Incident-Aware Distributed Signal Systems in Self-Organised Traffic Control Systems

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Abstract: Traffic congestion is a major contributor to carbon dioxide emissions and causes air pollution which poses various health risks. In response to such challenges, traffic management systems are becoming increasingly intelligent and adaptive. Particularly self-organised approaches such as the Organic Traffic Control (OTC) system offer additional advantages such as efficiency, scalability, and robustness. In addition to the local and traffic-dependent switching of traffic signals, a central task of such a system is the coordinated adaptation of traffic lights by means of Progressive Signal Systems. In this paper, we present a novel approach for establishing decentralised PSSs that takes into account recognised incidents and thus proactively ensures optimised traffic flows. We develop three different strategies and evaluate them using realistic simulations.

1 INTRODUCTION

After a decline during the COVID crisis, the traffic demands in urban areas have increased again, and congestion and traffic disruption cause major economic damage every year. Furthermore, it is often not feasible to expand the existing infrastructure which presents an additional challenge. Apart from a politically motivated reduction of traffic volumes, the only possible countermeasure is a more efficient utilisation of the existing infrastructure.

In addition to the traffic-dependent and proactive adaptation of traffic lights or routing solutions, Progressive Signal Systems (PSS, also known as "green waves") are a key factor for optimisation. Currently there are time-based static as well as centralised and decentralised dynamic solutions. However, these are not geared towards detected incidents within the underlying inner-city road network.

Building on existing work on self-organised and self-adaptive traffic management – the OTC system, (Sommer et al., 2016a) – this article explores a novel approach to an incident-aware establishment and maintenance of PSSs. We propose a corresponding algorithm that can handle different levels of information about incidents, and demonstrate that it can improve traffic flow compared to conventional PSS approaches.

The remainder of this paper is organised as follows: Section 2 provides a brief discussion of the state-of-the-art. After that, Section 3 presents the developed approach for incident-aware PSS. Section 4 analyses the behaviour of the approach in close-to-reality simulations and assesses the benefit in comparison to alternatives. Finally, Section 5 summarises the paper and gives an outlook on future work.

2 BACKGROUND

This section describes the underlying related work, specifically in the context of self-organised traffic control, automated incident detection, and progressive signal systems. It also introduces the OTC system as the basis of this work.

2.1 Self-Organised Traffic Control

Urban traffic light control is usually done via traffic control centres, with SCOOT (Robertson and Bretherton, 1991), SCATS (Sims and Dobinson, 1980), MOVA (Vincent et al., 1990), and UTOPIA/-SPOT (Mauro and Taranto, 1990) as the most prominent systems used world-wide. All of these ap-

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proaches establish a centralised control loop that collects the current traffic conditions and adapts the switching policies of the distributed intersection controller (IC). Typically, this adaptation is based on a certain cost function including aspects such as the expected travel times, emissions, or public transport priority. An overview and comparison of approaches can be found in (Studer et al., 2015).

These centralised approaches all are limited in terms of efficiency, scalability, and robustness as all information has to be passed to and collected by a one central controller. It then has to conduct the optimisations and distribute the derived plans to the ICs.

As a response, self-adaptive and self-organised (SASO) approaches with a local scope have been developed that perform decisions locally at each intersection controller and – in some cases – communicate with each other to achieve coordinated decisions. Examples include a multi-agent approach based on fuzzy control as presented in (Gokulan and Srinivasan, 2010), a distributed W-learning concept to optimise a phase-oriented signal control as discussed in (Dusparic and Cahill, 2009), or a model with predictive control as proposed by (Oliveira and Camponogara, 2010). The drawback of these approaches compared to the centralised one is that they are mostly of academic interest and just tested in simulations.

The third class of concepts is even more theoretical as it eliminates the standard phase-based traffic signal switching schemes: A fluid-dynamic model, discussed in (Helbing et al., 2005), uses waiting vehicles as pressure and counter-pressure for switching traffic lights policies. In contrast to the SASO concepts above, these control systems cannot consider further knowledge or coordinate their decisions as the model primarily reacts to local queues.

2.2 Progressive Signal Systems

Some of the aforementioned traffic control systems possess abilities to determine coordination plans for ICs, resulting in centrally planned PSS schemes. As an alternative self-organised approaches have been proposed. However, these are again mostly of an academic nature. One example presented in (Gershenson, 2007) is called "self-organising traffic lights" (SOTL). The approach does not explicitly establish a PSS but relies on traffic-responsive local controllers that take into account the number of waiting cars or the gaps between arriving vehicles. This behaviour is similar to uncoordinated traffic-adaptive controllers (e.g. following the NEMA standard). Traffic lights keep a count κ of the number of cars waiting in front of them. Each car is weighted by its waiting time and as soon as κ reaches a certain threshold, the traffic light changes. The SOTL control method employs several restrictions to avoid fast switching of traffic lights, the interruption of moving platoons, and deadlocks caused by long platoons. Although there is no explicit coordination, Gershenson describes the observation of coordination effects similar to those achieved by PSSs.

As an alternative, Bazzan described an approach to distributed traffic signal coordination in (Bazzan, 2005). Here, intersections are modelled as individually-motivated agents. Each agent possesses a set of predefined control strategies to choose from. The selection process is based on local events occurring at the intersection as well as on the results of "coordination games" that are played among neighbouring agents. The principal applicability of this approach is demonstrated in a simple scenario of an arterial road consisting of ten intersections. Each intersection agent has to choose between two strategies, each of which favours one of the two directions over the other. The distributed approach is compared to a central controller that creates synchronised traffic lights in one of the arterial directions, based on detector readings from the network. The agent-based approach proves to be better in situations where the flow of traffic in opposite directions is nearly equal. An important difference between Bazzan's approach and the organic system presented here is that Bazzan relies solely on the selection of predetermined strategies while the approach presented here is able to generate new strategies dynamically.

2.3 Traffic Incident Detection

Techniques for automatic recognition of incidents, accidents, and other road events, e.g. requiring emergency responses, have been the focus of research for more than three decades. Most of the resulting algorithms rely on sensor data from loop detectors. Chronologically, AID research started with the Standard Normal Deviate algorithm (Dudek et al., 1974), subsequently followed by the California Algorithm family (Payne, 1975; Payne and Tignor, 1978). These techniques essentially follow a simple decision tree structure and take thresholds into account.

Subsequently, approaches have been introduced which are based on time series analysis (Ahmed and Cook, 1980), identification of low-volume conditions (Dudek et al., 1975), filtering and smoothing-based algorithms (Stephanedes and Chassiakos, 1993), a dynamic-systems-model-based algorithm (Willsky et al., 1980), correlation-analysis-based approaches (Takaba and Matsuno, 1985), the

McMaster catastrophe theory-based algorithm (Gall and Hall, 1989), and a mathematical traffic-flow-model-based algorithm (Lin and Daganzo, 1997). More recently, video-based approaches have been outlined (Shehata et al., 2008) and combined with semantic annotations (Kamijo et al., 2004). In addition to these infrastructure-based approaches for estimating flows, probe vehicles have been considered (Jenelius and Koutsopoulos, 2013). Some work is especially dedicated to urban environments (Feng et al., 2014) which may serve the incident detection.

However, these approaches all come with some limitations: Either they are designed for highways only or they are based on experienced travel times through the underlying road network, and/or they do not distinguish between different incident types (and the corresponding reaction). Most importantly, there is no integrated traffic management solution that considers detected incidents, an estimation of their severity and impact, or takes this information pro-actively into account when, for instance, deciding about traffic control or progressive signal systems.

In response to these observations, we presented a novel clustering-based approach for AID in urban road networks that is based on standard loop detector technology again (Thomsen et al., 2021). Based on the ICs' responsibility zones (i.e. intersection area and incoming sections equipped with induction loop sensors), the controllers consider the time series of the detector loop data. They then apply techniques such as DBSCAN (Ester et al., 1996) to detect incidents online within a certain time window. We showed that appropriate detection accuracy is achieved for conditions with high traffic loads, while the approach still suffers in weak load conditions.

2.4 Organic Traffic Control

The *Organic Traffic Control* (OTC) system (Prothmann et al., 2009) and its extensions serve as a basis for this work. The OTC system is a self-adaptive and self-organised traffic control system that decides locally at each intersection about the behaviour of the underlying traffic light controller (TLC). Here, "organic" follows the ideas of Organic Computing (Müller-Schloer and Tomforde, 2017) and emphasises the transfer of principles from nature to technical systems: The decentralised structure, the cooperation of smaller, autonomous entities, as well as local adaptation and learning capabilities allow for high robustness, scalability, and flexibility.

Based on the Observer/Controller paradigm (Tomforde et al., 2011), the OTC system adapts the green duration of traffic lights using a phase-based approach and optimises this adaptation strategy at runtime. This is achieved by means of reinforcement learning and safety-oriented generation of novel behaviour within a simulation environment, see (Prothmann et al., 2009). The adaptation process is performed depending on the currently active cycle time of the traffic controller, i.e. an adapted control strategy is active for three cycles (typically 60s to 120s) before it can become subject to adaptations again. The current traffic flows for all turning movements passing the intersection (in $^{vehicles}/_{hour}$ and estimated from detector readings) are the basis for any adaptation decision. The estimated waiting times are then used as feedback to improve the behaviour over time. OTC is further able to establish PSSs in a fully self-organised manner (Tomforde et al., 2008) and to provide route recommendations to drivers which reflect the current state of the traffic network (Prothmann et al., 2012).

Based on OTC, further contributions investigated are robust traffic demand prediction (Sommer et al., 2013), integration of these predictions in the control strategies, and infrastructure-based anticipatory route guidance (Sommer et al., 2016b).

OTC is self-organised in a way that all nodes operate independently and collaborate to achieve system-wide goals, such as reducing waiting times, number of stops, emissions, etc. It is realised as a multi-layered adaptation and learning system on top of a standard TLC. Figure 1 illustrates the conceptual design.

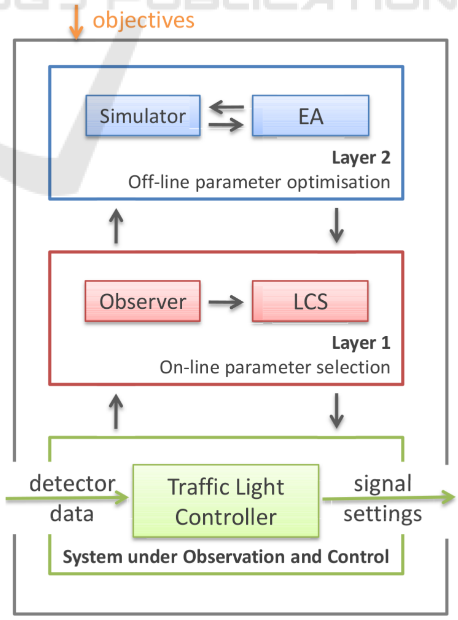

Figure 1: Overview of the multi-layered OTC architecture.

Here, Layer 0 represents the System under Observation and Control (SuOC) which is the actual TLC and offers interfaces to detectors and neighbouring nodes. The TLC (i.e. its green durations) is reconfigurable at runtime. This is done by the overlying Layer 1 which assesses the environment (using the sensors). Based on this observation, the controller employs a Learning Classifier System (LCS); in this case a variant of Wilson's XCS (Wilson, 1995). This LCS chooses rules from a rule set to modify the traffic signalisation appropriately at runtime.

Finally, Layer 2 is activated when Layer 1 is confronted with a situation for which no suitable rule or only insufficient knowledge exists. In this case, traffic simulation software (Aimsun Next, see (Aimsun, 2021)) is used to validate new rules which are generated by applying an evolutionary algorithm.

3 INCIDENT-AWARE PROGRESSIVE SIGNAL SYSTEMS

This section presents our novel incident-aware PSS algorithm for self-adaptive and self-organised traffic control systems which is integrated into the OTC system. To achieve this, we initially introduce the incident types under consideration, summarise the existing decentralised progressive signal system (DPSS) algorithm that serves as a basis for this work, and define the extension of this algorithm.

3.1 System Model and Incident Types

We assume regular urban road networks of varying topology and decentralised nodes with intersection controllers (ICs) that are responsible for controlling the TLCs. Each node covers the area of the intersection as well as the incoming and outgoing sections which are assumed to be equipped with detectors (e.g. induction loops). Furthermore, each node has the capability to (a) communicate with the neighbours that share its road segment as well as to (b) detect traffic incidents within the intersection, the incoming and the outgoing sections. Here, we consider three groups of possible static incidents as established in (Thomsen and Tomforde, 2022):

- Section closure: Complete closing of the section between two intersections in one direction
- Lane closure: Closing of one (or possibly more) lanes of a multi-lane section
- Partial lane closure: Similar to a lane closure, but limited to a segment of the section straight on)

Other types of incidents, e.g. both-way closures of sections, a partial or a full blockage of an intersection or a technical defect ("loss of function"), will be addressed in future work.

The incident detection mechanism employed by the node is not further specified. It can be based on machine learning technology as mentioned in Section 2.3 or the approach from (Thomsen and Tomforde, 2022) with a possible extension for validation. The only requirement is the ability to provide information according to these knowledge levels (KL):

1. The IC is aware only of whether an incident occurred in its sensor horizon or not.
2. It is additionally aware of the section or turning where that incident occurred.
3. It further knows the incident type.

Based on these model assumptions, the objective of this work is to establish a fully decentralised scheme for PSS that considers the uncertain incident information available. As a result, we aim to improve the traffic flow of the underlying road network.

3.2 The Basis: Decentralised Progressive Signal Systems

The Decentralised Progressive Signal Systems (DPSS) algorithm is performed by the local intersection controllers and follows a three-phased approach, as outlined in (Tomforde et al., 2008):

1. Phase: Each intersection controller informs its preferred predecessor that it would like to be its successor in a PSS. Afterwards, each IC checks if it was selected as a predecessor by its downstream node. In that case, a partnership is established. Finally, each node knows it is part of a PSS and what its predecessor and successor are.
2. Phase: The controllers agree on a common cycle time. Each IC has a desired cycle time (DCT) and keeps track of the agreed cycle time (ACT). The DCT is the one currently active at the intersection without coordination in a PSS. From the first controller to the last, the ACT is propagated through the PSS, with each node updating the ACT to its DCT if the local DCT is higher. After reaching the last node, the same process is continued back to the first controller. As a result, all nodes agree on the ACT – the common cycle time.
3. Phase: The offsets for the synchronised phases of the traffic controller are determined. These depend on the predecessor's starting time of the synchronised phase, the travel time between sections, the vehicle serving time and the nodes' own start

time of the synchronised phase. For this, each node propagates its parameters to its successor, using the same echo algorithm as in phase 2.

3.3 Incident-Aware DPSS

In the following, we present our novel Incident-aware DPSS (IA-DPSS) algorithm. It consists of four steps and is performed periodically by each intersection controller or as a response to incoming messages from other controllers and local incident alerts. Steps 2, 3 and 4 correspond to the 3 phases of the DPSS already outlined above.

Step 1: Incident-Aware Conditions

To achieve traffic-flow-based coordination, each controller adapts the currently observed local streams passing the turning movements. We refer to these manipulated traffic streams as "synthetic streams". The measured traffic flow is artificially increased or decreased by a certain degree on the sections towards the remaining possible neighbours (and possibly set to zero in case a path to a successor is blocked by an incident). The remaining neighbours are intersections reachable via an incident-free section. As an alternative, we re-distribute the traffic flow based on weights. This will be referred to as "weighted distribution" which are calculated by first adding up the total traffic flow f_τ between the remaining neighbours and then dividing the section's traffic flow f_i by the total flow:

$$w_i = \frac{f_i}{f_\tau}$$

Another alternative is re-distributing the traffic flow equally between all remaining neighbours. This will be referred to as "equal distribution". When no re-distribution takes place, this is referred to as incident flow reduction. How these synthetic streams are used depends on the knowledge levels (KL) introduced in Section 3.1:

1. KL: The controller does not know the location. Since waiting for sensor information to show an abnormal trend would exhibit similar behaviour as without incident awareness due to delayed statistics, the node is excluded from DPSS calculation: All synthetic streams at that node are set to zero.
2. KL: As no information regarding the incident type and impact are available, a default is used. For example, we estimate the averaged reduction of capacity by 50% and therefore determine the synthetic stream accordingly. Note that this is just a default value. It could be learned through experience over time and therefore would be subject to customisation by the local nodes.
3. KL: For section closures, the synthetic traffic streams over this section are set to zero. Optionally, the original flows are distributed to the remaining open streams.

   For lane closures, the reduction depends on the number of lanes: $r = {}^{BlockedLanes}/_{TotalLanes}$. The synthetic flow is then $f_s = f \times (1 - r)$. Again, we optionally distribute uniformly the decreased flows to all remaining streams.

   For partial lane closures, we decrease r by a weight that is determined by the impact of the incident (i.e. estimated length divided by the section's capacity).

   Finally, for turning closures, we use the same formula and calculate r for each outgoing section by considering the turnings with incidents. In particular, we calculate r as the count of disturbed turnings divided by the count of all turnings leading to this outgoing section. Again, a possible redistribution of reduced flow values is considered.

Step 2: Partnerships

Each node determines the currently strongest traffic flow running over its training movements. Let us assume that node j determines the turning from upstream node i to downstream node k as its strongest turning movement. For node j, the expected highest benefit lies in the coordination of the (longest) signal phase serving the selected turning from i to k with the respective upstream intersection i. We call this a "synchronised phase". Consequently, node j sends its desired predecessor i a message, asking it to be its successor in a PSS. This is performed in parallel by all nodes. As soon as all nodes have informed their desired predecessor, they perform a local matching.

The local matching verifies that the downstream node k selected the node as the desired predecessor. Then the partnership is confirmed and other possible registered nodes are rejected. For those nodes where this rejection prohibits the first choice, the process checks for the second-best solution and performs the same acknowledge/reject mechanism. As a result, all nodes know if they are part of a PSS and who their predecessor and successor are. Furthermore, the first and last nodes of the PSS know about their special position as they have no predecessor or successor.

Step 3: Common Cycle Time

Based on a short safety interval (usually 3s), the first node starts building the PSS which requires a common cycle time. Since this controls the capacity of the node (i.e. longer cycle times correspond to higher aggregated traffic volumes passing the intersection), the common cycle time follows the principle of the weakest link: Nodes have to identify the smallest possible cycle time for all participants of the PSS. Each node i keeps tracks of its own "desired cycle time" (DCT_i) and an "agreed cycle time" (ACT). The desired cycle time DCT_i is the cycle time node i would prefer for the current traffic situation if it was not part of a PSS. This can be retrieved from the learning component in OTC or, if this is not active, the current cycle time.

The participating nodes determine an agreed cycle time ACT. Since the DCT_i is as short as possible, due to the underlying objective to decrease averaged waiting times at the nodes, the ACT is selected as the maximum of all DCTs of the nodes i. A shorter ACT might reduce the capacity of the most heavily used node more than is acceptable, leading to rising queues in its approaches.

A fully distributed echo algorithm determines ACT: Initially, each node i stores its knowledge on the agreed time locally as ACT_i. The first node in the PSS updates its desired cycle time DCT_1 (by setting $ACT_1 := DCT_1$) and sends ACT_1 to its successor in the PSS. The succeeding nodes i, $i = 2, \ldots, n$ forward their ACT_i after updating it:

$$
\begin{aligned}
ACT_i &:= \max\{DCT_i, ACT_{i-1}\} \\
&= \max\{DCT_i, \max_{j \in \{1,\ldots,i-1\}} \{DCT_j\}\} \\
&= \max_{j \in \{1,\ldots,i\}} \{DCT_j\},
\end{aligned}
$$

The last node propagates the ACT_i back to the first node, while each participant repeats the above process. As a result, all nodes are aware of the most suitable ACT for the PSS.

Step 4: Offsets and Synchronisation

Finally, for the nodes respecting the ACT the offsets as well as an appropriate signalisation can be determined. All nodes proportionally increase the green durations of their signal phases until the sum of all phase durations, including interphases which are kept constant, corresponds to the ACT.

Naturally, the first node has no offset restrictions. For each successor node i, $i = 2, \ldots, n$, the offset o_i depends on:

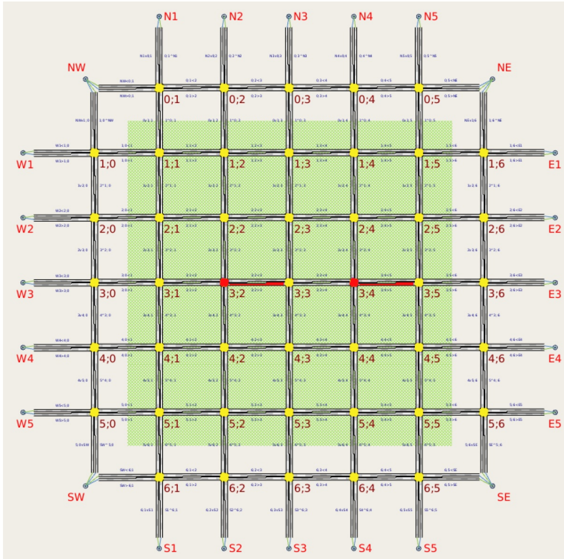

Figure 2: Test environment: A 7-by-7 Manhattan-style network. The green area marks the analysed junctions; those outside are simulated but not analysed, to avoid simulation artefacts. The sections marked red feature the incidents simulated in Section 4: The single incidents of the first 3 experiments are located in the left section. The additional one of the combined experiment is placed in the right section.

- predecessor's offset o_{i-1},
- start p_{i-1} of the synchronised phase within the predecessor's TLC,
- time $d_{i-1,i}$ cars need to arrive from a predecessor,
- start p_i of the synchronised phase within the node's own TLC, and finally,
- time q_i needed to serve queued vehicles for the synchronised phase.

All successors must know the absolute time s when the first node activates its TLC: the start time for the PSS. Again, an echo algorithm is used by the first node. It informs its successor about the start time s, its offset (without loss of generality $o_1 = 0$, the first nodes starts the PSS at time s) and the start p_1 of the synchronised phase in its TLC. The nodes i, $i = 2, \ldots, n$, shift their signal plan by calculating their own offset, relative to the first PSS node:

$$
o_i = (o_{i-1} + p_{i-1} + d_{i-1,i} - p_i - q_i) \quad \text{mod ACT}.
$$

Here, the time $d_{i-1,i}$ is assumed to be available locally at each node for all its neighbours j (one of which is node $i-1$). This assumption is reasonable since $d_{i-1,i}$ depends on the fixed distance and usually constant speed limits between nodes.

Furthermore, the current value of q_i is a small constant that will in the future be estimated based on local

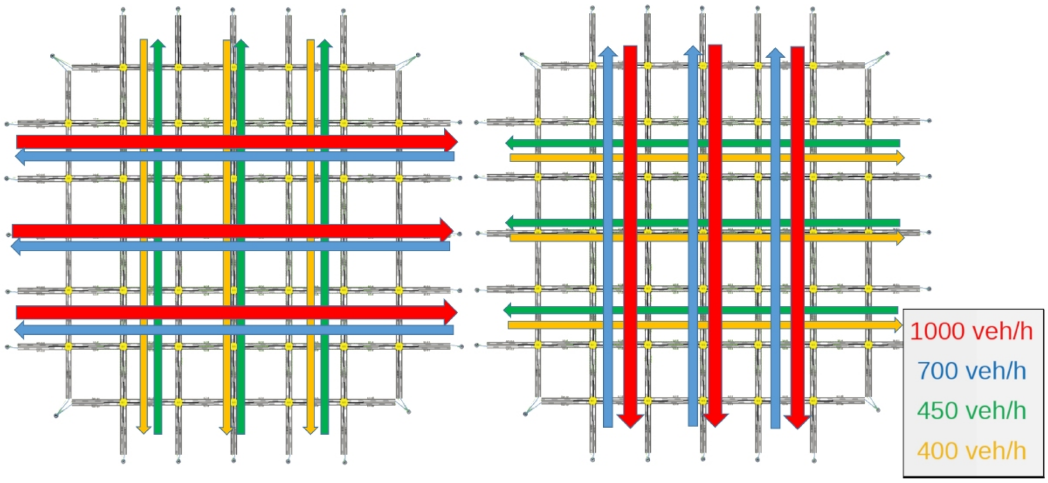

Figure 3: Simulated traffic demands. The left graph visualises the demand during the 90 min of the first half which has an emphasis on a west-east direction. The right graph depicts the pronounced north-south demands during the second half.

traffic. Once the offset calculation is finished, the values for s, o_i and p_i are forwarded to the successor in the PSS until the last node is reached and the offset calculation is completed. To avoid any violation of legal requirements, the change not done immediately but by using a statical handover signal plan, where the phase order is kept and the durations are adapted proportionally to fill in the required offset.

Further Features

The changing traffic conditions require a constant reassessment of the most promising PSS constellations. To this end, the update mechanism from (Tomforde et al., 2008) is reused. A global perspective on the status of the traffic conditions would allow for optimal constellations, while our IA-DPSS is a heuristic with local viewpoint (therefore, faster, more robust and scalable). Optimal constellations could be achieved by taking a global perspective on the traffic, such as the hierarchical extension introduced in (Tomforde et al., 2010) provides .

4 EVALUATION

4.1 Experimental Setup

To evaluate the IA-DPSS algorithm, we used the 7-by-7 Manhattan-style network in Fig. 2 which was simulated using Aimsun Next. This professional simulator was chosen since it provides close-to-reality simulations with realistic results. Traffic demands have been defined as shown in Fig. 3.

The experiments followed the same methodology as in (Tomforde et al., 2008) and have a duration of three hours, with an additional warm-up period of 15 min. All incidents occur 45 min after warm-up. OTC serves as a basis for the implementation and analysis of the behaviour. We compare the impact of the different knowledge levels and investigate the benefit over a standard DPSS approach. All results are averaged values over five runs of Aimsun experiments with different random seeds.

4.2 Experimental Results

Experiment 1: Section Closure

First, we analyse the effect of one central section being closed by an incident. Figure 4 shows the increasing number of stops during a 45 min closure: Compared to the standard DPSS, all three IA-DPSS variants lead to more stops at the beginning of closure as they react more efficiently to reroute the held back traffic. But after the new situation is established and towards the end of the incident, the standard DPSS exhibits the most stops per km and vehicle. Especially after the incident, the update is less successful, resulting in a benefit of about 5% for the IA-DSS variants.

When looking at the travel times, Fig. 4 illustrates how much the average travel time per car and km increased: While the standard DPSS performs the worst, KL 3 provides the highest benefit, compared to the other two levels and the reference. This is expected due to the more precise response. However, the equal distribution strategy for KL 3 seems to be less successful and should therefore not be used.

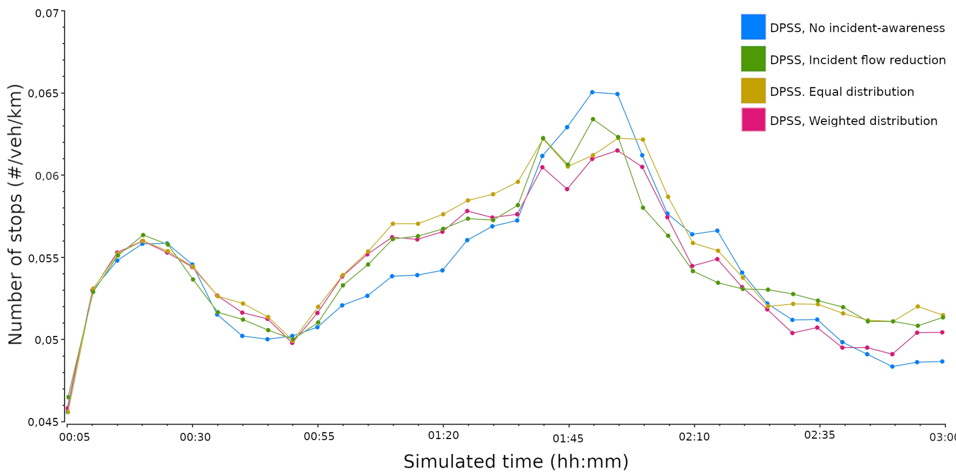

Figure 4: Average number of stops per car and kilometre with a section closure lasting from 0:45 to 1:50.

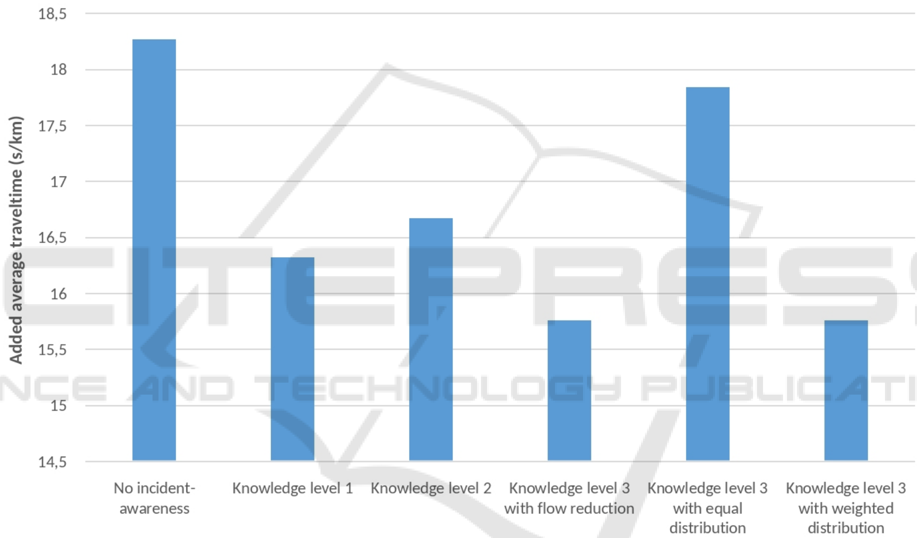

Figure 5: A comparison of the DPSS (with "no incident awareness") and the different IA-DPSS variants regarding the average time a vehicle takes longer per kilometre while the section closure in Fig. 4 is active.

Experiment 2: Lane Closure

Here, only one lane of the double-lane road is closed. Generally, the number of stops for an 15 min closure is lower than the in case of the section closures (Fig. 4), and all algorithms behave similarly at that level. One exception is the IA-DPSS with weighted distribution which reacts slightly faster but also with stronger fluctuations than the others.

While the number of stops does not give a clear indication, Fig. 6 illustrates the roughly 1 to 2 seconds of added average travel time in. Here, the IA-DPSS algorithm exhibits an apparent benefit when compared to the standard DPSS.

Experiment 3: Partial Lane Closure

Similar to the lane closures, the general number of stops is lower when compared to the section closures, and none of the algorithms deviates significantly during the 15 min partial lane closures. But Fig. 7 indicates that again one variant – IA-DPSS at KL 2 – performs better the others and the standard DPSS.

Experiment 4: Multiple Incidents

Here, we simulate two simultaneous incidents which are located at two different sections (see Fig. 2). The best-performing IA-DPSS uses a combination of reduction factor for (partial) lane closures and weighted distribution for section closures at KL 3. The comparison between the DPSS and the IA-DPSS in Fig. 8

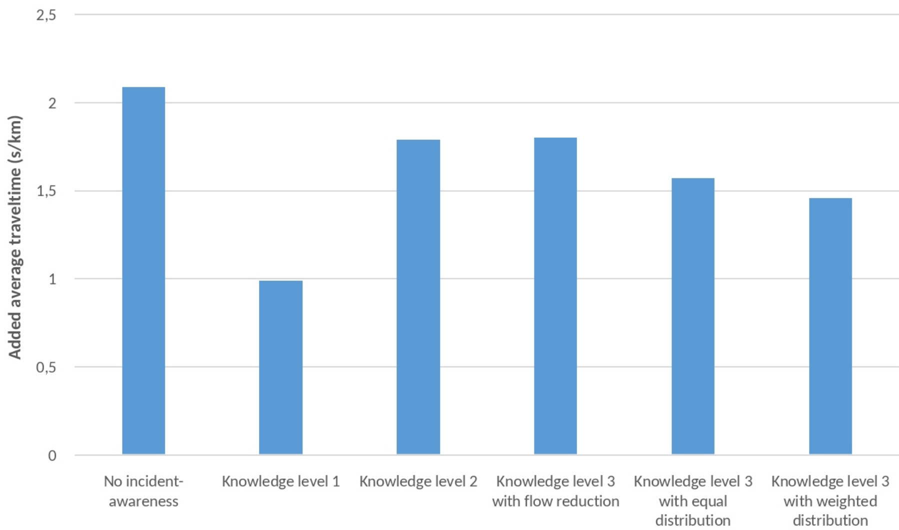

Figure 6: Average added travel time per kilometre and cars for the DPSS and the IA-DPSS variants in case of simulated 15 min lane closure.

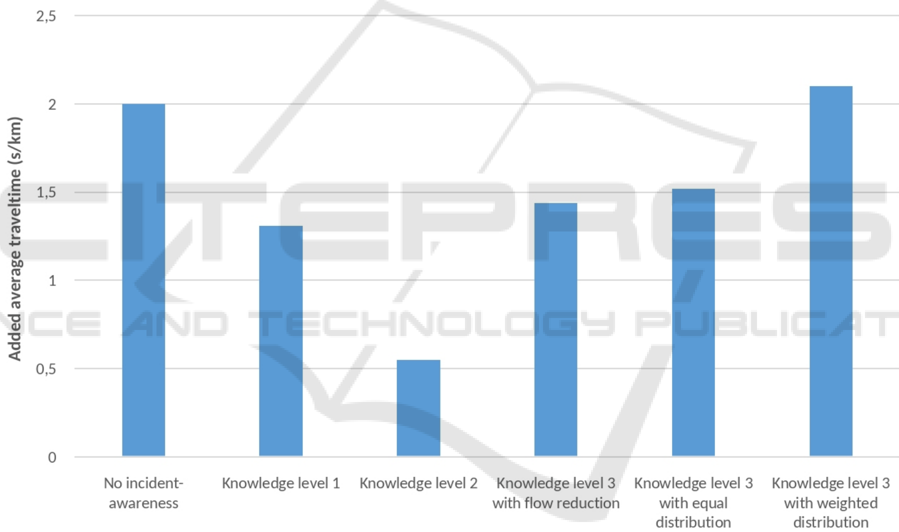

Figure 7: Average added travel time per km and car for the DPSS and the different IA-DPSS variants in case of a 15 min partial lane closure.

shows that the averaged travel time after the incidents have been removed increases for IA-DPSS, while it is slightly lower beforehand. This is because waiting times are only analysed as soon as the cars leave the network – and the result of the IA-DPSS is a slightly longer route due to avoidance of incident-regions. In other words: Although the key metric is not reduced, the desired effect has been achieved – longer incident times would lead to higher benefits. Figure 9 details the results for the different incident types. Here, homogeneous incidents have a benefit of 10% compared to DPSS. On the other hand, heterogeneous incident types still require more customisation.

5 CONCLUSIONS

In this work, we presented a fully distributed algorithm for establishing progressive signal systems in self-adaptive and self-organised traffic control systems. The IA-DPSS is a four-phased algorithm that adapts the local traffic demand representation at each intersection. It negotiates partnerships in a PSS, finds the common cycle time for all nodes of a PSS, and finally coordinates the signal plans by computing offsets. We analysed the behaviour in a 7-by-7 Manhattan-style network using close-to-reality simulations in Aimsun Next and using the Organic Traffic

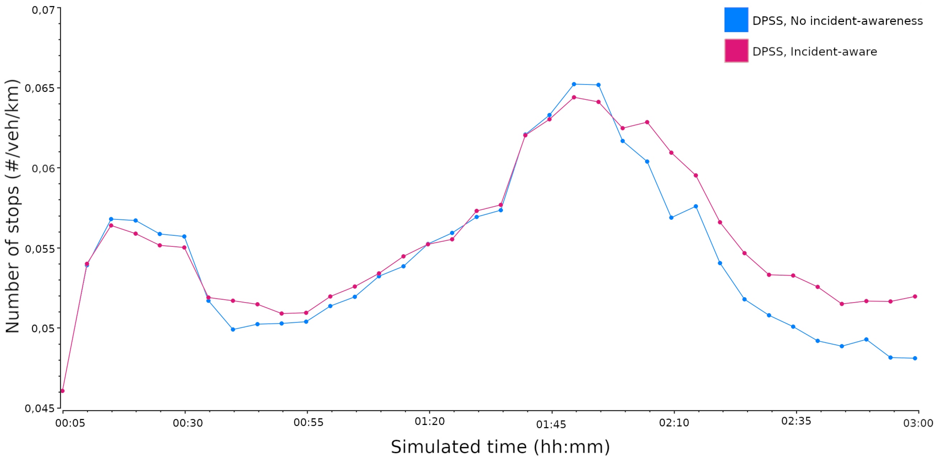

Figure 8: Average number of stops per car and kilometre for of the concurrent section and partial lane closure from 0:45 to 1:50. Here, the "incident aware DPSS" is a combination of algorithms which perform the best for these incident type.

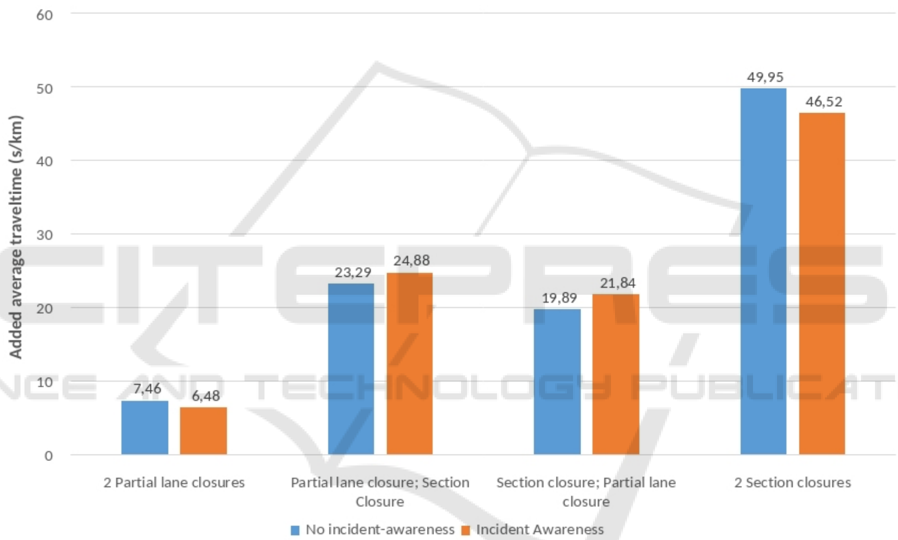

Figure 9: The increase of the added averaged travel time per car per kilometre due to a combination of the two concurrent 45 min incidents in Fig. 8.

Control (OTC) system as a basis. We showed that, depending on the levels of incident information available, a reduction of key figures such as the number of stops of vehicles and added average travel times can be achieved.

In future work, we will first apply this approach to less regular topology modelling in real city environments, as done in previous work. We will also investigate the impact of more complex incident conditions (i.e. interweaving and more heterogeneous) and the mutual influences on the self-learning behaviour of the underlying OTC system. From a machine learning perspective, we will also look into tuning the algorithms. Thresholds and adapting weighting factors of the IA-DPSS will be learned locally.

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