GLOSA for Adaptive Traffic Lights: Methods and Evaluation

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***Abstract*—Green Light Optimized Speed Advisory (GLOSA) systems have been shown to be able to reduce both CO_2 emissions and fuel consumption by giving drivers speed recommendations when approaching a traffic light. For the system to reach its maximum potential, is is necessary to properly predict all different types of traffic lights, that is, also adaptive traffic lights where signals may change with lead times as short as $1\,\mathrm{s}$. In previous work we presented an approach to predict these adaptive traffic lights using graph transformation.**

In this paper we demonstrate how to adequately parametrize such a graph based prediction approach and evaluate the accuracy of the signal prognosis. In a first step, we find feasible values for the proper creation of the prediction graph. This graph is the basis for all predictions and therefore directly influences the quality of the prognosis. We then assess the forecast in terms of correctness and deviation to measure the accuracy of the predictions. We were able to show a prognosis system with an accuracy of $95\,\%$ and a deviation of less than $2\,\mathrm{s}$. Lastly, we discuss some criteria to compare different approaches of prognosis systems for adaptive traffic lights.

I. Introduction

Green Light Optimized Speed Advisory (GLOSA) systems recommend an optimal speed to the driver to pass a traffic light without an unnecessary stop. These systems have been shown to potentially reduce CO_2 emissions and fuel consumption by up to $13\,\%$ [1], [2]. The main inputs for a GLOSA system to calculate the optimal speed are the distance to the next traffic light and the time to the next signal change. By using IEEE 802.11p [3] based communication or cellular network technology such as UMTS or LTE, information about signal changes can be transmitted to approaching vehicles. In the European ETSI ITS-G5 [4] system and the North American IEEE WAVE [5], this functionality is supported by the recently standardized Signal Phase and Timing (SPaT) messages [6], [7].

In [8] we have shown the necessity for a prognosis system that includes not only traffic lights with fixed programs but also adaptive traffic lights. Especially in larger cities, where adaptively controlled intersections comprise the vast majority of traffic light controlled intersections ($\approx 75\,\%$ in the 10 largest cities in Germany), a GLOSA system only supporting static traffic lights would not perform well. Signal changes for these intersections are complex to forecast because their controller can 'decide' to change signals with lead times as short as $1\,\mathrm{s}$. The need for an external prediction is based on the fact that the controller is stimulated by external inputs, e.g., vehicle and pedestrian detectors, and is therefore unable to forecast its own behavior.

GLOSA systems are an important part of future Intelligent Transportation Systems (ITS) and should be available for all different types of adaptive traffic lights. Adaptive traffic lights range from semi-adaptive controllers that don't change the order of signals but only alter their length to fully adaptive controllers with the ability to change every aspect of its program. The most important inputs for these traffic lights are detectors. They can count vehicles, detect waiting pedestrians, or identify approaching buses or emergency vehicles. Each of them stimulates the controller and can change its behavior. It is therefore crucial for a prognosis algorithm to consider these detectors as they have a significant influence on the signal transitions of an adaptive traffic light.

In a previous paper [8], we introduced an approach to forecast these dynamic signal changes by using graph transformation. The traffic light controller program, represented by the controller graph, focuses on the static phases. This graph is transformed to a prediction graph with assigned probabilities for the next transition. Once the probabilities are derived from real life observations (including detector occupation and other input signals provided by the traffic light) a prediction can be created by traversing the prediction graph and processing the attached information at each edge.

In this paper we evaluate several parametrizations of our prognosis approach to create a feasible prediction graph. A prediction graph is considered feasible when each possible branch has a high routing probability and the offset times for each change have very low deviation compared to real traffic light behavior. In a best case scenario, there would be no deviation and the predicted time to the next signal change would always be correct. To improve the prediction accuracy, the benefit of day classes as described in [9] is analyzed and the influence of varying amounts of sample data is evaluated. We then assess how to select the right detectors and how they can be taken into account to derive a better prognosis. The evaluation of these different aspects allowed us to optimize the parametrization for our prognosis approach.

The remainder of this paper is organized as follows: In Section II we discuss related work in the field followed by Section III with an introduction to traffic light controlling and our approach for the prognosis of fully adaptive traffic lights. Section IV describes several stages of development and assesses their impact on prognosis accuracy: We first take a look at different approaches and their parametrization (Section IV-A and IV-B). We investigate the influence of detectors on signal changes (Section IV-C) and present the overall accuracy of our prognosis system (Section IV-D). In Section IV-E we review limitations of our system, followed by a discussion on how comparisons between prognosis systems can be improved (Section V). Section VI concludes the paper and gives an outlook on future work.

II. Related Work

GLOSA systems date back as far as 1983, when the *Wolfsburger Welle* was introduced by the German car manufacturer Volkswagen [10]. This system already contained the core aspect of informing the driver about upcoming traffic light signal changes. Low market acceptance and technical difficulties lead to the discontinuation of the project. The introduction of IEEE 802.11p communication brought up new possibilities for data exchange between vehicles and infrastructure, allowing the Travolution project [11] to restart the work on GLOSA systems in 2008. Since then several other projects such as sim^{TD} [12] or PREDRIVE C2X [13] followed.

Various publications [1], [2], [13] used extensive simulations to offer indications to what extent stops can be avoided, fuel be saved, and CO_2 emissions be lowered. Most publications agree on a potential emission reduction of $\approx 13\,\%$ if all vehicles and all traffic lights are equipped with ITS devices. Further, the optimization and the extension of the system (queue length estimation or different driving strategies) to further decrease CO_2 emissions were covered in [2], [14]–[16].

In [17], Protschky et al. describe how to predict traffic lights by using floating car data. Like many other approaches they focused on static traffic lights only making their system not applicable for the majority of traffic lights in larger cities.

In [18] Weisheit introduces a mathematical prognosis approach using support vector machines. His system is one of the very few projects aiming at enabling GLOSA for adaptive traffic lights and reaches an accuracy of up to $83\,\%$. The presented approach requires a large knowledge base and a learning phase of about 40 hours. Unfortunately he gives no indication on how early forecasts can be given, which is one of the main requirements for GLOSA systems.

In [8] we presented a method to predict adaptive traffic lights using empiric data and graph transformation. In this paper we present an extensive evaluation of this system and show how it can be parametrized to further improve the prediction accuracy.

III. Traffic Light Controlling and Prognosis

Traffic lights are an easy and common way to regulate competing traffic flows. Competing flows include, e.g., crossing lanes on an intersection or pedestrian crossings on the road. By stopping one traffic flow and giving way to another potentially dangerous situations can be resolved safely.

Each traffic flow usually has its own traffic signal that visualizes whether this flow is stopped (red light) or opened (green light). All signals on an intersection are connected to a traffic light controller that manages the intersection and operates the signals to take care that two competing traffic flows are never open at the same time.

A widespread type of traffic light controller is a very simple one that uses a fixed program, that is a precise sequence of how long and in which order each traffic flow is opened and closed. The sequence is repeated endlessly and for each second in this sequence it is fully deterministic which signal shows which color. To account for different volumes of traffic, these traffic lights can be extended to run different programs depending on the day and the time of day. However, these controllers still cannot react to the current traffic they are supposed to manage.

The next step in the evolution of traffic light controllers was to equip the controller with detectors that measure the volume of traffic on each flows. This can be done by induction loops in the lane (counting passing cars or detecting permanent occupation), by buttons for pedestrians, by radio signals (e.g., from buses), or by visual detection systems. A traffic light controller equipped with detectors is called 'traffic adaptive'. There are two kinds of adaptive controlling: the first is to keep a predefined order of signal changes but to change only the duration of the signals depending on current traffic. The second kind is a fully adaptive controller, where also the order of signal changes can be altered dynamically.

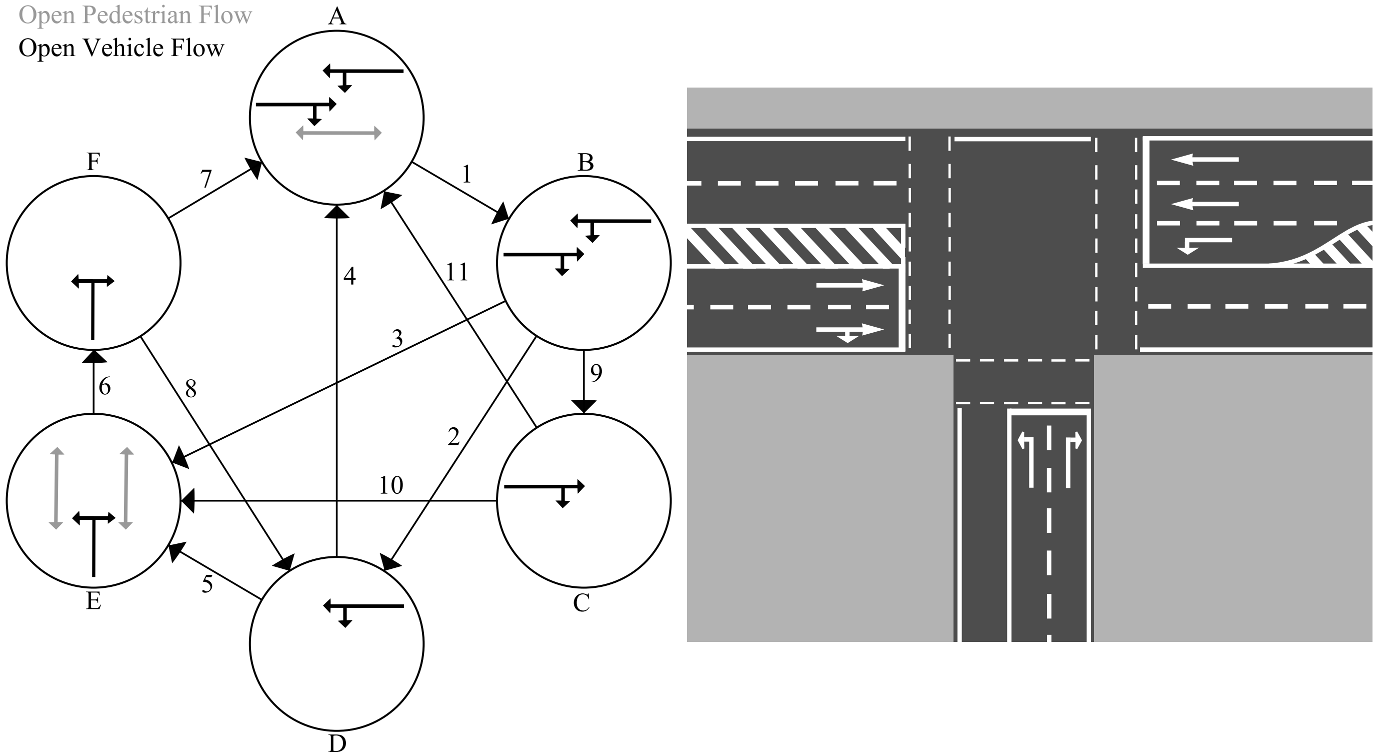
The operation of a traffic light controller consists of two kinds of phases, namely states and transitions. States are static phases where some traffic flows are opened and others are stopped. Transitions are phases where the traffic signals change and active flows are stopped and subsequently competing flows are opened. Together they can be displayed in a so-called controller graph.

The program of every fully adaptive traffic light controller can be visualized using such a graph, showing all possible signal combinations. Each node in the graph symbolizes a static state which is kept for a certain time to let an opened traffic flow pass the intersection. Each edge in the graph symbolizes a transition, that is, a short program that changes the traffic control signals in a safe order with long enough amber phases.

An example controller graph for a fully adaptive traffic light alongside the managed intersection is shown in Figure 1.

The traffic light controller can trigger a transition with a lead time of $1\,\text{s}$, making it difficult for GLOSA systems to predict these changes. In [8] we introduced a prediction algorithm that transforms the controller graph into a prediction graph (or transition graph), as the main goal of a GLOSA system is to predict the time of the transitions, and not the static states. Converting the controller graph of Figure 1a results in the prediction graph shown in Figure 2.

The transformation is done by dividing the controller graph into separate circles, converting the circles into transition-based circles, and combining the converted circles to form a new prediction graph. In the prediction graph, nodes represent the transitions of the traffic light and edges can be used to assign



(a) Controller graph

(b) Intersection topology

Figure 1. Controller graph (a) and corresponding simplified intersection topology (b)

probabilities and offset times based on empirical data. When this assignment is done, predictions can be given by simply traversing the prediction graph.

Furthermore, we use different probabilities and offset times depending on day classes and time windows as introduced in [9]. This means, that predictions for one certain time of a day are only based on observations for similar time slots. Interestingly, the time slots where GLOSA systems can reach the highest benefit are not rush hours, but times with low or medium traffic volumes [2]. The reason for this is the much higher degree of freedom for the traffic light controller if the same detectors are not occupied over and over again as this would lead to the same traffic light behavior. Additionally, drivers have only limited possibilities to adapt their speed in heavy traffic.

IV. Evaluation of System Accuracy

Comparing different prognosis approaches is a non-trivial task as the parameters to consider in these systems are manifold.

First, two prognosis systems can only be compared using the same intersection and traffic light, as these combinations are more or less unique. This alone is a difficult task because each project working on GLOSA systems uses its own test-bed and there exists no common reference traffic light yet. Even if prognosis systems are compared using the same intersection and traffic lights, results may be misleading when investigated under different traffic conditions. Ideally, both system would be evaluated under the exact same conditions. Without a common scenario, the variance of different traffic light types and their degrees of freedom makes it difficult to interpret forecast results. For example, it is misleading to compare a system predicting the behaviour of a fully adaptive traffic light with one that forecasts a traffic light with much fewer parameters.

Another challenge is the choice of metrics. Naturally, one would compare the prediction of the prognosis system (e.g, ”5 seconds until the traffic light turns green”) with the actual observation. However, the quality of the prognosis usually strongly depends on the lead time to the signal change, that is, how early the forecast has been given. A traffic light controller is stimulated by traffic via detectors and can change its behavior with very short lead times. Therefore it is easier to predict the next transition shortly before it happens than giving a prognosis when the triggering conditions were not present. To account for all these difficulties we created two reference traces.

The first trace was recorded for a common intersection in Ingolstadt, Germany in medium, consistent traffic (2pm till 3pm on a regular Monday) to give the traffic light controller enough degrees of freedom to work in the fully adaptive mode. The second trace we used serves as a worst case scenario for the prognosis algorithms as it was recorded at the beginning of rush hour with sharply changing traffic (from 4pm till 6pm on a regular Monday).

To consider the strong causality between lead time and prognosis quality, we do not give a single value for the prognosis accuracy but plot the forecast quality over the time to the next transition. This is achieved by storing all forecasts given by the system and subsequently sorting them according to their lead time allowing us to analyze the prognosis deviation w.r.t. to the time to the next signal change. Using this methodology we compare different approaches and different parametrizations.

A. Development Stages

In the beginning of the Travolution project [11] we started with the assumption that 'traffic changes slowly' to simplify the problem of adaptive traffic lights. This assumption implied that observing the recent and current behavior of the traffic light controller is sufficient to forecast upcoming transitions. If the assumption was right, the behavior of the traffic light would change as slowly as the traffic leading to a high prognosis accuracy. We refer to this approach as Slow Change Assumption (SCA). Evaluations showed that this assumption turned out to be wrong because even small changes in traffic can trigger a completely different behavior of the traffic light controller. The reason for that is that one detector triggered differently can cause a entirely changed control sequence.

After that we started a new approach using statical analysis of the traffic light behavior. By storing the controller inputs and outputs we were able to analyze how the traffic light reacts to different inputs and thereby derive transition probabilities. While we observed that this approach increased the prognosis quality significantly, we encountered problems when traffic was changing quickly or traffic volume was atypically high or low, e.g., in rush hours. This was caused by the fact that our statistical analysis did not differentiate between different times of day or different types of days. To circumvent this problem we collect empirical data for different time slots and days, as introduced by Dittrich et al. [9].

For this, we used 11 different day classes:

- Monday, regular
- Monday, vacation
- Tuesday - Thursday, reg.
- Tuesday - Thursday, vac.
- Friday, regular
- Friday, vacation
- Saturday, regular
- Saturday, vacation
- Sunday, regular
- Sunday, vacation
- Holiday

Additionally, we divide each day into time slots with a length of $15\,\mathrm{min}$. By using this classification we were able to further improve the accuracy of our prognosis. To assess the benefits of these slots we simulated our reference traces with all three approaches resulting in more than 7000 forecasts each.

In Figure 3a the results for slowly changing traffic are shown, error bars mark the $95\,\%$ confidence intervals. Predictions with a lead time of more than 30 seconds are omitted because they are likely to be inaccurate and have a low confidence value attached to them as we will discuss later. Additionally, long-term forecasts do not introduce benefits in terms of traffic efficiency. For example, assume a vehicle $100\,\mathrm{m}$ away from a traffic light is informed that the signal will change to green in $30\,\mathrm{s}$. With the GLOSA system being restricted to legal limits, it cannot give a speed recommendation to the vehicle as it would

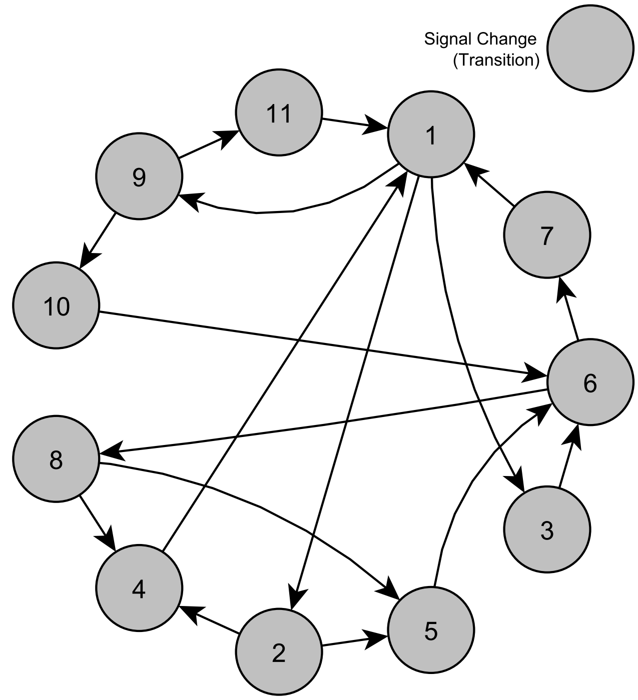
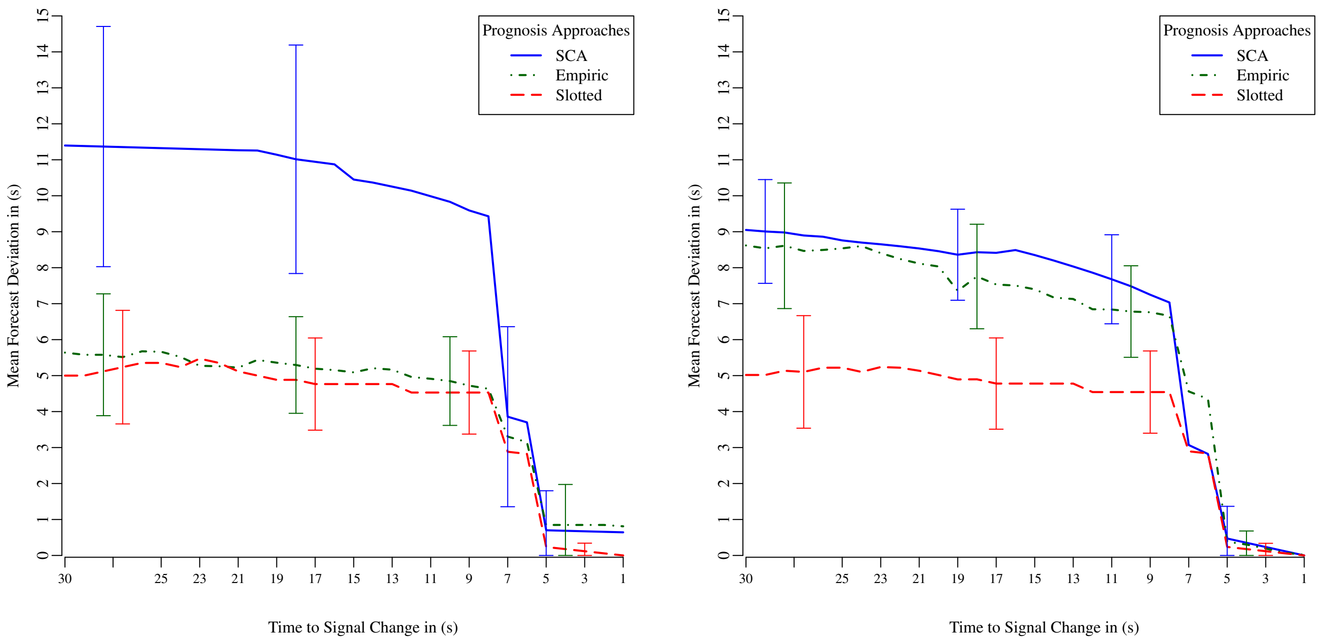


Figure 2. Prediction Graph

be below a minimum speed limit v_{min}. From this it follows, that a vehicle has to be at least $v_{\text{min}} *$ forecast away from the traffic light. The resulting distances have been shown to be too high to be beneficial for GLOSA systems [1], leading to our decision to omit forecasts higher than $30\,\mathrm{s}$.

It can be seen that the SCA approach (solid blue line) performs poorly compared to the approaches utilizing empiric data and day classes (green and red lines). On average, predictions made by SCA are off by $11\,\mathrm{s}$ to $12\,\mathrm{s}$ when the transition is longer than $8\,\mathrm{s}$ away. This confirms that SCA is not a suitable prognosis algorithm for GLOSA systems. When traffic changes slowly, the average benefit gained from the time slots is marginal ($\approx 0.5\,\mathrm{s}$) and both statistical approaches perform similarly.

To better understand how the concept of time slots and day classes improve the system, we investigated the different approaches in fast changing traffic, that is, the beginning of rush hour. Interestingly, the SCA system performed slightly better than in consistent traffic, caused by the now denser traffic and therefore less adaptive traffic light controller. As expected, the performance of the general empiric approach (green line) now deteriorates ($8\,\mathrm{s}$ to $9\,\mathrm{s}$ for long-term predictions), while the time and day aware system remains at the same level of accuracy. The reason for this is that traffic behaves very similar every week and the empirical data collected for, e.g., a regular Monday rush hour, is a very good indication for all rush hours on regular Mondays. Especially for prognoses with shorter lead times the mean forecast deviation is noticeably lower.



(a) Consistent traffic

(b) Beginning of rush hour traffic

Figure 3. Mean Time to Signal Change when Forecast is given

We also observe that all approaches perform particularly well 7 s and shorter to the signal change. Especially the slotted approach shows almost no deviation in the last 5 s with a confidence interval width of less than 0.5 s. This is a direct result from comparing similar time slots instead of using a generalized approach that does not distinguish between different times of day.

To better understand the quality of the prognosis, we compare over- and underestimations of the given forecasts. Figure 4 can be read as follows: each forecast value given on the x-axis is compared to the real time to the transition when the forecast was made. Therefore, a perfect forecast would result in a $45°$ diagonal. For every system we distinguished between the cases where the forecast underestimated and overestimated the real time to the transition and plotted the average values for each case. Plotting the overall average would be misleading as both cases would cancel each other out to a certain extent. We observe, that up to a forecast value of about 10 s the slotted approach never overestimates the time to the next transition. This means that a vehicle will never arrive too early at a red light and therefore can avoid stopping, however, the results show that the GLOSA system may recommend speeds slower than actually required. Especially for forecasts longer than 11 s, there is room for improvement as all systems over- and underestimate the time to the transition. Please note, that it is not possible to improve the system by simply subtracting or adding the average error, as at the time of the prediction the system is not aware whether it over- or underestimates. The spikes of the SCA approach result from the approach's strong tendency to underestimation. If SCA announces a signal change for the next second and this signal change does then not take place, it will continue announcing 1 s until the signal actually changes.

The results clearly show that the slotted approach is the most promising one, leading to the decision to further investigate its performance and parametrization even though it requires more data to be stored and processed.

B. Effect of Sample Size in the Learning Phase

The amount of stored data needed for the system to operate properly is an important parameter. The time aware approach uses 11 different day classes and each day is split into time slots with a length of 15 min. A usual traffic light controller logs its input and output signals with a resolution of one second, leading to a total of 900 data values per time slot. The traffic light controller will also inform the back-end only once a second, limiting the maximum frequency of the prognosis system to 1 Hz. Please note, that this data does not necessarily need to be stored, as it could be discarded once the transition probabilities have been computed.

To be less prone to outliers during the sampling phase, it is desirable to use a high number of observations. However, increasing the sample size does not necessarily lead to a higher prognosis accuracy: the more observations are considered, the further back in time the algorithm looks. Especially for rare day classes like, e.g., 'Monday vacation', looking back too far in time can result in the use of data that does not represent current traffic conditions for this intersection anymore.

Another important aspect to consider is the time needed to collect enough sample data as too long ramp up phases would

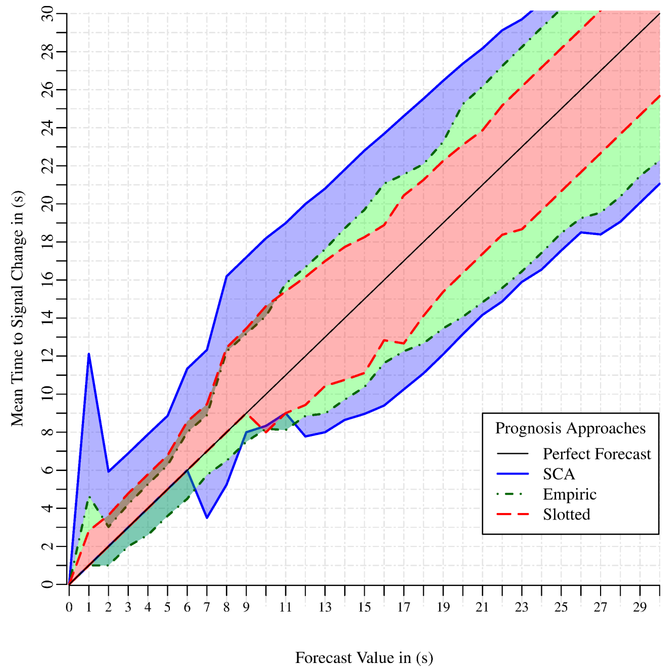


Figure 4. Mean over- and underestimation of the forecast

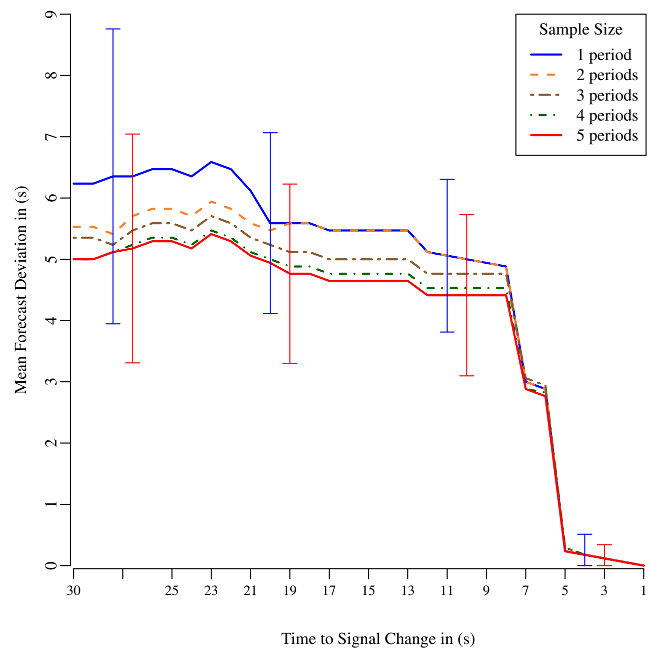


Figure 5. Sample size vs. forecast accuracy

hinder the deployment of the GLOSA system. It is therefore a challenging task to determine the number of observations used for the transition probability computation to both enable the prognosis to work accurately for any traffic light in any city and for this process to be fast enough to ensure a prompt deployment.

Figure 5 shows the effect of the sample size on the prognosis accuracy. We computed the transition probabilities based on different sample sizes and then ran the prognosis using our reference trace. A sample size of 1 means that this time slot (e.g, a regular Monday, 8:00am till 8:15am) has been observed exactly one time and all future prognoses for this time slot are based on these observations. From this it follows, that a sample size of 5 for said time slot requires at least 5 weeks. Again the $95\,\%$ confidence interval is given by colored error bars.

In general, the results indicate that a higher number of samples leads to a better forecast; this benefit decreases for lead times shorter than $8\,\mathrm{s}$ where the general prognosis accuracy is very high.

While for long-term forecasts the average deviation improvement between 1 observation period (solid blue line) and 3 (brown dashed line) is nearly half a second, increasing the sample size from 4 (green dot-dash line) to 5 (solid red line) did only marginally improve the overall accuracy.

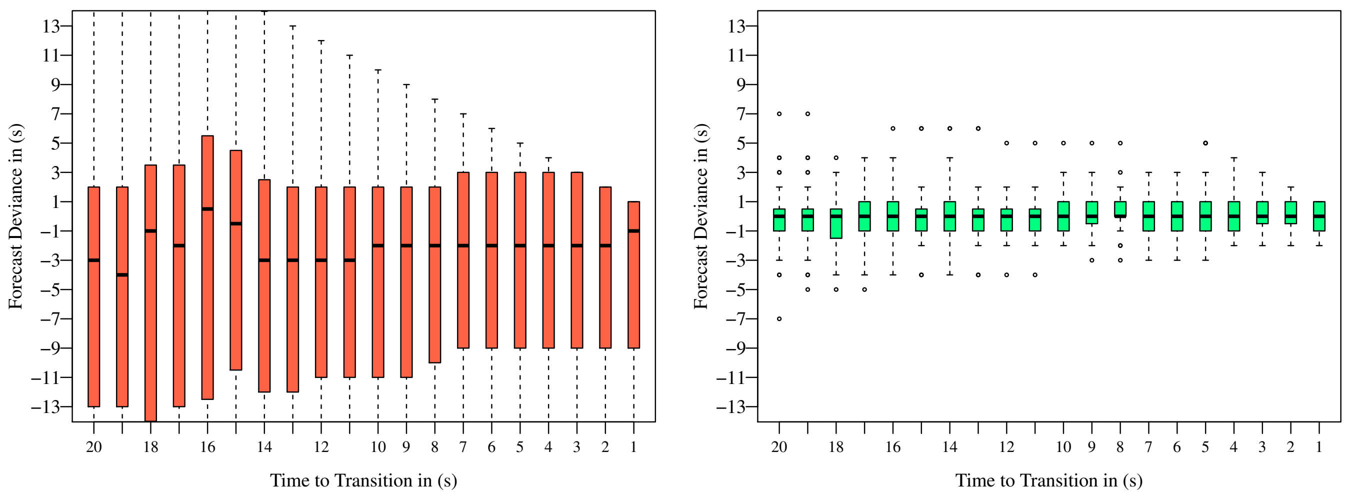
We therefore decided to parametrize our approach with a look back time of 4 comparable time slots which seems to be a good compromise between prognosis accuracy and the duration of the initial data collection phase.

C. *Influence of Detectors*

As we introduced in [8] it is crucial for the prognosis of adaptive traffic lights to consider the state of the detectors connected to the traffic light controller. Their occupation does not only influence the time of signal change but also *which* transition will be triggered next. This feature of adaptive traffic lights improves the flow of traffic through the intersection but complicates prognoses for GLOSA systems. Despite the resulting complexity alongside the requirement for larger amounts of sample data they have to be accounted for in any GLOSA system as their effect on the traffic light is too significant to neglect them [8].

The detectors influence the transitions, that is, a short program to change the control signals in a safe order. For example, waiting cars occupying a detector can cause the next transition to be triggered earlier to open their traffic flow. Cars passing a detector give an indication that the traffic demand on that flow is still high and therefore postpone the transition that would change the signal for this flow to red. Special detectors, such as for buses, can influence which transition will be chosen next. Additionally, some detectors (e.g., radio signals from emergency vehicles) not only influence the next transition but the whole behavior of the traffic light. The prognosis system can deal with them quite easily because they are usually present for a long time and do not occur too often. To consider the regular detectors for vehicles and pedestrians, however, it is important to focus on the relevant ones for each transition.

A simple intersection like the example in Figure 1b can have 12 detectors (not considering signals from buses). To keep the amount of required sample data at a manageable



(a) Without consideration of detectors

(b) With consideration of detectors

Figure 6. Transition prognosis accuracy with and without the consideration of detectors for a fully adaptive traffic light strongly depending on detector readings.

level, we introduced a simplification that allows us to treat every detector separately instead of additionally considering all their combinations [8]. To determine which transitions depends on which detectors we run a χ^2 analysis and mark detectors with a high correlation as relevant. Note, that this process has to be done only once per configuration phase and should be automated to ensure fast deployment in larger cities.

The consideration of detectors introduces another challenge to GLOSA systems: the need for live data exchange. This requires a communication link between traffic light and prognosis system with a latency lower than $1\,\mathrm{s}$.

To illustrate the impact of detectors, assume the traffic light in Figure 1a is at the state 'D' where only the open traffic flow through the intersection is from right to left including turning. Depending on the occupancy states of the detectors, in this case for the cars coming from the bottom and from the right, the next transition could either be 4 or 5. Transition 4 additionally depends on the detector counting the vehicles coming from the right and turning left, influencing the time when the transition is started.

A comparison of our prognosis algorithm with and without the consideration of detectors is shown in Figure 6 in the form of a box plot: The boxes are drawn from the 25% to the 75% quartile, the thick line marks the median. The whiskers extend no further than 1.5 times the inter-quartile range, data points outside of this range are drawn separately as outliers.

Please note, that these are results for an example transition that heavily relies on detector readings. It can be clearly seen that the quality of the prognosis without detectors (Figure 6a) is considerably lower. Even few seconds before a transition the forecast is significantly off, showing the traffic light's high dependency on detectors. Running the prognosis with consideration of relevant detectors improves the forecast quality. There are still deviations as the system is unable to foresee when and for how long a detector will be triggered. Especially more than $10\,\mathrm{s}$ before a transition the upcoming traffic light behavior is not always clear demonstrated by the existence of outliers. Coming closer to the start of the transition almost all forecasts lie within a $2\,\mathrm{s}$ window around the real value which we deem a very good result for a transition that strongly depends on the readings from multiple detectors.

D. Overall System Accuracy

To assess the overall system accuracy we used the medium traffic trace followed by the rush hour trace to evaluate the prognosis system in different scenarios. In total, we analyzed more than 10,000 forecasts and measured their accuracy.

Please note, that for the system accuracy we do not use the time to transition but the time to the signal change as a reference value. The reason for that is twofold: firstly, not every transition is relevant to the driver (e.g., if only pedestrians are influenced) and, more importantly, the only sensation of quality a driver experiences is how accurate the forecast fits the signal change.

Figure 7 shows our results: the high accuracy shortly before the signal change also results from the fact that the prognosis additionally benefits from transitions of other control signals first. Amber phases and blocking times provide some easy-to-predict seconds to the forecast of control signals that follow later in the transitions program. In the last 10 seconds of the forecast the deviation is less than $2\,\mathrm{s}$ in more than $80\,\%$ of all cases, reaching $95\,\%$ in the last $3\,\mathrm{s}$.

The overall accuracy assessment of our approach using detectors, day classes and time windows shows a quality good enough to start a GLOSA system even for fully adaptive traffic lights.

In ETSI ITS-G5, SPaT messages [6] sent from the traffic light or a prognosis server allow to attach a confidence value to

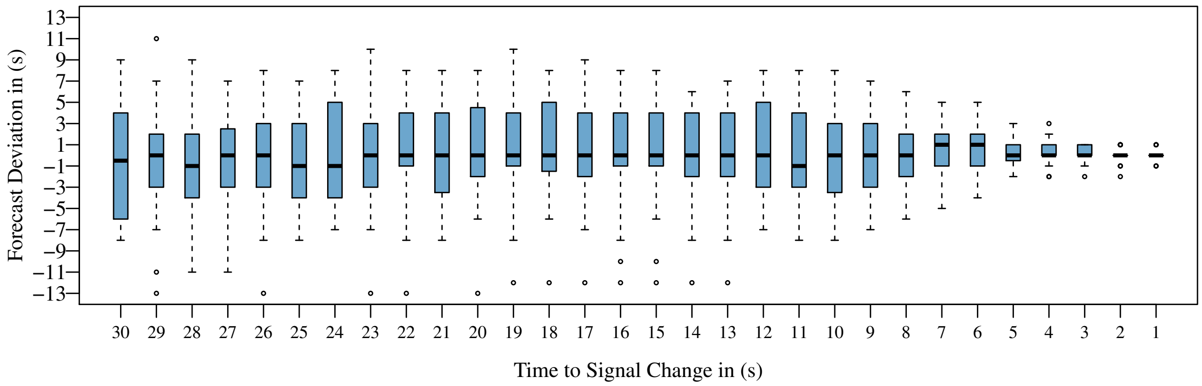


Figure 7. System accuracy

every flow-specific prediction. This information is then handed to the receiving on-board unit to decide whether or not to display a speed recommendation. One approach to derive such a confidence for a forecast is to look at the variance or the interquartile range of the forecast data. This confidence assessment could be done repeatedly on the fly as the error of each forecast can be measured in retrospect.

E. Limitations

Figure 5 and Figure 7 show the current limitations of our approach in terms of forecast accuracy. As the behavior of an adaptive traffic light depends on the occupation of its detectors, a prediction of signal changes is a prediction of the chronological sequence of future detector occupations. Short-term predictions close to the signal change can be done well with our approach, predictions with higher lead times can become inaccurate. Our approach is using empiric information and live data to identify similar situations and to generate a forecast. Considering the degrees of freedom within an adaptive traffic light controller it is probably impossible to give long-term prognoses with absolute accuracy.

One possible way to significantly reduce the forecast deviation of long-term prognoses is the prediction of traffic in a microscopic fashion, that is, the prediction of the mobility of single vehicles. With such an extension it would be possible to forecast detector occupations and therefore predict the resulting reaction of the traffic light. Possible approaches to achieve such a high level of detail are the utilization of inter-vehicle communication, that is, vehicles continuously transmitting their whereabouts to allow the prognosis system to build up some kind of situational awareness or the use of traffic simulation tools. These systems would then have to deal with the issue of computational performance, as predictions have to be calculated with low latencies right after new live data from the traffic light becomes available.

A general strategic approach is to accept inaccuracies to a certain degree (especially for long-term predictions) to allow for an efficient calculation of forecast values and to enable a quick real life deployment without overly long learning phases.

V. Discussion on Comparability

The diversity and uniqueness of intersections and traffic light controllers makes a comparison between different prognosis systems a difficult task. As different approaches perform differently for each type of traffic light, it is hard to reduce the quality of a prognosis system to a single number. This is especially problematic as most of the prognoses systems currently developed are still in their development phase and implemented in specific test-beds. We believe that the best way to allow for comparability between these systems is the introduction of a benchmark test to investigate their performance under the same traffic conditions. Such a benchmark needs to fulfill multiple requirements: As all systems would be compared using the same traffic lights, they would also have to work on the same data, that is, historical data to allow all kinds of statistical analysis and classifications. The structure of this data and the communication between the traffic light controllers and prognosis systems should therefore be standardized to enable easier integration of different approaches. Input data for the traffic light controller should be fully stored and no information should be discarded. For example, detectors cannot only detect whether they are occupied or not but also measure the velocity and dimensions of a passing vehicle. Removing this information limits the possibilities to create systems that take these readings into consideration to create a forecast.

The traffic lights in this benchmark test should represent all different types of traffic light and also include a worst-case traffic light that is difficult to predict as it utilizes all degrees of freedom. Experiences made in this and earlier projects showed that the complexity of the intersection topology itself has only a minor influence on the prognosis quality. The challenging part are the traffic light's degrees of freedom and the fact that these can be just as high at a 'normal' intersection.

Additionally, the traffic lights should also be predicted in different scenarios. These scenarios should represent the different challenges of traffic light forecasts. Among others, these include:

- rare events (e.g., big sport events)

- quick changes of traffic volume
- contradicting detector occupations
- immediate reactions of the controller to detector occupations
- combined signals (e.g., green turn arrows overruling red lights for the same traffic flow)
- different amounts and kinds of detectors
- external triggers (e.g., buses, emergency vehicles)
- traffic management commands for dynamic green waves
- fluctuation in latency of traffic light live data

We believe that a unified benchmark test can considerably improve comparability between different GLOSA systems and therefore contribute to improving the systems themselves.

VI. Conclusion and Future Work

Green Light Optimized Speed Advisory (GLOSA) systems are believed to be one of the pillars of future Intelligent Transportation Systems as they can help prevent avoidable stopping at traffic lights and thereby reduce fuel consumption and CO_2 emissions. To reach their maximum potential, GLOSA systems have to be available for all different types of traffic lights, including semi and fully adaptive ones. The capability of adaptive traffic light controllers to change their behavior with lead times as short as 1 s introduces a major challenge for prognosis systems.

In our previous work [8] we presented an approach to forecast adaptive traffic lights by using graph transformation. In this paper we presented an extensive evaluation to fully understand its performance under different conditions. We demonstrated the benefit of several development stages and discussed parametrization like sample size and detector consideration.

We found that a time-aware system that uses empiric data from similar time slots to predict future signal changes outperforms general approaches. Furthermore, our results show that the consideration of traffic detectors substantially improves the overall forecast accuracy. From this it follows that traffic light controllers need to continuously report the detector readings back to the prognosis system. Our system was shown to be able to even forecast adaptive traffic lights with a high enough accuracy to be used in GLOSA system.

We validated our approach by means of simulations and also in real life test drives in the Travolution test-bed in Ingolstadt, Germany.

In the future we want to further improve our forecast by also considering traffic management commands. These are sent by the operator e.g., to improve the flow of traffic by prioritizing one stream over another. In this paper we discussed the need for a unified benchmark to test different prognoses systems. As such a benchmark does currently not exist, we will focus on creating one that fulfills all the identified criteria.

VII. Acknowledgments

We would like to thank the city of Ingolstadt, Germany. Since the beginning of the Travolution Project they have been supporting us not only in building our test-bed but also by providing us information and their expertise.

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