Deployable Yet Effective Traffic Signal Optimisation via Automated Planning (Extended Abstract)*

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Introduction

In this paper, we report on the process of adapting previous automated planning techniques for traffic signal optimisation (McCluskey and Vallati 2017; Percassi et al. 2023) to cope with a legacy traffic control infrastructure which is common in *urban* areas of the UK, forming the basis of Urban Traffic Control (UTC) technology. To do so, the knowledge models must be redesigned to incorporate extra constraints and features that consider the peculiar deployment constraints of the infrastructure. Two main technological constraints emerged from recent trials on the target UTC: (i) for each junction, the length of the stages can not be modified arbitrarily; instead, the configuration of cycles (i.e., the specification of the length of every stage in the cycle) can only be selected from a predefined set, and (ii) traffic engineers involved in the trials require all the cycles to have the same duration. The reason for (i) is that configurations need to be uploaded into the UTC system at least one day in advance; the reason for (ii) is that the synchronisation between junctions needs to be maintained to avoid disrupting the green wave along a corridor of connected links.

We introduce three new PDDL+ models which enable domain-independent planning engines to produce signal plans on UTC. For comparison, we use a region where normally the traffic reactive SCOOT control system is active within the UTC architecture. We test the introduced models to assess their capabilities with domain-independent search techniques and heuristics. Finally, we show that the generated plans are comparable with the state-of-the-art, and ready to be deployed.

PDDL+ Models for Deployability

We propose three planning models whose resulting plans can be deployed in the UTC infrastructure: *Cycle by Cycle* (CBC), *Fixed Repetition* (FIRE), and *Variable Repetition* (VARE). The common feature is that cycle configurations have to be selected from a provided pool of candidates.

In the proposed models, each junction has a set of associated predefined configurations. A configuration fully specifies the sequence of stages and the duration of each stage.

Cycle by Cycle In CBC, flexibility is maximised, allowing the configuration of a junction to be selected in every cycle transition. The flexible behaviour is achieved by the action *changeConfiguration*(j, c_1, c_2), where j represents a controllable junction, and c_1 and c_2 are two distinct configurations for j. In this context, c_1 denotes the currently active configuration on j, while c_2 represents the new configuration that will be adopted by j. Importantly, the configuration can be changed only at the end of a cycle's execution.

Fixed Repetition. The FIRE model enforces the selected configuration to remain unchanged for a minimum of k cycles at a specified junction, empirically set to four. Once the minimum number of cycles has been reached, there is the option to change the configuration for the junction. To track the number of completed cycles associated with the current configuration for each junction, we use a numeric variable, and event *triggerChange*(p_1, p_2, j), which models stage transitions from p_1 to p_2 for j. When *triggerChange*(p_1, p_2, j) is triggered and p_1 is the last stage of the cycle, the cycle counter is increased by one. The FIRE model adopts the same action *changeConfiguration* as the CBC one, with an additional check on the number of cycles for which the current configuration has been in operation.

Variable Repetition. This model takes control to a deeper level by allowing decisions on the minimum number of times a configuration must be kept for a specific junction. Specifically, the action *changeConfiguration* enables an additional action, *changeLimit*(j, l), where j is a junction, and l is the minimum number of repetitions for a configuration. Once the number of repetitions has been set, the remaining part of the model for handling the duration of the stages and the cycle count remains unchanged w.r.t. the model FIRE.

All the models are available at: https://github.com/anas-elkouaiti/utc-models-deployable.

Empirical Evaluation

An extensive experimental analysis of the models is provided by El Kouaiti et al. (2024). In this abstract, we focus on FIRE, that demonstrated to be the most promising model, producing plans with less computational effort due to its good tradeoff between flexibility and effectiveness, particularly when used together with the PDDL+ planner ENHSP version 20 (Scala et al. 2020) with GBFS and h^{max}.

*We report on the work by El Kouaiti et al. (2024).

Scenario	Approach	μ_Z	$count_{\mathcal{C}}$	in	$middle$	out
A-morn	FIRE	0.16	1085.6	**417.1**	248.4	224.9
	h^{TSO}	**0.13**	**1108.8**	**417.1**	**253.6**	**235.8**
	$\mathcal{H}$	0.28	887.4	**417.1**	221.0	181.7
A-noon	FIRE	0.3	1212.6	**551.5**	243.8	250.3
	h^{TSO}	**0.16**	**1268.4**	547.6	261.2	**264.8**
	$\mathcal{H}$	0.35	1138.3	**551.5**	**270.9**	227.3
A-eve	FIRE	0.39	1209.0	**614.7**	245.1	260.3
	h^{TSO}	**0.15**	**1437.0**	599.9	298.5	**292.8**
	$\mathcal{H}$	0.4	1317.9	**614.7**	**309.1**	271.9
Concert	FIRE	0.73	1408.5	**612.8**	244.3	344.9
	h^{TSO}	0.64	1492.8	**612.8**	269.2	386.6
	$h^{\text{TSO}}_{\star}$	**0.45**	**1628.2**	**612.8**	**308.7**	**409.7**

Table 1: Comparison between GBFS+h^{max} applied to FIRE, and the state-of-the-art results, i.e., GBFS+h^{TSO} applied to EXRE, and the historical strategy implemented by SCOOT ($\mathcal{H}$) or $h^{\text{TSO}}_{\star}$. The best results are in bold.

We consider four scenarios from a major corridor of Huddersfield, UK. Three scenarios are on the 26th (referred to as day *A*), which is a Wednesday, in January 2022; they are at different time slots: the morning peak hour at 8:30 am (*morn*), noon at 12:30 pm (*noon*), and the evening peak hour at 4:30 pm (*eve*). This variation aimed to assess diverse traffic volumes and conditions. The notation used for the scenarios is expressed as *day-slot*, e.g., *A-morn*. Further, we include a fourth scenario (*Concert*) involving exceptional traffic circumstances, pertaining to a concert held at John Smith's Stadium on Tuesday the 20th of June 2023, which attracted an approximate audience of 30,000 people.

We compare the plans generated by FIRE with the strategies historically implemented by SCOOT in the reference region. Additionally, we consider plans obtained by a domain-specific planning approach designed for a model, EXRE, having actions that can arbitrarily extend or reduce the duration of each stage, and which utilises a domain-specific heuristic, h^{TSO}, combined with GBFS (Percassi et al. 2023).

All plans generated have been validated and simulated on historical data via the architecture designed by Bhatnagar et al. (2022). Experiments were run on an Intel Xeon Gold 6140M CPU with 2.30 GHz, 8 GBs of RAM.

For the comparison, to provide a well-rounded performance overview, we rely on the metrics proposed by Percassi et al. (2023): $0 \leq \mu_Z(occ_{\mathcal{C}}) \leq 1$, represents the average occupancy, normalised in relation to the maximum capacity of the links in the west-to-east corridor direction; a value close to one indicates a high level of congestion. $count_{\mathcal{C}}$ is the total number of vehicles that have moved in the corridor during the simulation. $in/mid/out$ is the total number of vehicles that have entered from the western entry points, crossed the middle of the corridor, and exited from the eastern exit points, respectively.

Table 1 presents the results of our analysis. The use of FIRE yields a value of $count_{\mathcal{C}}$ better than the one for $\mathcal{H}$ in two out of three *A* scenarios. On the other hand, the counter is marginally lower than that obtained by h^{TSO} in all instances. It is worth reminding that the comparison with h^{TSO} favours h^{TSO} because it relies on a model that offers flexibility beyond what FIRE can achieve. More importantly, h^{TSO} leads to signal plans that can not be deployed in the region due to the technological constraints of the UTC infrastructure. Another observation is that FIRE consistently generates plans that reduce corridor congestion w.r.t. $\mathcal{H}$, albeit to a lesser extent compared to h^{TSO}.

The *Concert* scenario differs significantly from the previous ones. Firstly, it involves exceptional traffic conditions, and secondly, historical data where SCOOT is in operation are unavailable. This is because the strategy implemented in the real-world on that occasion was generated by leveraging a plan produced by h^{TSO} and then manually modified by traffic engineers, according to their knowledge, to make it deployable on the SCOOT infrastructure. This variant of h^{TSO} is denoted as $h^{\text{TSO}}_{\star}$, and should be regarded as the best possible performance achievable by merging human experience and planning capabilities. Unsurprisingly, $h^{\text{TSO}}_{\star}$ delivers the best overall performance. FIRE achieves slightly lower results than h^{TSO} in terms of vehicles moved through the corridor. All the approaches allow the same number of vehicles to enter from the West entry point (in), but for FIRE and h^{TSO}, the values $middle$ and out are lower than for $h^{\text{TSO}}_{\star}$; this is because the implemented plans –being generated in advance– include all stages of all cycles, while the SCOOT system that operates in real-time can skip optional (demand-only) stages, such as pedestrian crossings or cross-flow traffic, if there is no demand.

Overall, the introduced FIRE model allows a domain-independent planning engine to deliver plans comparable with the state-of-the-art and that, differently from the state-of-the-art, can be continuously deployed.

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