOSA approaches

In this article we compare following GLOSA approaches:

- **Approach FUEL**: multi-segment GLOSA, with minimisation of fuel consumption as the objective (method: GA-based optimisation with F-ECO fitness function).
- **Approach TIME**: multi-segment GLOSA, with minimisation of traveling time as the objective (method: GA-based optimisation with F-TT fitness function).
- **Approach FUEL-IND**: single-segment optimisation.

The first two approaches (FUEL/TIME) represent the multi-segment GLOSA introduced in this article, i.e., they take into account all segments on a vehicle's route (see Fig. 1b).

Before entering the first segment of its trip a vehicle uses a GA to compute speed advisory for all segments of the trip (see Sec. III). The difference between FUEL and TIME approaches is in the objectives, that is, according to the former the aim is to minimise fuel consumption, while according to the latter the goal is to minimise traveling time. The last approach—FUEL-IND—is introduced for purposes of comparison between the multi-segment and single-segment GLOSA. Unlike the first two approaches, it calculates speed advisory on per-segment basis, that is, it evaluates the speed for the single segment immediately after entering the segment (see Fig. 1a). The advisory for segment i is defined as a minimal speed that will allow the vehicle to arrive at the end of the segment when the light is green. Hence, the underlying objective of the approach—minimisation of fuel consumption—is the same as in the approach FUEL.

Solutions found with all approaches were evaluated using F-ECO and F-TT functions. For instance, solutions found with approach FUEL (driven by F-ECO fitness function) were also evaluated using F-TT function.

B. Generation of problem instances

A problem instance consists of at least one road composed of n segments. Each segment is specified by the following parameters: length, minimum allowed speed, maximum allowed speed (speed limit), and timing of traffic lights placed at the end of the segment. A road composed on n segments is randomly generated using parameters specified in the next section. Size of a problem instance is defined by the number of road segments that it consists of. In the experiments reported in this article it ranges from three to fifteen segments. A problem instance of size s was constructed by generating an additional segment to a problem of size $s-1$, that is, larger problems were generated by extending smaller ones. For each problem instance we generated k independent roads (hereafter referred to as test cases). For example, if size of the problem instance is six and k is set to one hundred, this means that the problem instance is composed of one hundred independent roads with six segments differing in traffic light schedules and distribution of speed limits.

In the first step we report results of the experiments, where k was set to one, while in the remaining steps k was set to one hundred.

C. Evaluation of solutions

Each solution is evaluated under the assumption of traffic conditions allowing vehicles to change their speed according to the calculated advisory.

D. Experimental setup

Experimental parameters are specified in Table I. For each problem instance one hundred independent runs were carried out. Binary tournament, one-point crossover and uniform mutation were used.

Experimental results are reported in three steps. In the first step some preliminary results are presented and discussed. In the second step we compare our multi-segment GLOSA with single-segment speed advisory. In the final step we further analyse multi-segment approach.

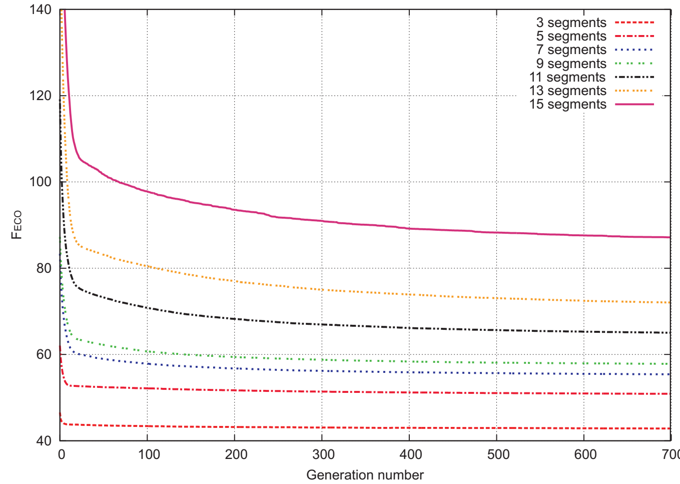

Fig. 3. The mean best fitness values for seven problems (ranging from three to sixteen segments) at every generation.

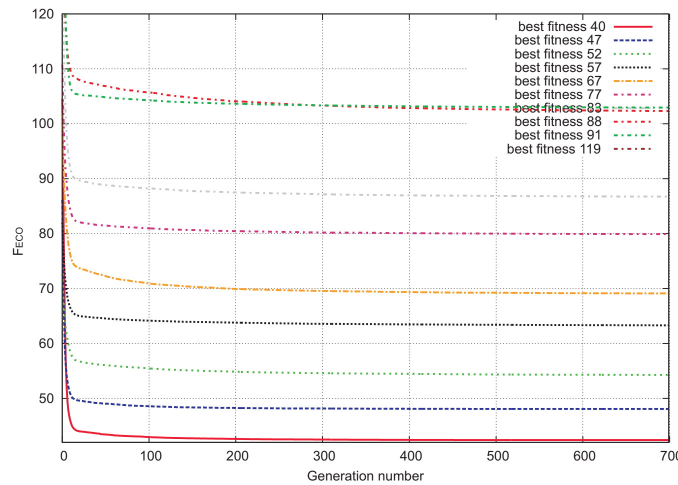

Fig. 4. Comparison of nine problem instances from the same sizes (seven segments): the best fitness values at every generation.

E. Step1: preliminary results—k equal to one

Fig. 3 presents the best fitness values (i.e. mean value calculated over the best fitness values found in all independent runs of a GA) recorded at every generation for seven randomly generated problem instances. The smallest instance consists of five segments, while the largest case is composed of fifteen segments. The best mean fitness scored in the final generation ranges from 42.86 (three segments) to 87.15 (fifteen segments).

However, as illustrated in Fig. 4, problem instances of the same size (i.e. composed of the same number of segments) vary in terms of difficulty (the number of required GA generations to find the solution) and in terms of the solutions itself. The figure compares nine problem instances, each composed of seven segments.

Depending on the problem instance, the best mean fitness found in the final generations ranges from 42 to 119. Therefore, in the remaining experiments one hundred test cases were generated for each problem size (i.e. k was set to one hundred). The results were calculated as the mean value over all test cases of a given problem instance.

TABLE III. NUMERICAL RESULTS FOR PROBLEM INSTANCES COMPOSED OF THREE TO FIFTEEN SEGMENTS. TWO APPROACHES COMPARED: FUEL (F-ECO FITNESS FUNCTION) AND TIME (F-TT FITNESS FUNCTION).

# of segments	**approach FUEL** F-ECO (standard deviation), Q1/Q2/Q3	**approach FUEL** corresponding F-TT	**approach FUEL** avr. # of generations	**approach TIME** F-TT	**approach TIME** corresponding F-ECO
3	48.98 (14.18), 40/43/49.5	126.59	35	105.23	66.32
4	49.89 (14.05), 41/46/50	167.21	70	138.74	70.08
5	50.34 (13.89), 42/46/51.5	207.91	110	173.24	72.17
6	51.07 (14.10), 43/47/52	248.37	153	207.22	74.91
7	51.85 (14.29), 44/47/52	288.17	192	241.71	76.64
8	52.29 (14.27), 44/48/52	328.41	239	276.84	81.16
9	53.24 (14.22), 46/48/53	369.35	262	311.01	83.79
10	54.05 (14.47), 47/50/53	409.85	310	346.07	87.30
11	55.06 (14.42), 47/51/56	449.38	336	380.64	91.34
12	55.69 (14.55), 47/51/57	490.58	404	416.99	91.45
13	56.78 (14.65), 48.5/52/58	531.15	401	453.08	94.01
14	57.77 (12.35), 49/53/59	568.83	415	487.41	99.89
15	59.01 (14.87), 50/55/61	609.15	455	521.40	106.83

TABLE II. MULTI-SEGMENT GLOSA (FUEL) VS. SINGLE-SEGMENT GLOSA (FUEL-IND): COMPARISON OF PERFORMANCE MEASURED BY F-ECO AND F-TT FUNCTIONS.

# of segments	**F-ECO** FUEL/FUEL-IND	**F-TT** FUEL/FUEL-IND
3	48.98/54.88 (+12.00%)	126.59/134.18 (+5.99%)
4	49.89/61.40 (+23.07%)	167.21/178.52 (+6.76%)
5	50.34/66.44 (+31.98%)	207.91/223.10 (+7.30%)
6	51.07/73.01 (+42.96%)	248.37/267.60 (+7.74%)
7	51.85/78.71 (+51.80.%)	288.17/312.02 (+8.27%)
8	52.29/84.15 (+60.93%)	328.41/356.61 (+8.58%)
9	53.24/87.83 (+64.96%)	369.35/402.62 (+9.00%)
10	54.05/92.25 (+70.67%)	409.85/448.73 (+9.48%)
11	55.06/96.83 (+75.86%)	449.38/495.01(+10.15%)
12	55.69/102.72 (+84.44%)	490.58/540.00 (+10.07%)
13	56.78/109.25 (+92.40%)	531.15/584.30 (+10.00%)
14	57.77/114.17 (+97.62%)	568.83/629.06 (+10.58%)
15	59.01/118.84 (+101.38%)	609.15/674.22 (+10.68%)

F. Step 2: multi-segment GLOSA vs. single-segment GLOSA

The comparison between multi-segment GLOSA (represented by approach FUEL) and single-segment GLOSA (approach FUEL-IND) is made by evaluating the solutions with F-ECO and F-TT functions. The results comparing the two approaches are given in Table II. Both GLOSA were applied to the same problem instances.

The speed advisory found with the multi-segment GLOSA method is better when compared with the single-segment approach, regardless the fitness function used as a performance measure. Two general observations can be made. Firstly, the bigger the problem is (i.e. the more segments a road is composed of) the greater differences between the solutions can be observed. Secondly, the differences are greater if performance is measured using the F-ECO function. For instance, in a three-segment problems the switch from multi-segment to one-segment optimisation degraded performance by 12% according to F-ECO (increase from 48.98 to 54.88) and by almost 6% according to F-TT (increase from 126.59 to 134.18). In the most complex problem instance (fifteen segments) degradation was around 100% according to F-ECO and around 11% according to F-TT.

G. Step 3: analysis of multi-segment GLOSA

In the previous step we demonstrated how multi-segment GLOSA outperforms single-segment speed advisory. In this section, we further analyse performance of the multi-segment FUEL approach. The following results of are shown in Table III: the average best fitness (F-ECO) with its standard deviation and quartiles denoted by Q1, Q2 (median) and Q3, additional performance evaluation of the solutions according to the F-TT function, and the mean number of generations after which the best solutions were found. In addition, for purposes of comparison Table III presents the following results for the alternative multi-segment TIME approach: the average best fitness (F-TT) and performance of the solutions according to the F-ECO function. In both cases (FUEL and TIME) the average best fitness was calculated as the average value of the best values found in each problem instance in the final generation.

In general, when the objective was to minimise the F-ECO function, the optimisation results range from 48.98 (three segments) to 59.01 (fifteen segments) (F-ECO fitness values). The corresponding traveling times (measured by the F-TT function) ranged from 126.59 seconds (three segments) to 609.15 seconds (fifteen segments). When the objective was to minimise the F-TT function, traveling times improved (range 105.23–521.4). Naturally, corresponding performance measured by F-ECO fitness increased (range 66.32–106.83).

VI. CONCLUSION

Keeping a constant speed as much as possible significantly improves fuel economy and minimises tailpipe emissions. However, traffic lights often impose stop-and-go movement pattern, increasing fuel consumption and vehicle emissions. Smoother driving in the presence of the lights can be achieved by means of GLOSA systems. In this article we have introduced a new infrastructure-less multi-segment GLOSA. The main novelty of the proposal is that unlike the existing single-segment systems that consider traffic lights independently, our approach takes into account several lights in sequence on a vehicle's route. We have demonstrated how the optimisation problem in our method can be solved using a GA. Finally, we have shown, that in free-flow conditions the multi-segment speed approach gives much better results than single-segment GLOSA. Consequently, multi-segment speed advisory is the best solution during off-peak hours or in restricted traffic lanes.

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REFERENCES

[1] E. Rune, *The Handbook of Road Safety Measures*, 2nd ed. Emerald, 2009.

[2] H. Frey, A. Unal, N. Rouphail, and J. Colyar, "On-road measurement of vehicle tailpipe emissions using a portable instrument," *Journal of the Air & Waste Management Association*, vol. 53, pp. 992–1002, 2003.

[3] North Carolina Department of Transportation. [Online]. Available: $http://www.ncdot.gov/travel/drivegreen$

[4] Adaptive Signal Control, FHA, U.S Departament of Transportation. [Online]. Available: http://www.fhwa.dot.gov/everydaycounts/technology/adsc/

[5] P. Koonce, "Traffic signal timing manual," U.S. Department of Transportation, Tech. Rep. FHWA-HOP-08-024, 2008.

[6] M. Selinger, P. P.E., and L. Schmidt, "Adaptive traffic control systems in the United States: Updated summary and comparison," HDR Engineering, Tech. Rep., 2009.

[7] K. Katsaros, R. Kernchen, M. Dianati, and D. Rieck, "Performance study of a green light optimized speed advisory (GLOSA) application using an integrated cooperative ITS simulation platform," in *Proc. 7th International Wireless Communications and Mobile Computing Conference (IWCMC)*, 2011, pp. 918–923.

[8] E. Koukoumidis, L. Peh, and M. R. Martonosi, "SignalGuru: leveraging mobile phones for collaborative traffic signal schedule advisory," in *Proc. 9th international conference on mobile systems, applications, and services (MobiSys 2011)*, 2011.

[9] M. Seredynski and P. Bouvry, "A survey of vehicular-based cooperative traffic information systems," in *Proc. 14th International IEEE Conference on Intelligent Transportation Systems (ITSC 2011)*. IEEE, 2011, pp. 163–168.

[10] "ITS strategic research plan, ITS strategic research plan, 2010–2014, executive summary," U.S. Department of Transportation, Research and Innovative Technology Administration, Tech. Rep. FHWA-JPO-10-028, 2010.

[11] M. Barth and K. Boriboonsomsin, "Traffic congestion and greenhouse gases," *ACCESS Magazine*, vol. 35, pp. 2–9, 2009.

[12] W. Recker, X. Zheng, and L. Chi, "Optimization of control parameters for adaptive traffic-actuated signal control," *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, vol. 14, no. 2, 2010.

[13] D. McKenney and T. White, "Distributed and adaptive traffic signal control within a realistic traffic simulation," *Engineering Applications of Artificial Intelligence*, vol. 26, pp. 574—583, 2013.

[14] D. Zhao, Y. Dai, and Z. Zhang, "Computational intelligence in urban traffic signal control: A survey," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 42, no. 4, pp. 485–494, 2012.

[15] J. Garcia-Nieto, E. Alba, and A. C. Olivera, "Swarm intelligence for traffic light scheduling: Application to real urban areas," *Engineering Applications of Artificial Intelligence*, vol. 25, no. 2, 2012.

[16] Y.-C. Chiou and Y.-F. Huang, "Stepwise genetic fuzzy logic signal control under mixed traffic conditions," *Journal of Advanced Transportation*, vol. 47, no. 1, pp. 43—60, 2013.

[17] H. Ceylan and M. G. Bell, "Traffic signal timing optimisation based on genetic algorithm approach, including drivers' routing," *Transportation Research Part B 38*, vol. 38, no. 4, pp. 329—342, 2004.

[18] K. Almejalli, K. Dahal, and A. Hossain, "An intelligent multi-agent approach for road traffic management systems," in *Proc. Control Applications, (CCA) & Intelligent Control, (ISIC)*. IEEE, 2009, pp. 825–830.

[19] L. Prashanth, "Reinforcement learning with function approximation for traffic signal control," *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 2, pp. 412–421, 2011.

[20] J. Hu, D. Zhao, and F. Zhu, "Neural network based online traffic signal controller design with reinforcement training," in *International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 2011, pp. 1045–1050.

[21] DSRC: The future of safer driving, U.S departament of transportation, RITA, [online] http://www.its.dot.gov/factsheets/dsrc_factsheet.htm.

[22] A. Wegener, H. Hellbruck, C. Wewetzer, and A. Lubke, "VANET simulation environment with feedback loop and its application to traffic light assistance," in *Proc. IEEE GLOBECOM Workshops*, 2008, pp. 1–7.

[23] D. Krajzewicz, L. Bieker, and J. Erdmann, "Preparing simulative evaluation of the GLOSA application," in *Proc. 19th ITS World Congress*, 2012.

[24] C. Li and S. Shimamoto, "An open traffic light control model for reducing vehicles' emissions based on ETC vehicles CO2 emissions based on ETC vehicles," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 1, pp. 97–110, 2012.

[25] M. Mitchell, *An Introduction to Genetic Algorithms*. MIT Press, 1998.

[26] E.-G. Talbi, *Metaheuristics: from design to implementation*. Wiley, 2009.