A Concept for Collaborative Incident Validation in a Self-organised Traffic Management System

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Abstract: The strong and, in part, further increasing traffic volumes of individual and heavy goods traffic in urban regions lead to a utilisation of the networks close to or above the capacity limit, especially during rush hours. Traffic light control is ideally traffic-dependent, which can be realised either centralised or distributed as a self-organised approach. However, these systems are typically not able to detect disruptions or incidents (such as accidents, road works, etc.) and take them into account in the control logic. A key problem here is that either there is no incident detection in place or it is not reliable enough. In this paper, we discuss the need for collaborative validation of locally detected incidents in a self-organised traffic control system. We show that this can increase the reliability of detection to the point where incident-dependent switching becomes possible.

1 INTRODUCTION

The constant growth of individual and freight traffic is causing delays and congestion worldwide, especially in urban areas (Schrank et al., 2019), even if recent studies showed that travel delays were heavily reduced from 2019 to 2020 due to the COVID lockdowns (Schrank et al., 2021). Since infrastructure expansion is typically not an option, a more intelligent and efficient traffic management is pivotal. In the literature, different approaches can be found, ranging from a purely centrally organised, static to hybrid to a fully distributed (at the level of intersections) optimisation of traffic-dependent clearance times.

Due to the inherent advantages such as problem locality, scalability, or avoidance of single-point-of-failure, science has focused mainly on distributed approaches in the last two decades, partly with more centralised elements. Such solutions can adapt green times locally, automatically learn the best adaptation strategy and establish self-organised coordination with neighbouring intersection controllers (for progressive signal systems or route guidance). However, these approaches are still reactive in the sense that they are focused on measured and estimated traffic flows – while ignoring the expected developments due to actual incidents in the underlying network.

In preliminary work, we presented an approach to automated incident detection (AID) in urban road networks in contrast to established approaches at highways. Since local detection is fundamentally uncertain, more global knowledge is needed to increase the reliability. Therefore, the contribution of this paper is (a) to address the challenges of local incident detection in urban networks, (b) to outline a collaborative, self-organised validation of incidents to increase accuracy and (c) to derive a fitting research agenda.

The remainder of this paper is organised as follows: Section 2 gives an overview of related work by outlining self-organised traffic control and traffic incident detection. Section 3 describes our system model and the Organic Traffic Control system as the basis for our approach. Section 4 then shows our concept for collaborative incident validation in self-organised traffic control systems with the Organic Traffic Control system as example. 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 and automated incident detection.

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2.1 Self-organised Traffic Control

Traffic lights in urban areas are usually operated by a traffic control centre. The most prominent systems are SCOOT (Robertson and Bretherton, 1991), SCATS (Sims and Dobinson, 1980), MOVA (Vincent et al., 1990), and UTOPIA/-SPOT (Mauro and Taranto, 1990). These systems typically rely on a centralised control loop that adapts the behaviour of distributed intersection controller (IC), based on a given cost function, which may include different aspects, like travel times, emissions, or public transport priority. Despite being centralised, these systems come with at least some self-adaptive and self-organising (SASO), i.e., being adaptive and policy-driven. The adaptation mechanism works on top of a parametrisable system configuration. For classification and comparison of approaches, see (Studer et al., 2015). In addition to these popular approaches, several systems focusing on SASO and learning capabilities have been proposed: A multi-agent approach based on fuzzy control was presented in (Gokulan and Srinivasan, 2010), distributed W-learning was used to optimise a phase-oriented signal control in(Dusparic and Cahill, 2009), and (Oliveira and Camponogara, 2010) used a model with predictive control. As an alternative to phase-based systems, a fluid-dynamic model has been discussed in (Helbing et al., 2005) that uses waiting vehicles as pressure and counter-pressure for switching traffic lights policies. In contrast to the aim of this proposal, these traffic control systems do not autonomously identify and classify incidents and adapt their signalisation according to detected incidents.

2.2 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 data of 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 are essentially following a simple decision tree structure considering threshold. Subsequently, approaches 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) have been presented. More recently, video-based approaches have been presented (Shehata et al., 2008) and combined with semantic annotations (Kamijo et al., 2004). In addition to these infrastructure-based approaches, probe vehicles have been considered to estimate traffic flows (Jenelius and Koutsopoulos, 2013); with some work specially 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 deciding about traffic control or progressive signal systems, for instance.

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 responsibility zones of ICs (i.e., intersection area and incoming sections equipped with induction loop sensors), the distributed ICs are considering the time series of the detector loops and apply techniques such as DBSCAN (Ester et al., 1996) to detect incidents online in a certain time window. We showed that appropriate detection accuracy is given for high load conditions, while the approach still suffers in weak load conditions. Current work focuses on an improvement of the approach and subsequent classification of incidents. This should serve as a basis for predicting properties such as duration and impact of the incident.

3 ORGANIC TRAFFIC CONTROL

Below, we consider collaborative incident detection to improve the detection accuracy and reliability in distributed and self-organised traffic control. We present our system model with the possible incident types and discuss the Organic Traffic Control System as a basis.

3.1 System Model

We assume urban road networks with varying topology and decentralised nodes that are responsible for controlling the traffic light controllers (TLC) of the intersection. Each node is responsible for the area of this controlled intersection as well as the incoming sections – where induction loop sensors are assumed to be available. Further, each node is capable of detecting traffic incidents in its inbound and outbound sections, and it communicates with its neighbours (i.e., other nodes that share a road segment).

We consider five groups of possible static incidents while dynamic events such as the partial closure of a lane on a multi-lane section (e.g. heavy goods traffic) will be addressed future work. The groups are:

- Complete closing of the section between two intersections – called a section closure (Fig. 1a)
- Lane closure in a multi-lane section (Fig. 1b)
- Partial lane closure in multi-lane section (Fig. 1c)
- Closure or limited use of an intersection by blocking one or more turnings (Fig. 1d)
- Technical defect at an intersection (e.g. loss of function of a traffic light or a detector)

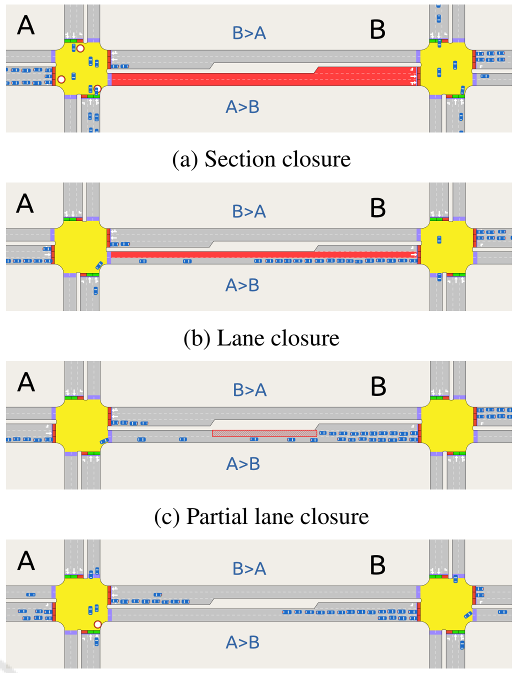
At the very least, nodes have to work with the following information: They only know with a certain probability that there is a possible incident. This information can also be passed on to their neighbours. Moreover, the nodes send their data in two scenarios – direct or with a certain delay.

Based on these model assumptions, the objective of a collaborative validation scheme is to improve the incident prediction of the underlying self-organised traffic control and management system based on decentralised communication – or to reduce its false positive rate. To increase the confidence towards the own data, a periodic self-diagnosis of each node, the associated TLC, and detectors is required. The communication is used to specify the nature and origin of a possible incident and to validate the disturbance by other traffic signal controllers. All nodes only have knowledge about their own state (paired with a certain confidence), while the state is either ‘everything is okay’ or one of the following levels:

1. The node knows of an incident somewhere.
2. The node knows that there is an incident in an outgoing or incoming section.
3. The node can assign the incident to a specific section or junction.
4. The node can assign the incident type to one of the previous mentioned groups.

3.2 The Basis: Organic Traffic Control

The *Organic Traffic Control* (OTC) system (Prothmann et al., 2009) and its extensions serve as a basis



(a) Section closure

(b) Lane closure

(c) Partial lane closure

(d) Turn closure

Figure 1: Examples of incidents simulated in the Aimsun Next traffic simulator (Aimsun, 2021) in the road section from A to B, or in the last case, in intersection A itself, when cars cannot turn right towards intersection B.

for automatic detection of incidents in urban road networks, their self-organised collaborative validation, and finally their consideration in signalisation strategies at ICs. 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 IC. Here, “organic” follows the ideas of Organic Computing (Müller-Schloer and Tomforde, 2017) and emphases 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 in a phase-based approach and optimises this adaptation strategy at runtime by means of reinforcement learning and safety-oriented generation of novel behaviour within a simulation environment, see (Prothmann et al., 2009). This 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 60 to 120 sec) before it can become subject to adaptations again. As decision basis for any adaptations, the current traffic flows for all turning movements passing the intersection (in $\frac{vehicles}{hour}$ and estimated from detector readings) are considered. The estimated waiting times are then used as feedback to improve the behaviour over time. OTC is further able to establish progressive signal systems 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., 2016).

OTC is self-organised in a way that all nodes operate independently and collaborate to achieve system-wide goals, such as reduction of waiting times, number of stops, emissions, etc. Therefore, it establishes a multi-layered adaptation and learning system on top of a standard TLC. Figure 2 illustrates the conceptual design. Here, Layer 0 represents the System under Observation and Control (SuOC), which is the actual TLC and the interfaces to detectors and neighbouring nodes. This TLC (i.e., its green duration) is re-configurable at runtime, which is done by the layer above. Consequently, Layer 1 adapts dynamically to the state of the environment (assessed using the sensors) and its controller which uses a Learning Classifier System (LCS, here 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 an environment for which it has no suitable rule or only inappropriate knowledge. In this case, a traffic simulation software (Aimsun Next, see (Aimsun, 2021)) is used to validate new rules which are generated using an evolutionary algorithm.

4 COLLABORATIVE, SELF-ORGANISED INCIDENT VALIDATION

Based on the OTC approach and the presented system model – including the incident detection approach from (Thomsen et al., 2021) – this section derives the challenges for establishing a collaborative incident validation procedure. This outlines a research agenda in addition to the basic concept.

Traffic conditions as observed by detectors are the result of vehicles traversing the network. In consequence, the patterns observed at consecutive detector stations are not independent. Individual vehicles may temporarily be delayed due to parking (includ-

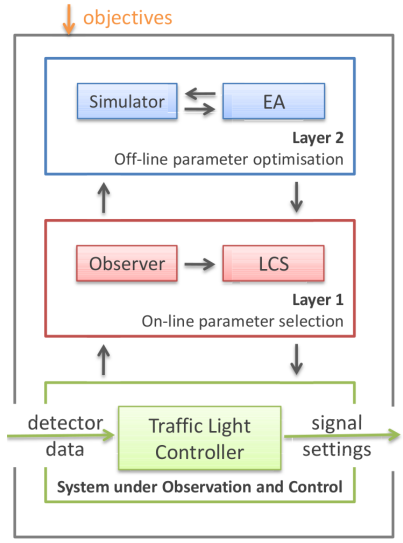


Figure 2: Overview of the multilevel OTC architecture.

ing long-term stays in parking lots) – but they do not completely appear or disappear. This also implies that the observed traffic conditions are strongly related to those of the preceding detector station a short period before. We consequently, aim at utilising this information to (i) further decrease the false alarm rate and (ii) detect disturbed sensors.

The goal of the collaborative self-organised incident validation approach is to turn a self-adaptive incident detection system (here: The OTC-based approach from (Thomsen et al., 2021)) into a cooperative solution. This initially implies using the knowledge of preceding and succeeding ICs for the validation purposes of incident notifications (Challenge 1). Afterwards, we require novel techniques for assessing the observation success of detector stations based on the same information (Challenge 2). Finally, we need to explore how ICs can learn the accuracy and impact of the detection success of their neighbours using a reinforcement approach (Challenge 3). This will be the basis for the actual response to alarms in OTC (and which must be learned, not just communicated since the impact are not visible for the neighbour).

Our starting point is preliminary work for establishing PSS (Tomforde et al., 2008). Here, information exchange protocols based on communication and processing techniques to consider the knowledge of other ICs have been developed. We need to adapt the communication protocols and develop novel techniques to make use of sensor information and classification knowledge from neighbouring ICs.

Challenge 1: Collaborative Validation of Stream-based Incident Classifications

To begin with, the existing unicast-based communication protocols in OTC have to be enabled to exchange information about traffic volumes running over shared roads and the underlying aggregated detector signals. Based on these communication capabilities, we propose to investigate a pull-based mechanism where ICs can ask their neighbours about observations and classifications of traffic behaviour. Here, we distinguish two cases: an event-driven approach (e.g., in case of abnormal traffic behaviour or if incidents have been signalised) and a self-testing loop (i.e., in cycles to verify the correct functioning of a particular sensor).

For the event-driven approach, the IC has to identify the relevant neighbour with respect to the detector location (upstream or downstream). Taking the estimated travel time (i.e., following the approach in (Prothmann et al., 2012) based on Webster's formula (Webster, 1959)) to/from this intersection controller into account, the patterns of traffic flow can be compared with the neighbour's information. If the comparisons show a correlation of effects, the incident alarm is confirmed. Otherwise, it should be delayed – and an additional validation step has to be done in the other direction of the traffic stream. We further have to investigate which features can be used in addition to the traffic volume to improve the validation effect (e.g., slope, curvature, and variability of the data).

In turn, the self-testing approach aims at assessing the behaviour of the own sensors. Therefore, the traffic behaviour of all road segments approaching a detector station of a turning, the corresponding detector data, the detector data of the road segment taking up the turning's traffic stream, and the information of the IC where this road segment leads must be evaluated. In general, the smoothed and averaged traffic volumes of all three involved intersections have to account for to the same level. Based on a comparison of these figures, deviations can be detected – and they can be related to an individual source of information (i.e., a detector station or a neighbour). As a result, either a neighbour can be triggered that the received information is conspicuous or the impact of the disturbance of the own detector is analysed in detail (i.e., repeating this analysis based on historical data backwards in time until deviations are no longer significant).

Challenge 2: Collaborative Self-assessment

The concept of the previous Challenge 1 is based on a bilateral comparison of detector data and aggregated traffic flow estimations. In this Challenge 2, we increase the focus towards a network-wide collective self-assessment of incident information and detector plausibility. Therefore, we need to further investigate if and how the validation effect can be improved by considering longer streams than just pairs of ICs. This implies higher uncertainty due to detector-inherent differences and traffic splitting into lanes at each intersection (or between lanes on road segments), but it also allows to follow traffic streams for sequences of detector stations. As a result, we aim at estimating the expected traffic volume and use this as ground truth for computing how the individual detector deviates from the expected stream. This approach has its advantages in cases where, e.g., two consecutive detector stations are disturbed simultaneously. In general, we have to estimate a time series of detector readings where the travel times between detector stations refer to the time steps of the time series. We propose to approximate the time series linearly and use this information to detect outliers. This process can be further improved by considering more features than just the traffic volumes.

However, the effort of such an approach is dramatically higher than the bilateral approach of Challenge 1: All-to-all communication between several ICs burdens the underlying communication network. In order to (i) keep the effort at a feasible level and (ii) narrow the overall traffic stream estimation problem down to a certain part of the network, we propose to follow an event-based approach again: All incident alarms that cannot be validated by the corresponding neighbour serve as an event to start the distributed mechanism. Consequently, a responsible IC is available to manage the process. The mechanism itself runs conceptually in iterations: We propose to increase the horizon hop-wise in both directions in each iteration. This can then be augmented by a subsequent outlier detection approach as outlined above to identify incorrect detector information or to finally explain the deviations by normal variations from the underlying stream information (e.g., if the stream is characterised by highly heterogeneous readings).

Challenge 3: Reinforced Reliability Estimation of Neighbouring Intersection Controllers

The approach as outlined by the previous two challenges means that ICs notify their neighbours of detected incidents by starting the distributed validation process (both, the bilateral and the multilateral variant). In Challenge 4, we propose to develop techniques to take this information into account when deciding about adapting the current control strategies. However, such a reaction is only successful if the underlying information is quickly available and highly reliable. The reliability is affected by characteristics that do not depend on the incident detection techniques. For instance, different aspects such as the topology of the intersection, parking areas between intersections, or large taxi and bus stopping areas may result in temporal abnormality. Some of these characteristics have a constant impact while others (e.g., large bus areas) have a situation-dependent impact (e.g., the time of the day). Challenge 3 focuses on learning the reliability of the incident alarms of an IC, depending on the current situation.

Since this information is not directly available, we have to learn the corresponding reliability at runtime. The basic idea of this Challenge 3 is (a) to combine the observations of neighbouring ICs and (b) to use their situation-dependent reliability estimation for the IC under consideration in an ensemble-based approach again. For the first step (a), we propose to follow a similar approach as already used in OTC for the online signalisation adaptation: We make use of reinforcement learning capabilities. The concept utilises a variant of an XCS that maps a traffic situation (measured at the neighbouring intersection) to a reliability estimation of the incident alarm of the considered IC – and then learns the accuracy and fitness of the reliability estimation over time. This has to be done for all neighbouring intersections. For the second step (b), we propose to use the reliability estimations of each neighbour as input and compute an aggregated measure. Initially, each neighbour has one vote and we will have to investigate if it is possible to improve the behaviour by adapting these votes (i.e., the weights assigned to the input of a neighbour). Another aspect of the challenge in this context is that for the bilateral approach only one or two neighbours are involved in most cases (based on the design of the approach). Consequently, the ensemble itself faces a dynamic constellation of participants. We need to further investigate how this affects the success of the estimation.

Challenge 4: Consideration of Incident Information in Control Strategies

Based on OTC, we have to investigate how reliable incident information can be considered in the different aspects of the controller decisions: (a) for adapting the signalisation, (b) for maintaining PSS, and for (c) modification of route guidance information.

For aspect (a), we have to investigate possibilities to modify the decision system of the adaptation cycle. Alternatives include: (i) extending the situation description as basis for the adaptation loop with incident information (drawback: is not part of initial rules, increases the search space), (ii) artificially decreasing the traffic volumes of the situation description towards an outgoing section if the incident is part of this road segment (drawback: affects the learning mechanism, the exact value for reduction has to be determined), or (iii) modify traffic volumes by extrapolating the (estimated) impact of the incident (drawback: affects the learning mechanism). However, in all cases, we have to assess the implications on the learning feedback and the resulting self-improving adaptation behaviour.

For aspect (b), the PSS algorithm needs to be modified – which select partners based on the current traffic flow volumes and coordinates the signalisation of those ICs that serve the traffic streams with the highest number of vehicles (i.e., negotiating common cycle times and offsets). Incident information can be used to alter these mechanisms in different ways, including the following:

1. Anticipatory switching to alternative PSS since the incident is expected to decrease the traffic volumes to be served by the current PSS.
2. Favouring coordination schemes that are expected to alleviate the impact of the incident (e.g., those that faster release traffic affected by the incident).
3. Prefering PSS that avoid reported incidents.

Since each IC decides autonomously, the incident information (such as reliability, severity, expected impact, and type) has to be considered in the decision process when choosing partners and signalising the need for a PSS update. An incident-aware approach has to estimate the benefit of changing the PSS in response to the incident, where “benefit” is computed in terms of cars being served and the uncertainty assigned to this result.

For aspect (c), we rely on existing work, i.e. two variants of fully decentralised route guidance mechanisms imitating the Distance-Vector Routing (DVR) and the Link-State Routing (LSR) protocols (Prothmann et al., 2012). Both are based on broadcasting local traffic data: ICs exchange either a topology graph of the controlled intersection (i.e., including in- and outgoing roads, neighbour information, and destination information) augmented with the current traffic conditions (i.e., occurring delays and expected travel times – LSR variant) or propagate shortest paths through the network (DVR variant). In the LSR variant, shortest paths have to be determined for each incoming section based on, e.g., Dijkstra’s algorithm, while the DVR variant directly provides this information. The resulting shortest path information (i.e., the list of considered destinations together with the next hop/turning advice at the intersection and the expected travel time) are displayed via Variable Message Signs (VMS) for each road approaching the intersection. Here, incident awareness requires modifications of these concepts.

Assuming a static acceptance rate, i.e. a given percentage of drivers that will follow the recommendations displayed via VMS, leads to the question of how a variation of the acceptance rate within simulations has an impact on the outcome (following the method suggested in (Bazzan and Kluegl, 2005)). Hence, we have to investigate how (i) the routing protocol and (ii) the computation of route recommendations has to be modified to consider incident information. For the LSR variant, this initially means to further annotate the topology graph representation to be communicated via broadcasts. Therefore, edges of the graph representation can be annotated with additional values representing the incident status, the estimated impact (i.e., severity and duration), and the reliability of this information. After broadcasting this topology information, each IC can build a complete graph representation of the underlying road network on its own and can compute shortest paths. However, we have to investigate how these computations are impacted by incident information: (a) individual roads suffering from incidents have to be avoided, (b) intersections affected by incidents have to be avoided, and (c) paths that bypass incident areas have to be preferred. For instance, this can be done by introducing static penalty values for links and nodes, introducing varying penalty values (e.g., in a gradient approach surrounding the incident area), or removing links and nodes from the graph representation. We have to analyse and compare these concepts. As an alternative, a multi-objective variant of Dijkstra's algorithm may be developed. For the DVR variant, similar considerations as for deriving shortest paths have to be done when updates of routing entries arrive via broadcast messages.

5 CONCLUSIONS

In this work, we argued that traffic incident detection in urban road networks is different to that at highways. Following recent results, clustering approaches allow for appropriate reliability of detected events – which can be performed locally at intersections. However, to incorporate incident information in signalisation strategies (for green duration modification, progressive signal systems, and even for route guidance), the uncertainty has to be reduced. Consequently, we propose to utilise of local dependencies in self-organised road networks as traffic flows pass several intersections. This spatio-temporal behaviour can be used to collaboratively compare and analyse flow information – and to either confirm incident indicators or to reject them in a self-organised manner.

We proposed a research agenda comprising four major challenges: (a) collaborative validation of stream-based incident classification, (b) collaborative self-assessment of sensory equipment, (c) learning the reliability of estimations, and (d) Consideration of incident information in signalisation strategies. We provided conceptual approaches to tackle these challenges – based on an integration in the Organic Traffic Control system and the available cluster-based incident detection approach. Our current and future work focuses on the subsequent implementation of the concepts and the subsequent tackling of these challenges.

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