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Concepts for Resilient Traffic Management based on Organic Computing

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This report aims at investigating forecast-based control of Organic Computing (OC) systems, especially the Organic Traffic Control (OTC) system. OTC is a self-organising traffic management system for urban road networks. Making forecasts of future system states can make complex technical systems more robust against failures. We present concepts for the creation of forecasts at runtime and how these forecasts can be integrated in OC systems and OTC, and discuss how this can lead to higher resilience.

1 Introduction

Organic Computing (OC) postulates that the steady growth in complexity of technical systems demands for a paradigm shift. Instead of anticipating all possible system configurations during the design process, a system has be empowered to adjust itself during runtime – design time decisions need to be transferred into the system's runtime components. This architectural paradigm shift allows us to engineer systems that can provide flexible, adaptive, and robust solutions. Previous and current research in the OC domain mainly focuses on providing self-adaptive and self-optimising solutions by embedding context-awareness and reactive processes already at design-level. This report aims at extending the concept of decisions at runtime, especially in terms of expanding the decision space, by improving the decision-making policy's effectiveness based on the particular decisions' impact.

We want to improve the decision-making policy based on its impact. Especially making prediction-based decisions and assigning them credit in accordance with their contributions are two major challenges that have not been investigated in the context of OC systems, yet. Since a variety of different techniques exists to realise the prediction tasks,

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the question arises which of them is the best possible choice in general or in each particular situation. Hence, we will investigate the possibility to let the system automatically learn a situation-to-prediction-technique mapping as well as an automated configuration of these in order to decrease the deviation of prediction and reality over time.

Urban vehicular traffic control has been shown to provide an adequate domain for the fruitful application of OC research. Traffic control can be characterised along different research directions. Some of the most prominent directions are the traffic-responsive signalisation of intersections, the coordination of traffic light controllers, and route guidance of individual drivers. In the context of the *Organic Traffic Control* (OTC) project [Pro11, STH16], a traffic-adaptive system has been developed that utilises all of the respective infrastructure. It reacts to changes in the observed traffic conditions and self-optimises its control strategies. The insights of OC research in the traffic domain have been generalised and transferred to further application domains, which yielded a generalised approach to developing OC systems.

First, we want to investigate the possibilities to adapt *pro-actively* to changes in the traffic situations by developing learning mechanisms to automatically select promising prediction methods for each intersection controller based on the OTC system. Afterwards, we will integrate this into the signalisation and coordination strategies and finally use the result as basis to investigate a resilient route guidance system, one which is characterised by avoiding oscillating behaviour and identifying shortages in capacities before they occur.

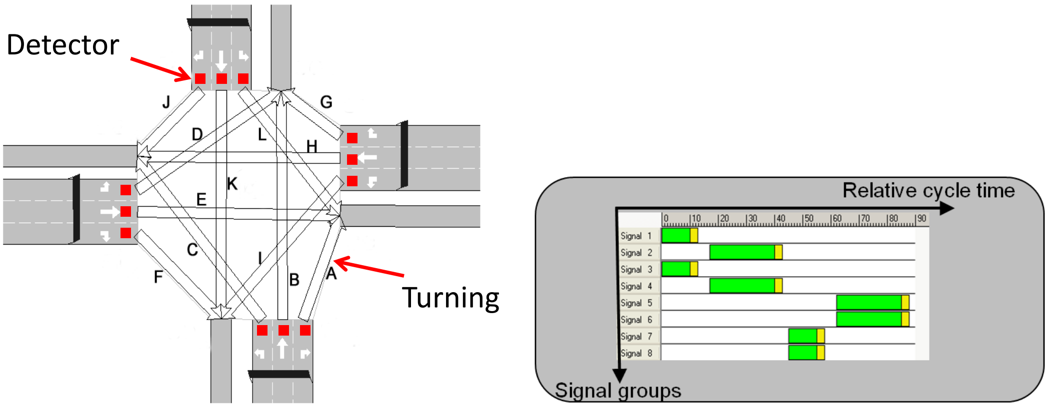
2 Related Work

2.1 Traffic Engineering

This section briefly introduces the corresponding state of the art. First, we explain some necessary **details of traffic engineering** by means of a conceptual traffic intersection. The four-armed intersection shown in Fig. 1(a) consists of four approaching and four leaving sections. The intersection's topology is defined by the turnings between these sections. Each turning might be signalised by its own traffic light or it might share one traffic light (e.g. turnings for straight-ahead and turn-right). We assume that detectors are installed at each turning which are typically realised as induction-loops in the street surface.

Those turnings that direct traffic through the intersection without a potential conflict form so-called *signal groups* (see Fig. 2). This is done by choosing non-conflicting streams. Based on these signal groups, the *signal plan* can be defined. As an example, consider the signal plan in Fig. 1(b) that shows the duration of green and yellow periods for signal groups A to D from Fig. 2. At other times, the so-called *interphases*, the traffic lights are flashing red in order to avoid accidents with conflicting streams. Together, the green, yellow and red periods define the *cycle time.* After completing a full cycle, the signalisation starts again.

Typically, traffic engineers design the best possible signal plans. Different metrics help to quantify the performance of signalisation strategies, e.g. a major goal is to



(a) Examplary four-armed intersection.

(b) Signal plan with a cycle time of 90 seconds and 8 signals.

Figure 1: An exemplary four-armed intersection and the corresponding signal plan.

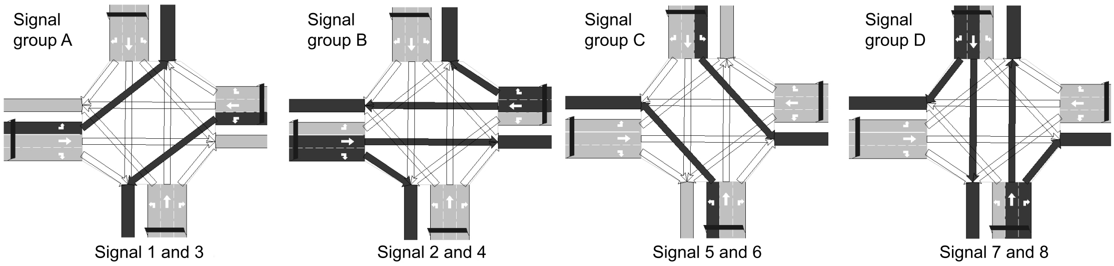


Figure 2: Setup of an examplary signal plan for the example of Fig. 1.

decrease waiting times in front of red traffic lights. For instance, in order to reduce the waiting times due to red lights, one might utilise the Level of Service (LOS). It is defined as sum of flow-weighted waiting times for all turnings. More network-wide goals include the minimisation of total stops or a minimisation of total fuel consumed. In most cases, isolated intersections are designed based on the LOS metric. The resulting increase in green phase durations tends to increase the intersection's throughput (or capacity). But it also tends to increase the waiting time for some of the participants. Accordingly, decreasing green durations tends to decrease waiting times but also reduces an intersection's capacity.

2.2 Road Traffic Control Strategies

Deriving the best trade-off between both aspects resulted in the establishment of **control of urban traffic lights** as prominent research domain in academia for decades. Additionally, several industrial systems are available, since traffic control has a large environmental and economical impact. In general, two approaches are distinguished:

fixed-time control and traffic-actuated control. Fixed-time control relies on switching pre-defined phases with static phase durations and ordering. Traffic-actuated control, in contrast, allows e.g. for skipping phases where no vehicles are waiting and for increasing the green durations within certain boundaries. Certifications, e.g. according to the NEMA standard (common for the US, [Nat03]) or the VS-Plus standard [Swi08], ensure the required, great degree of reliability of traffic-response controllers. In addition, acyclic systems (e.g. systems without fixed phase orderings) are known like Utopia/Spot [DMRV84], OPAC [Gar82], or CRONOS [Boi92]. Currently, most of the installations world-wide perform the cycle-based fixed-time strategy due to cost and easier planning reasons.

SCOOT (Split Cycle and Offset Optimisation Technique, [RB91]) and *SCATS* (Sydney Coordinated Adaptive Traffic System, [SD80]) are prominent (commercial) representatives of yet another kind of control system – they optimise signal plans online based on observed traffic conditions. These systems are powerful and provide traffic-depending configurations, but they are complex to manage, hard to configure and they are only applied to very few, very specific streams in urban traffic networks (i.e. arterial roads). Although the manageability of these systems is difficult and the applicability is restricted, they provide traffic-adaptive solutions; either by calculating signalisation strategies online or by providing optimised coordination sequences. These abilities render them superior to the majority of installed systems that solely execute pre-defined sequences of static signalisation strategies. In fact, this technological edge has motivated further research into the automated optimisation of control parameters of large-scale traffic systems. For instance, multi-objective optimisation has been applied to estimate the best signalisation times and coordination of intersection controllers [SBW03, SMS07]. Typically, such optimisations rely on heuristics as provided by Webster [Web59] and Akçelik [Akc81]. Although this approach may serve as a good rule of thumb, it does not take the inherent diversity of real-world traffic scenarios into account, for instance by pro-actively adapting to local traffic patterns and by applying strategies based on short-term traffic forecasts. It neither considers the scalable interplay of a large number of intersections.

2.3 Forecasting of Traffic Conditions

Independent of traffic control strategies, the **prediction of traffic volumes** is an active field of research. Current approaches rely on means of statistical analysis to detect and extrapolate trends or they make use of averaged daily load curves. *Statistical analysis* tries to detect trends and extrapolates them, while daily load curves assume standard behaviour for classes of weekdays (analogously to Fig. 6(a)). In addition to learning from observation, the viability of traffic simulations for traffic forecasts has been investigated [CPMS02]. Specifically, a Cellular Automaton simulation has been devised that yields "faster than real-time" information about the traffic flow and travel times for the freeway network of North Rhine-Westphalia. Its model data is provided by detectors installed on freeways. Current information is used to correct deviations of the online simulation from the real-world by locally entering vehicles into or removing vehicles from the simulation whereas historical data is combined with the simulated future development to obtain traffic predictions. The idea to use local traffic counts as input for traffic simulations that provide network-wide information will also be applied. We focus on decentralised approaches for urban areas where traffic data can be obtained from (traffic-responsive) traffic lights.

In [CKWS04], a constant and a linear model for short-term traffic prediction are presented. In the constant model, the prediction is derived from a rolling average over the last measured values, whereas in the linear model a linear curve fitting was applied. Based on traffic data collected by inductive loops in the inner city of Duisburg, both models are evaluated using the mean absolute deviation and the mean relative deviation to the measured value. These metrics suggest that the models are suitable for a short-term prediction of up to approximately 15 minutes. In [HR02], genetic programming is used for predicting the travel times on motorways. Several authors investigate the use of neural networks for traffic prediction: For instance, [Yas99] applies recurrent Jordan networks and [STH15a] investigates an approach to optimise the performance of neural networks for short-term traffic prediction. In conclusion, all of these approaches focus on the prediction component in detail, while the usage within a certain system is not evaluated according to a realistic setup, yet.

2.4 Dynamic Route Guidance

Thirdly, **route recommendations and driver guidance** are used to enable traffic management capabilities and therefore turn the reactive traffic control system into a pro-active one. In today's road networks, GPS-based navigation systems [KH06] are installed in a large number of vehicles. They guide the drivers, relying on their destinations. The systems rely on an internal map of the traffic network which is used by variants of Dijkstra's algorithm [Dij59] to compute the preferred route (e.g. shortest or fastest route). The route calculation is either based purely on data stored in the map or it can incorporate up-to-date information from other sources that is transmitted via the radio's *Traffic Message Channel* (TMC) or a mobile Internet connection. TMC provides digitally coded traffic and travel information via public radio, but covers highways and major roads only. Another drawback is its limitation to about 300 different messages [BEF02]. Data provided via an Internet connection covers urban areas, but its topicality and quality usually depend largely on the penetration rate of a system since the provided data is based on travel times experienced by other drivers.

In standard traffic signalisation and coordination systems, the route choice of drivers is not influenced actively. In contrast, current route recommendation systems rely mostly on Variable Message Signs (VMS) alongside the road, informing drivers about traffic-related events such as road-closures, traffic-jams or route recommendations. VMS can be controlled remotely and automatically, but the number of different messages is limited by the size of the sign. Alternatively, *floating car data* can be used to inform drivers about the traffic conditions ahead. For instance, Wedde et al. modified their Internet routing protocol *BeeHive* to be applicable to the traffic domain [Wea07]. Vehicles are routed from one intersection to the next based on recommendations of local servers that collect and aggregate vehicle information and derive route recommendations. This routing approach makes heavy use of Car-to-Infrastructure communication and relies on correct information provided by the drivers. Floating car data was also investigated as part of the OC initiative. Here, researchers developed techniques that move the focus from the infrastructure towards the autonomous entities themselves by introducing self-organised communication between all vehicles in the network. The work is based on the *Autonomos* system [WHF$^+$09] where methods for mobile ad-hoc networks are used for short-distance communication between vehicles. Thereby, so-called *Hovering Data Clouds* (HDC) are established in reaction to specific traffic structures like traffic jams. Such a HDC is a functional entities within the traffic flow independently of individual vehicles and used to inform drivers about the traffic conditions ahead of them. Autonomos is dedicated to short-term information with a restricted decision-horizon and cannot perform routing within larger areas like cities.

Further research investigated possibilities to include route guidance mechanisms into urban traffic control systems. One major example is the European COSMOS project [BC99] – here, incident management and re-routing strategies for various adaptive network control systems (e.g. MOTION [KB02]) have been developed. The COSMOS approach relies on a centralised simulation-based optimisation for the complete network based on traffic data available to the control system. Unfortunately, such a centralised approach does not scale with the network size. Therefore, we propose a fully decentralised approach but with the means to dynamically interface at higher organisational levels.

3 Anticipatory Control of OC Systems

This report aims at investigating **forecast-based control of OC systems**. If at all, forecast-based control surfaced only rarely in the field of Organic Computing—with rudimentary functionality and very application-specific concepts and implementations. The most prominent approach outside of the field of OC is *Model-Predictive Control* (MPC) [CB04] which arose in the domain of control theory in the 1980s. It is one of the most widely used control techniques in process control, e.g. in oil refineries and chemical factories. It is based on a multi-variable control algorithm containing a dynamic model of the process, knowledge about past control actions, and an optimisation cost function for the considered prediction horizon. Based on these components, the MPC controller derives a strategy for adapting the independent variables of the observed process. Different from OC systems, MPC relies on the assumption that all possibly occurring situations are known in advance. OC designs also need to work for systems of greater complexities and especially for those open and dynamic systems that may yield unanticipated situations.

3.1 Reactive and Proactive OC Systems

Current OC systems and projects mainly focus on reactivity as the means to self-adapt to changing environmental conditions and to find *as-well-as-possible* configurations for the underlying OC systems (see e.g. the OC_μ middleware [TPSU07], or the OCOM project [WMS+10]). In addition, most of the systems contain learning components to self-optimise the system's behaviour in case of re-occurring situations (i.e. patterns in situation descriptions, see e.g. the System-on-Chip project [BZS+06] or the Trusted Desktop-Grid [KBMSH12]). We assume that this leads to a significantly better performance compared to standard static configurations and behaviours, but there is room for further improvement: A system that considers the upcoming situations rather than only the current one will most probably adapt faster to changes. One reason could be that predictions become increasingly important with a decreasing number of opportunities to make decisions. This holds especially for those systems where adaptations can only be made in (relatively long) discrete time steps.

In terms of the previous definitions, we want to transform *robust* OC systems into *resilient* ones by making use of forecasts [STHA15]. Furthermore, we aim at developing a unified approach for a class of OC systems. Our generalisation of the forecast component targets to benefit all OC systems. An engineer should be relieved of implementing, testing, and analysing forecast methods. This approach will relieve the designer from choosing specific optimisation techniques – instead, the system will be able to learn which technique is the most promising within a given situation in order to achieve the best possible predictions. This is especially important for OC systems as they may consist of large sets of autonomous entities that have to cooperate to achieve a system-wide goal.

3.2 Robustness & Resilience

The main purpose of adding adaptation and self-optimisation capabilities to OC systems is to allow for robust and flexible solutions. In this context, *robust* means that the system is able to deal with a certain set of disturbances by keeping the system performance within a predefined corridor or at least guaranteeing to guide it back within a certain period of time [SMSc+10]. Complementary, *flexible* means that the system automatically adapts to changing goals provided by the users at runtime [SMSc+10]. We define the term *resilient* as "pro-active robustness", which means that the control mechanism encapsulating the organic capabilities of the system does not only react to detected disturbances and dissatisfying system performances but that it also uses machine learning techniques to predict upcoming problems. In this case that an undesired environmental state is predicted (i.e. disturbances or shortages characterise the predicted situation), the control mechanism will guide the system's behaviour in such a way that these disturbances and shortages will be prevented from occurring.

4 Preliminary Work: Organic Traffic Control

In the field of OC, the Multi-level Observer/Controller (MLOC) architecture [Tom12] (see Fig. 3) has been developed alongside a corresponding meta-design process for self-adaptive systems [THMS13]. The application of this general concept achieves self-adaptation and self-configuration of existing parametrisable systems. Besides the sole aspect of adaptation, the augmentation of systems with the additional Observer/Controller functionality equips them with further OC characteristics such as robustness against a set of disturbances, flexibility, and self-improvement. To achieve these characteristics, machine learning techniques are used. The group identified applicable techniques for the given problems, and additionally adapted the most promising approaches for the restrictions of real-world systems and their safety demands [Tom12].

Most importantly in the context of urban traffic control, our group has been highly involved in the development of the OTC system. OTC [PBS+09] has been developed to provide a solution for traffic control that is based on the principles of OC. OTC is able to adapt the signalisation of traffic lights to changing traffic demands, establish Progressive Signal Systems in a self-organised manner, and provide route recommendations to drivers which reflect the current state of the traffic network. Furthermore, the insights of OC research in the traffic domain have been generalised and transferred to further application domains in order to gain a broader understanding of the development of OC systems in general. OTC and its generalisation to a broader class of OC systems focus on reactive system reconfiguration based on observed changes in the environment and the controlled system's state. We showed that this approach increases the system's robustness and performance. The corresponding projects (OTC, OTC2, and OTC3) have been funded by the DFG within the priority programme 1183 "Organic Computing". The OTC system consists of three modules: 1) Autonomous and self-optimising control of traffic signals at intersections, 2) distributed coordination of neighbouring intersection controllers, and 3) infrastructure-based route recommendations following an Internet-inspired routing protocol. The following paragraphs explain these three aspects in more detail.

1) Autonomous and self-optimising control of traffic signals at intersections has been achieved by applying the MLOC architecture to the control of traffic light controllers at urban intersections. Based on simulations of the existing infrastructure and without the need for more sophisticated detector technology, we developed a safety-based adaptation strategy that determines the best green durations for all traffic lights of the intersection. Hence, the OTC system as depicted in Fig. 3 is applied to isolated intersection controllers in the first place. A variant of Wilson's Learning Classifier System "XCS" [Wil95] has been developed that learns the best mapping of traffic situations to phase duration (Layer 1 of the architecture). Due to safety reasons, novel rules are derived in simulations at Layer 2 (also called "sandbox-learning"). The result is a traffic-aware controller that improves automatically over time [PBS+09]. The installation of such self-adaptive controllers at all intersections of a network also results in a network-wide improvement, especially compared to actual installations. Thereby, reference solutions from Hamburg and Hannover have been used for comparison purposes [Tom12] as well as related techniques from the state of the art.

2) Distributed coordination of neighbouring intersection controllers overcomes the isolated control of intersections by means of scenario-specific collaboration patterns. Thereby, Progressive Signal Systems (PSS – often also called "green waves") are established [TPR+08]. The mechanism (DPPS – Decentralised PSS) works in three

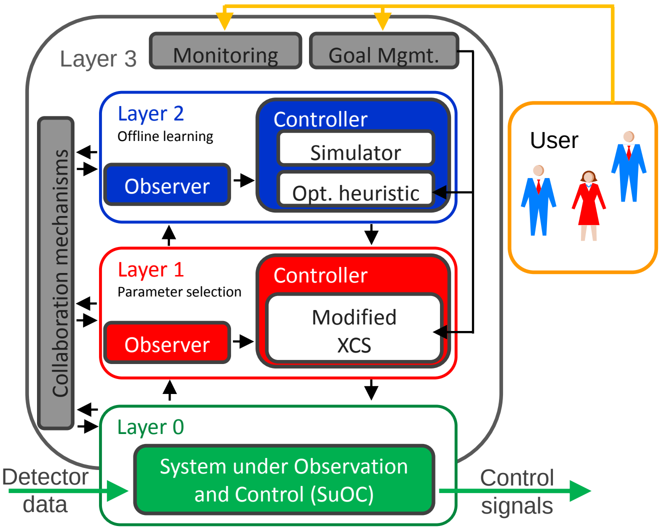


Figure 3: Multi-level Observer/Controller Design.

completely decentralised phases: 1) identification of partners, 2) negotiation of timing restrictions, and 3) establishment of the PSS. As a result, PSS emerge that cover the most promising streams and increase the throughput of the network for the most heavily used connections.

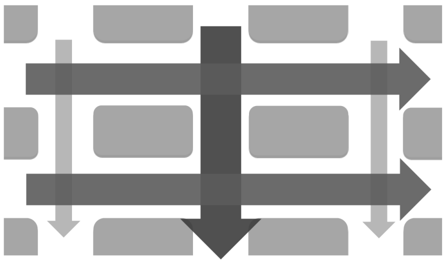


Figure 4: Progressive signal systems for the strongest streams within the network.

In most cases, DPSS comes up with the best solution for the creation of a PSS, but there can be situations where establishing a PSS for the strongest traffic stream might not be the optimal solution as it can impede the coordination of several other streams which serve more vehicles in total (Fig. 4). Therefore, the DPSS mechanism was extended by an additional hierarchical component, called the Regional Manager (RM) [TPB+10]. The RM combines traffic flows of several intersections and uses the resulting, regional model to choose the best combinations of intersections for the establishment of a PSS. Thereby, it substitutes the first step of the DPSS mechanism.

3) Infrastructure-based route recommendations following Internet-based routing protocols make further use of the collaboration possibilities. Inspired by

Internet-based routing protocols like the Distance Vector Routing protocol [Tan02], intersection controllers exchange information about currently observed travelling times to prominent destinations within the network. Thereby, each intersection controller measures its turning delays (from flows and green times with the help of Webster's formula [Web59]) and estimates travel times. These travel times are communicated to preceding intersections, where the expected travel time to the information-sending intersection is estimated, augmented with a local delay, and provided to drivers via VMS. This concept has been further extended based on a consideration of the Border-Gateway protocol (again from the Internet domain) to improve the scalability [PTL+12]. As a result, the distributed route recommendation approach improves the robustness of a road network (with respect to traffic jams) and lowers the network-wide travel times and the number of stops [Tom12]. Although the benefit of the approach is visible in most of the cases, drawbacks can be identified. As the routing concept relies on an exchange of current traffic conditions, oscillating behaviour and sub-optimal re-routing can be observed in high-load and quickly changing traffic situations.

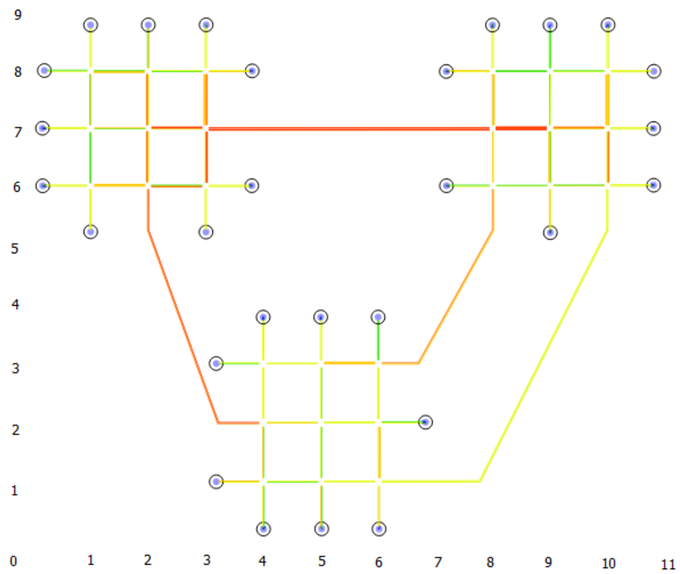


Figure 5: Simulated travel times within a manhattan-style road network with three regions (green links depict free-flowing traffic, red colours depict congested links).

These issues are addressed by deriving a decentralised look-ahead solution that estimates the impact of the decision to be taken [STH15b]. Furthermore, the routing approach covers only a description of the currently observed traffic conditions (Fig. 5). Finally, route recommendations are based on communicating the currently shortest route to the drivers, which does not include reasoning about the impact of these route recommendations and the fact that traffic conditions will have changed when the drivers will arrive at the next intersections. Hence, we aim at turning the existing reactive traffic control system into a pro-active (resilient) traffic management system [Som13].

5 Objectives: Proactive Self-organisation

Organic Computing (OC) [MS04] is a young research area focusing on self-organisation to handle complexity in large-scale interconnected systems. An OC system consists of a potentially large set of autonomous entities. These entities act without strict central control and they achieve global goals although their decisions are based on local knowledge only. Due to the interconnectedness of the tasks to be solved and the corresponding global system goals, the effort for anticipating all possibly occurring conditions the system will be exposed to at runtime is not feasible. Therefore, OC systems have to be adaptive and equipped with learning capabilities. This leads to the ability to self-optimise their own behaviours over time and throughout their life-times. In particular, the systems have to be able to (collaboratively) learn novel behaviour for previously unknown situations (situations that have not been anticipated by designers at design time).

We provide an integrated solution for **resilient traffic management** that is easily adoptable by the existing traffic infrastructure. In order to reach this goal, we need to work at and stretch the boundaries in several fields of research. We will analyse existing techniques in the field of traffic forecasting, apply the most promising ones to the forecast problem, and allow the system to figure out which technique has to be used in which situation. This approach combines the advantages of (automated) reinforcement learning with the possibility to choose between different solutions at runtime – depending on their particular strengths. Furthermore, our approach considers the states and measurements of neighbouring nodes of the traffic system. Data that is sent ahead of traffic allows to learn the reliability of the local system's peers. The set of reliability-weighted input values from neighbours in combination with locally accrued data provides a rich, extended basis for adapting to current and future traffic demands.

The enhanced traffic management capabilities of our approach will lead to a novel contribution to the field of route guidance. In particular, we demonstrate its use as an infrastructure-based recommender system that integrates the current traffic conditions, predicted situations at different time scales, and capacity [STH15b]. This application increases the speed of adaptivity to changing traffic conditions, the robustness of traffic flow against disturbances (and oscillation effects), and it improves the communication of traffic information to affected drivers.

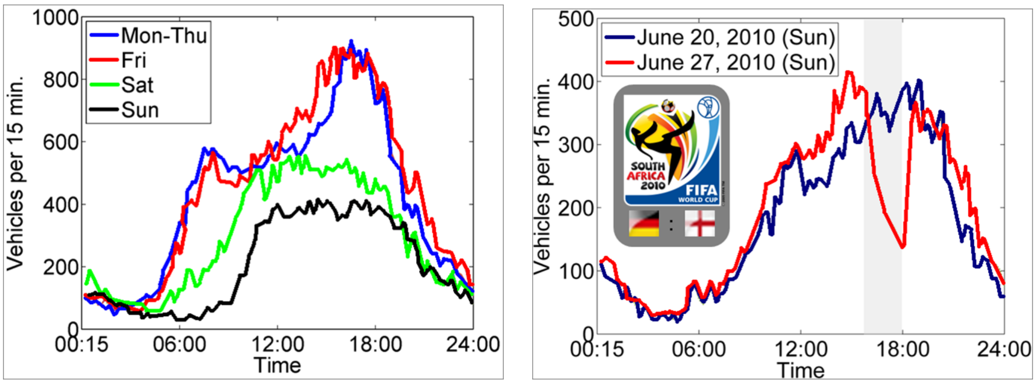
5.1 Urban Traffic Control

Urban (vehicular) traffic control is an ideal test-bed for research on resilient systems[1]. Vehicular traffic is characterised by reoccurring patterns in traffic (as depicted in Fig. 6(a)). Traffic engineers develop their signalisation strategies according to (averaged) load curves since these traffic patterns can be known at design time as a result of a census. Fig. 6(a) shows the daily load curves at an arterial road in Karlsruhe, Germany[2]: the traffic flow in

[1] See e.g. the 2013 competition on self-x concepts in traffic control, held together with the IEEE ITS conference in The Hague, NL – where our system received the first place [STH13a]

[2] The figure is based on census data provided by local authorities in Karlsruhe.

both directions of the road (see y-axis, in $\frac{vehicles}{15\ minutes}$) is depicted according to the time of the day and categorised into several classes (regular weekdays, Fridays, Saturdays, and Sundays). Fig. 6(b) illustrates the drawbacks of preplanned strategies and schedules. The figure compares the traffic demands of the same arterial road in Karlsruhe (for one direction only) for two subsequent Sundays. June 20, 2010 was a regular Sunday and the corresponding traffic profile was handled according to the preplanned schedule in a satisfying manner. The irregularity occurred one week later in the afternoon of June 27, 2010. The German soccer team played against England in FIFA's World Cup. The game took place at Bloemfontein, South Africa, but also affected the traffic in Karlsruhe. Until noon, the observed traffic evolves similarly to the previous week, which serves as standard profile. Afterwards, a dramatic change is visible: an unanticipated peak before and a dramatic drop after the beginning of the match. Such unanticipated behaviour cannot be handled with preplanned strategies and motivates the need for concepts of the OC domain like runtime reconfiguration and robustness against disturbances.



(a) Regular demand

(b) 2010 FIFA World Cup

Figure 6: Traffic demand of an arterial road at Karlsruhe, Germany

5.2 Forecasting and Pro-activeness

We start with investigations on how the existing OTC system could extended to pro-actively adapt to changes in traffic situations, i.e. we want to make use of predictions to better select good signalisation behaviours. Appropriate prediction/forecast methods for each intersection controller need to be selected and implemented, and automated machine learning techniques need to be applied that are able to determine the most useful prediction methods in any given situation [SSH16].

At first, we focus on an isolated intersection controller and develop forecasts based on its local sensory data. Afterwards, we enhance this approach by considering knowledge collected by neighbouring intersection controllers. This follows the basic OC principle of distribution of complex control problems among a large set of collaborating entities. In general, current prediction techniques in the traffic domain try to identify streams at a macroscopic level or they focus on local information only (cf. Section 2). Neighbours, i.e. road intersections in the given context, can observe certain changes in traffic behaviour earlier than the next upstream intersection. This knowledge can be taken into account when pro-actively adapting the controller's strategy. Here, the prediction values are integrated into the signalisation and coordination strategies [SH16]. Finally, we use this information about upcoming changes as a basis to investigate a resilient route guidance system. The resilience of the route guidance system is characterised by avoiding oscillating behaviour (in this context, oscillating behaviour means alternating route recommendations) and identifying shortages in capacities before they occur.

6 Forecasting of traffic streams for individual intersections

Hypothesis: "Forecasting techniques have different strengths and weaknesses. It is therefore more efficient if the system figures out which forecasting method to use in which situation than to let the designer find a static solution that works best on average for all foreseen cases."

The first step towards a resilient and anticipatory traffic management system is the self-organised generation of forecasts for local traffic states at intersections. Here, historical and current traffic flows of turning movements are used to estimate the most probable traffic state at a certain future point in time [STH13b] (Fig. 7). Considering Fig. 1(a), a predicted traffic flow value for each of the turning movements (A to K) is needed. In our scenario, we are interested in the next traffic state that will be observed when performing the Layer 1 adaptation loop again (see Fig. 3). In terms of OTC, Layer 1 operates with respect to the actual cycle time defined by the currently active traffic light controller (cf. Fig. 1(b) for the cycle time). Hence, this *next* point in time is typically 3 times the duration of the current cycle time (typically about $3 \times 90sec = 270sec$). So the goal is to initiate the adaptation early enough to have it take effect when the system state changes.

When working with forecasts one always has to consider probabilities, especially since traffic forecasts that directly impact traffic control need to be very reliable [STH14]. For instance, if during rush-hour, a slight decrease in traffic demand was predicted instead of an abrupt and drastic increase, the corresponding links, i.e. sections of the road that flow into the respective intersection, could become congested leading to severe traffic jams due to an overload of the links' capacities. Therefore, the certainty of the predicted evolution of traffic demand has to be high.

Considering the state of the art in traffic prediction, different approaches can be found (see Section 2). The most prominent ones originated from the domains of statistics (trend detection and extrapolation), traffic engineering (static daily load curves), and automated learning methods (e.g. using Artificial Neural Networks, ANN). We were able to show that all techniques have their particular strengths and weaknesses [STH13b]. For instance, ANN can reflect non-linear reoccurring behaviour, whereas trend extrapolation works well with constant or low-dynamic behaviours. In addition, most of the techniques

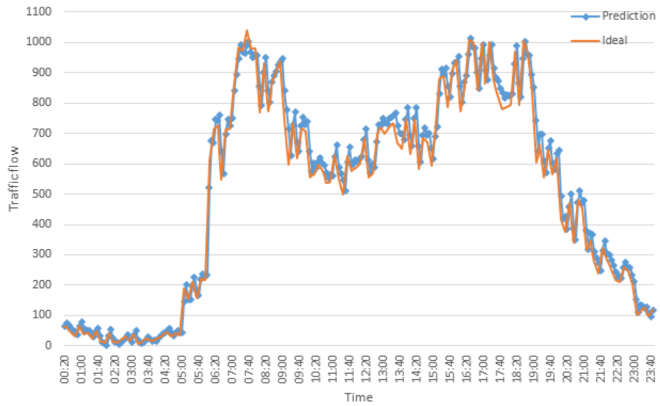


Figure 7: Exemplary time plot depicting the actual traffic flow in vehicles per hour and the respective forecasts made by an artificial neural network.

we considered provided satisfying results in case of regular traffic patterns but exhibited weaknesses in case of disturbances and unforeseen events. It is hardly possible to predict singular events similar to the one recorded in Fig. 6(b), but irregularities that are close to known patterns should allow for good estimates.

6.1 Daily Load Curves

The approach is based on a combination of two directions: a) take the re-occurring patterns of daily load curves into account (domain knowledge available at design time) and b) learn from experience (knowledge derived at runtime). At first, we will develop the means to learn load curves at runtime which strongly contrasts with the current state of the art that relies on static predefined curves. Current observations will be compared to locally maintained curves that are defined by observed time series and their deviations. Either the observations match an existing curve within a certain threshold, or it defines novel behaviour resulting in learning a new curve. In the former case, the current observations can be used to refine the representative curve (the forecast is based on the representative curve) and in the latter case it is stored as the representative of a new class of behaviours (Fig. 8).

6.2 Selecting Forecast Techniques

Secondly, the system will not only make use of one prediction technique but it will choose the most promising one from a set of variants (we refer to a variant as different techniques and their varying configuration possibilities). While all variants can predict the desired forecast value, the deviations of the forecasts are used as reinforcement afterwards to automatically learn which technique leads to the best result. We will tackle this “algorithm selection problem” [Ric76] also based on the insights from theoretical concepts, e.g. for estimating the best algorithm to solve the SAT problem [XHHLB08]

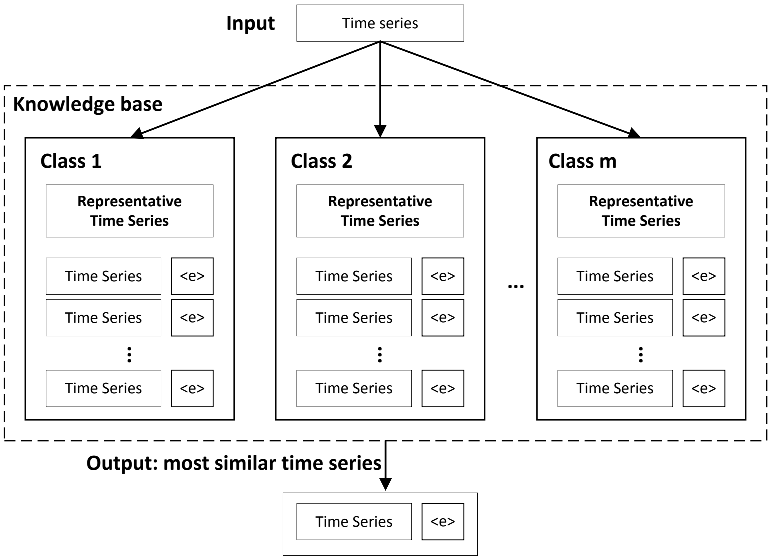


Figure 8: Forecasting time series based on daily load curves.

and on hands-on meta-learning approaches [GCVB04].

Our meta-learning approach, i.e. learning and applying the best prediction technique, is further extended to be context-aware, i.e. to consider the errors of a prediction technique in any given situation [SSH16]. The resulting *prediction learning system* works on basis of a knowledge base that contains a set of different conditions and entries for all prediction techniques, i.e. the experienced deviation of the prediction values. This concept maps perfectly on the Layer-1-based learning mechanism in the MLOC architecture (see Fig. 3) as realised with the modified LCS-variant.

All investigated prediction methods need a standardised setup. They have to take the same values as input (the last n traffic flow values) and derive the forecast value for each turning for a specific time in the future. Formally, this can be defined as the prediction function p: $p(n_1, \dots n_t) \rightarrow x_{pred}$. In this formula, p receives a set of t historical values (ordered by time) with the t-th value equal to the currently observed flow. As the prediction horizon can be dynamically adjusted, we can generate different values utilising a single method. OTC's Layer 1 can take these prediction values into account when deciding about the next adaptation of the signalisation. To this end, different strategies are possible, ranging from using the current situation only (default solution) to using large periods of predicted traffic demand. We assume that a trade-off between both extremes will be the best possible approach (i.e. considering the prediction to a certain degree).

Besides predicting traffic flows for the next adaptation cycle of the signalisation, forecasts can be used to pro-actively generate knowledge. Within the MLOC framework, Layer 2 generated new rules in case of missing knowledge (see Fig. 3). Predictions can be used to discover the need for new rules in due time, and thus, to make the pro-active generation of new adaptation rules for Layer 1 possible. This will lead to a better performance of the signalisation-adaptation strategy.

Finally, intersection controllers are able to adapt their signalisation (in terms of durations of green times) to changing traffic conditions ahead of time. Hence, a pro-active selection of traffic controller parameters (green durations for signal phases) is possible as well as a pro-active generation of completely new parameter sets to meet future demands [SH16]. We expect the extended OTC system to adapt much faster to changing traffic conditions compared to the current reactive solution, and, as a consequence, to perform better in terms of traffic-related metrics.

7 Collaborative extension of the prediction mechanism

Hypothesis: "Predictions can be improved considering knowledge of spatially close collaborators. The reliability of the collaborators' information can be learned at runtime."

The previous step improved the speed and the quality of adaptation of a single node by means of predictions based on locally available sensor data. The second step is to incorporate data from neighbouring nodes. One important observation is that neighbouring nodes, i.e. intersections connected by roads, witness the upcoming traffic patterns ahead of time (the time horizon depends on e.g. the length of the linking section and the speed limit). Our previously developed methodology can be extended by taking the neighbours' knowledge into account and thereby increasing the sensor horizon. Alternatively, it can be used to validate local predictions.

Our approach will be based on a short-term communication of macroscopic traffic patterns. In particular, neighbouring nodes communicate the current drain of traffic (time resolution and abstraction are part of the research focus) which will be analysed by the receiving node. As a result, the algorithm receives additional, valuable input, potentially rendering local predictions more accurate. Alternatively, the communicated information can help to validate local predictions. In this case, the neighbour's information impacts local decision making only indirectly, achieving a mitigated effect. In both cases, a communication protocol and an estimation of the reliability of the neighbours' information are needed. The reliability is learned at runtime by comparing the communicated information with the data observed afterwards. Such a reliability value is needed as basis to decide to what degree the prediction method will rely on neighbouring data – the assumption made here is that between two nodes traffic can appear/disappear, e.g. due to parking spaces or residential areas, which decreases the reliability of the communicated traffic information. Reinforcement learning techniques [SB98] will lend themselves well for learning and updating reliability values.

The consideration of multiple nodes allows to perform abstract flow analysis. Similarly to previous work on establishing PSS (see [TPB^{+}10]), an additional hierarchical layer can be established for subsuming certain regions, e.g. cities are organised in regions by means of urban districts. This layer would be responsible for conducting high-level flow analysis from the local observations. Since traffic consists of individual elements traversing the network, traffic flows are an abstracted and averaged description of individual behaviours. The local views of intersection controllers only reflect the current situations of these flows with deviations due to sensor effects. By tracking streams at a higher level of abstraction, generalised movements through the network are described and local measurement errors can be mitigated, local estimations be smoothed and their reliability be improved.

Finally, the local predictions of individual intersection controllers are augmented with neighbouring (i.e. intersections with a direct connection) and regional (e.g. all intersections within an urban district) traffic information such that even more reliable forecasts are possible, especially for predictions with extended time horizons. In addition, forecast information is ensured to be consistent with the current observations of surrounding areas.

8 Anticipatory Decentralised Route Guidance

Hypothesis: "An Internet-inspired routing protocol can provide a solution to distributed, prediction-based traffic control involving several intersection controllers."

With predicted values for all traffic streams being available at each intersection controller for different points in time, a time-aware routing protocol can be developed. In current networking approaches, such as Distance-Vector-based and Link-State-based routing protocols [PTL+12], the observed traffic situation is communicated and made available to route-recommendation mechanisms. The result is an up-to-date description of the network's traffic situation, from which routes to arbitrary destinations can be derived. This yields, however, one significant problem: While the drivers follow the recommended route, the traffic situation changes continuously and might already be outdated when arriving at the next intersection. Currently, OTC minimises this issue by providing new route recommendations at each intersection. The purpose is to provide a time-dependent routing mechanism that is based on sets of varying predictions provided by several intersection controllers, covering different time-spans, such as 3, 5, or 10 minutes. We assume that this approach reduces the re-routing demands and drivers will stay on their initially recommended route with a higher probability. This should, in turn, lead to broader acceptance of route recommendations in the first place and, thereby, make the whole system more reliable.

In order to minimise the out-dating problem, the existing routing protocol has to be replaced by a version that is able to consistently and simultaneously handle heterogeneous sets of traffic predictions. One possible approach is to modify the existing Link-State-based routing protocol by broadcasting graph-series that encode the predicted time series associated with several edges at once. Even only propagating local graph series, with an edge length of one, results in high communication overhead as the data increases linearly with the number of predicted states for each node as well as quadratic with the number of nodes. To alleviate this scalability effect, another mechanism from the Internet-domain could be adopted, for instance the distinction between intra- and inter-network routing as performed by the Border-Gateway protocol (Fig. 9). Also, graph series information might be broadcast efficiently if updated incrementally.

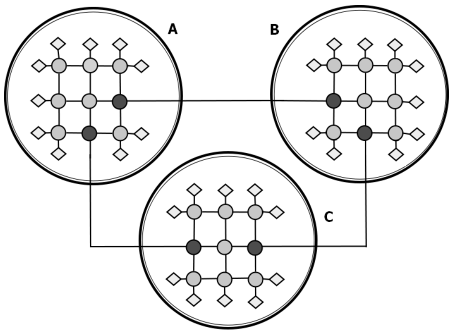


Figure 9: Separating a road network into three regions with the border-gateway protocol.

Finally, intersection controllers possess graphs representing their surrounding traffic network similar to the result of the existing Link-State-Routing-based protocol. However, the graph does not only reflect the current traffic state but also arbitrary time periods. This means that the graph's edges possess a set of weights: one for the current state and arbitrary many for future states (i.e. a future when a driver would approach this part of the network in relation to the particular intersection for which the graph was calculated). This results in a time-dependent representation of the network's status. Based on this graph, route recommendations can be derived (Fig. 10).

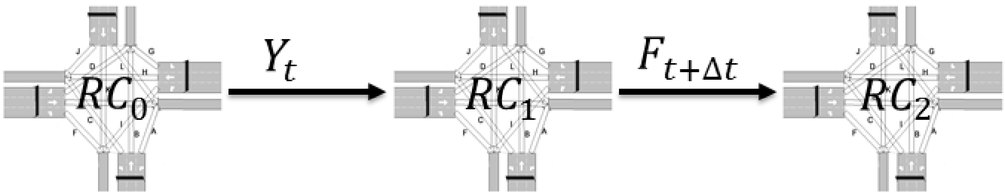


Figure 10: Anticipatory route guidance based on time-dependant travel time estimations and forecasts.

9 Reliable Route Recommendations considering Forecast Errors

Hypothesis: "A decentralised and self-organising routing mechanism can optimise the throughput in large-area traffic networks by taking advantage of reliable prediction-augmented graphs representing a flow model of different time scales."

The goal is to derive and manage the route recommendations that fill the routing tables for each incoming road of an intersection. It extends previous work that introduces destination-based recommendations such as "To destination x turn right and it will take you z seconds to go there" [PTL^{+}12]. The derivation of performant route recommendations depends greatly on the degree to which predicted values should be taken into account based on the communicated graphs. Their potential utilisation ranges from a) not at all, only relying on current traffic simulation, which is similar to the existing approach in OTC, to b) considering long periods of predicted traffic demands. The graph representation as defined previously provides the required information to cover the complete range of degrees.

Selecting the best degree of predictive information depends on the intersection controller's estimation of the reliability of the prediction values received from its neighbours. We estimate the reliability of the direct neighbours' information while deriving local prediction values. A similar concept is now needed for the considered network as a whole. Since we do not want to evaluate each intersection controller within the network due to scalability reasons, the reliability estimation will be based on an abstract representation that delivers reliability values for complete graphs, for different classes of relative travel times, or for specific parts of the network, e.g. according to outgoing sections. The reliability estimation can be used to determine the relative weights of currently observed and forecast information. This step individualises the general graph information as available to all intersection controllers and allows for context-aware information management.

Independently of the consideration of reliability in terms of graphs, classes, and controllers, the individual controllers have to automatically learn reliability estimates. This can be done locally by each node, or intersection controller, by comparing the received prediction values with the actual state information that is recorded and communicated afterwards. Based on this comparison, it can determine the degree of considered predictions, which may serve as a guideline for making forecast-based decisions. Concepts from Temporal Difference learning [Sut88], and Reinforcement Learning [SB98] can provide a basis for our investigations. Hereby, we will focus on the identification of the most promising partitioning scheme for the network and the subsequent assignment of corresponding reliability values.

Based on the estimated reliability values, a reliability-sensitive Dijkstra algorithm [Dij59] has been developed to calculate the route recommendations [STH15b]. In order to do so, the weight of the edges is calculated from the current state and the prediction values: Gradually, the consideration of predictions is extended with respect to the reliability estimation. Afterwards, the route recommendations are stored in the routing tables which parallels the existing approach.

Finally, the route recommendations that are provided to the individual drivers reflect the future state of the network based on local predictions made by individual intersection controllers. This predicted information is gradually taken into account based on the experiences a local intersection controller has made with previously received prediction data communicated by its neighbours. Highly deviating predictions will lessen the impact on the calculated recommendations; good reliability estimates, on the other hand, will yield the desired effect of pro-actively considering future traffic states. Eventually, all routing tables of inbound road sections store route recommendations to all prominent destinations known in the network.

10 Hierarchical Regional Route Guidance

Hypothesis: "An additional hierarchical component can be used to reason about the impact of route recommendations in order to avoid shortages due to over-saturation of capacities."

The mechanisms developed previously result in an anticipatory control of intersections and reliable prediction-based route recommendations. This leads to an increase of resilience of traffic management systems – compared to both our OTC framework and acquirable, state of the art solutions. The goal is to further promote resilience by increasing the self-awareness and collaborative analysis of the impact of the implemented routing measures. In the previous steps, we assume links between intersections as static, with their capacities and the vehicle's velocities being constant. This assumption has to be dropped: The greater the strain on a link (in terms of capacity), the lower the speed of vehicles passing this road segment. In addition, speed limits may apply. Hence, instead of representing the time to pass each road segment as a linear function of distance, the calculation of travel times needs to consider these factors, yielding dynamic, individual, situation-dependent values for each link. As a prerequisite, the intersection controllers at the ends and at the beginnings of each link have to continuously observe the number of in- and outgoing vehicles to collaboratively measure the current usage and to infer the current speeds (a direct calculation based on detector information is not possible as induction loops embedded in the street surface only signal whether they are occupied by a vehicle or not). Making according speed estimates available, the intersection controllers can calculate dynamic travel times.

The regional component developed already implements high-level nodes to conduct flow analysis across sets of contiguous traffic nodes and to refine and smoothen local predictions. The same infrastructure can be used to derive potential capacity shortages. In particular, the consideration of dynamic travel times, based on communicated capacities and other information, can identify potential capacity shortages at a higher level (this identification works based on the calculation and simulation of route recommendations and their effect on the traffic network). Possible techniques to achieve this can be found in graph theory and network flow modelling [AMO93], traffic simulation [BCC^{+}05], and approximation formulas [Akc81].

We further introduce the regional components to be able to analyse the impact of the route recommendations on the traffic flow. The outcome of this analysis may result in a reorganisation of flows, which, in turn, could change the basis of calculating local prediction values. In the context of OC, this phenomenon refers to a "self-referential fitness landscape" (cf. [CTMS11]) meaning that the actions taken (here: the route recommendations) change the optimisation criteria (here: the traffic states) which changes the optimal solution. Hence, consistent and smoothed route recommendations need to

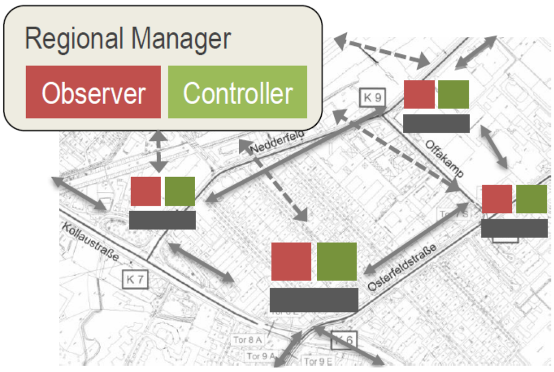


Figure 11: A regional manager controlling several decentralised, autonomous OTC controllers.

be generated that avoid state oscillations.

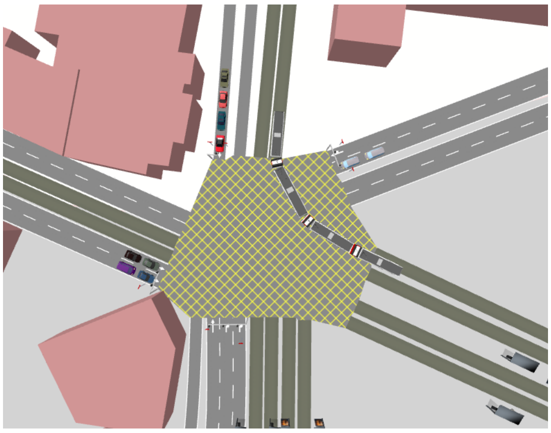
Finally, a regional component, which is responsible for an urban district of about 10 to 20 intersection controllers, is able to detect capacity shortages in advance. By means of analysis of the routing behaviour of the underlying traffic management system, models are found that fit the accumulated data. Detected capacity shortages are taken into account by re-arranging stream-based recommendations. This is accomplished by a hierarchically organised modification of routing table entries. In particular, the hierarchical organisation of controllers in accordance with their level of abstraction (local and regional) defines their abilities of changing the routing data. The resulting traffic management system is assumed to behave more robustly against undesirable emergent effects of self-organised routing decisions and to avoid possibly oscillating behaviour in the routing recommendations.

11 Future Work

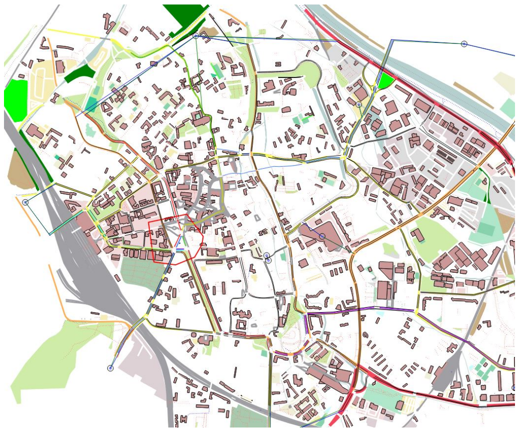
Some very interesting issues are not addressed, either because these topics are investigated by other research groups or because they will be in the focus of our own future work. Examples for the former category are phase-free traffic control systems, individualised route-guidance based on car-to-car communication, or non-optimal flow equilibria (cf. Braess's paradox [Bra68]).

We will evaluate these concepts based on simulation studies with Aimsun 8 [Bar01]. We have already created a model of the central road network of Augsburg, Germany, following the real topology and actual signal plans (Fig. 12).

One important example for the latter category is automated incident detection. Fully resilient traffic control must also cover the possibility to react on further disturbances besides the "normal" capacity-related problems. Therefore, anomalies in terms of incidents have to be considered. This consists of two basic parts: a) the consideration of knowledge about occurred incidents by the traffic management system's decision making process and b) automatic incident detection. In this context, an *incident* refers to ab-



(a) Simulation model showing the Knigsplatz at Augsburg, Germany.



(b) Simulation model of Augsburg, Germany.

Figure 12: Screen captures showing the simulation model of Augsburg, Germany in Aimsun 8.

normal events that affect the traffic state. Examples are construction work, accidents, or capacity reductions due to parking vehicles. Current concepts from the literature try to detect such events by means of different traffic-pattern-based algorithms but they focus on highways only. The challenge is to transfer these highway-based concepts to urban areas where e.g. traffic patterns caused by red traffic lights are similar to those caused by incidents.

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