Sensitivity analysis on information quality for signalized traffic control

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1. Introduction

Signalized traffic control is an important traffic management measure to reduce congestion problems and keep urban regions accessible. More data becomes available to feed the controller, varying from historical to real-time data, and from location-based data (like loop detectors) to floating-car data. Advanced state estimation and prediction methods are designed based on these data (Vlahogianni (2014), van Lint and van Hinsbergen (2012)). Some of these methods are already applied in controllers to pro-actively optimize traffic conditions (van Katwijk (2008), Li-et-al. (2014)). To be able to fully benefit from these estimation and prediction techniques in signalized traffic controllers, it is important to look at the quality of the estimated and predicted input quantities in relation to the performance of the controllers. For the development of estimation and prediction methods on the one hand, and traffic controllers on the other hand, it is important to have insight into what extent an improvement of the estimation and prediction accuracy will improve the performance of the controller, or the other way around, into what extent estimation and prediction errors will decrease the performance of the controller.

Therefore, in this paper, the sensitivity of signalized traffic control for errors in the input quantities is addressed. A general framework for sensitivity analyses is proposed, to analyze the effect of errors in the measured, estimated and predicted input quantities on the performance of different types of signalized traffic control. The framework is applied to a predictive controller, to analyze to what extent a prediction increases the performance of the controller, considering that the prediction contains errors.

In this paper, first a problem description and a short state-of-the-art will be given on traffic control and sensitivity to input quantities. Then the framework for the sensitivity analysis is presented. The framework is illustrated for predictive control, results are presented, followed by conclusions and directions for ongoing and future research.

2. Problem description

In Figure-1, the process of signalized traffic control is outlined in terms of control theory. The controller influences the traffic process by its control signal. The traffic process is evolving in time, based on the internal traffic relations and external disturbances (demand,route choices). The traffic process can be monitored real-time by sensors, resulting in observed quantities. The observed quantities can be used to estimate the actual state of the traffic system expressed in derived quantities (like queue lengths). Likewise, the observed quantities can also be used to estimate (and predict) the disturbances.

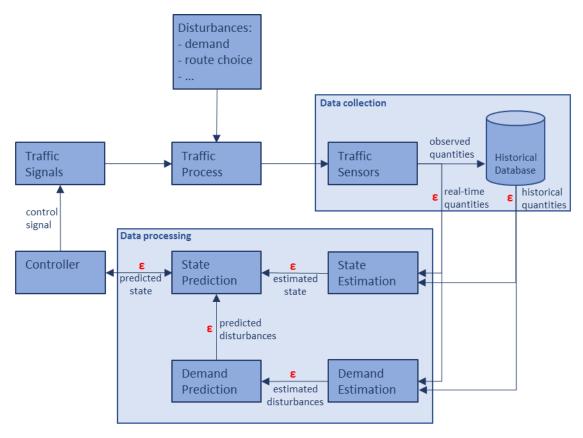


Figure 1: Process scheme of signalized traffic control

Based on the estimated state of the traffic system and a prediction of the disturbances, the future state of the traffic system can be predicted. Information on historical, actual and future traffic states (combined with information on disturbances) is used as input for the controller. Based on this information, the controller can determine the control scheme that implicitly or explicitly optimizes the performance of the traffic system.

In this control process, errors may arise that can influence the control decision. In general, errors in the input quantities will eventually decrease the performance of the controller. Therefore, it is important to look at all elements in the control process where errors may occur. In monitoring the traffic system, an observation error will occur, caused by the inaccuracy of the sensor and observation method that is used. In the estimation of the traffic state (and disturbances) an estimation error is introduced, which may represent errors introduced by the estimation method itself, or represents errors that were already present in the observed quantities. In the prediction of the traffic state (and disturbances), a prediction error is introduced. This error depends on the original error of the estimated state, and the prediction method. This prediction error will increase with the prediction horizon.

In the design of the controller as well as the estimation and prediction methods, it is important to know to what extent these errors influence the control decision and the performance of the traffic system. In this paper, this question is addressed by proposing a framework for sensitivity analysis on the observed, estimated, and predicted input quantities of signalized traffic control.

3. State of the art

There is a wide variety of types of signalized traffic control. For an overview is referred to van Katwijk (2008), Papageorgiou-et-al. (2003), and more recently Li-et-al. (2014). Signalized traffic control methods can roughly be divided into two categories, fixed-time control and traffic-responsive control. In fixed-time control, the control is optimized off-line based on historical demand data. In traffic-responsive (or adaptive) control, the control is adapted real-time on on-line data. The controller can react on the currently measured or estimated traffic situation, or the controller can pro-actively anticipate on predicted traffic conditions. In general, the more detailed information is used, the more sensitive the controller performance likely will be for errors in this information. Fixed-time control is quite robust for errors in the input quantities containing margins by design (implicitly in Webster-based cycle times, explicitly in robust control (Li (2011)). Traffic-responsive (or adaptive) control will be more sensitive to information errors, depending on the degrees of freedom of the controller.

Different levels of adaptive control can be distinguished by the degrees of freedom in the controller (van Katwijk (2008)). In the first generation, predefined control schemes are selected from a library based on the actual traffic condition. In the second generation, the control schemes are assumed to be cyclic, and cyclic parameters (like green-splits) are adapted, based on information of the traffic conditions for current and upcoming cycles. In the third generation, the control scheme is considered structure-free (no cycles). The phase definitions and transitions can be adapted, together with the green-times. In general, the more degrees of freedom in the controller, the better performance can be reached, the more sensitive the controller performance will be for errors in the estimated or predicted traffic conditions.

In the field of transportation, sensitivity analysis on information errors is not given much attention yet. This is a wider gap, not only for signalized control, but for dynamic traffic management in general, as was stated by Klunder-et-al. (2014). The attention to this kind of analyses have seemed to increase due to the introduction of floating-car data in the field of dynamic traffic management, and signalized control in special, for which the influence of penetration-rates and additional data errors needs to be addressed. (Waterson and Box (2012)). With the increase of adaptivity of traffic controllers and availability of more detailed information, the need for these sensitivity analyses on information errors is still increasing. This paper contributes to this rising issue.

4. Experimental Framework

In this section, a general framework for sensitivity analyses is proposed, to analyze the effect of errors in the measured, estimated and predicted input quantities on the performance of different types of signalized traffic control. Assuming perfect information, the ideal situation for a signalized traffic controller is created. Perfect information can either be perfect observed historical or real-time data, a perfect state estimation, or perfect prediction (no errors). Using a Monte-Carlo approach, the perfect information randomly is disturbed, and the degeneration in performance of the controller is monitored. The outcome of the experiments will be an experimental relation between the level of information quality and the performance of signalized traffic control in the traffic system. The experimental framework is outlined in Figure-2.

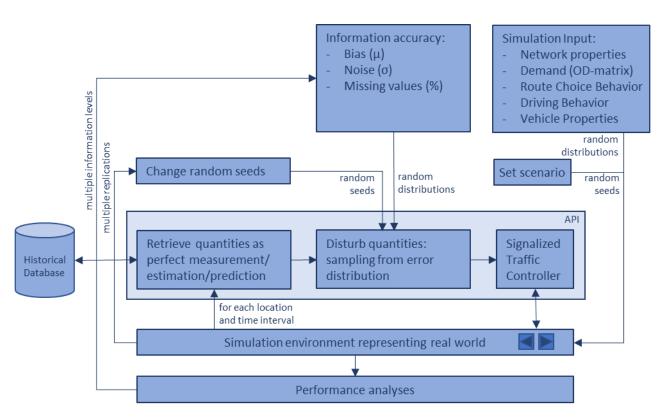


Figure 2: Experimental Framework

The framework makes use of a simulation environment to represent the real world. In an additional API the controller of interest is interacting with the simulation environment. A network configuration and an interesting demand scenario is chosen. Since the main goal of the experiments is to determine the effect of errors in the input quantities for control and not the effects of fluctuations in the scenario itself, the realization of the scenario is kept constant during the experiment.

Main input to the experiments is the information quality of the input quantities for the traffic controller. Information quality consists of many aspects. In this framework, information accuracy of the input quantities is considered, expressed in a structural bias, a random noise, and a percentage of missing data, described by a random error distribution (of a properly chosen form). It is assumed that the information accuracy only depends on the observation, estimation or prediction method, and does not depend on location and time, resulting in the same error distribution for each location and time. The realizations of the errors, however, differ over locations and time instances, and are independently drawn from the distributions. The effect of the errors can be simulated as follows:

- 0. Initialize the input error to no bias, no noise, no missing data (no error distribution yet) and simulate the situation with perfect information for the scenario. In this way, the ideal performance for the traffic controller is measured and set as a reference.
- 1. Increase the error by increasing the bias, noise, or percentage of missing vehicles. Adapt the random distributions for the control input errors accordingly.

- 2. Simulate multiple realizations of the errors to level out random variations over different locations and times. For each realized error pattern, for each control interval:
 - Retrieve for each location the perfect input quantities from the simulation.
 - Disturb the input quantities by the random realization of the error
 - Determine the control scheme based on the disturbed input quantities.
- 3. Measure the performance (note that it is assumed that the performance is measured perfectly in the simulation) and average over the simulated error realizations. Repeat the process from 1.

The output of the sensitivity analysis will be an experimental relation between the error in the input quantities and the performance of signalized traffic control in the traffic system for a given scenario.

5. Case: predictive phase-based control

The outlined framework is in principle suitable for all types of signalized traffic control. In this paper, the framework will be illustrated for traffic-responsive control with a predictive component. Main goal of the experiment is to analyze to what extent a prediction increases the performance of the controller, considering that the prediction contains errors. In this section, the experimental setting will be explained, starting with the junction configuration and demand, followed by the type of predictive controller, ending up with the sensitivity analysis and a discussion of the results. The experiments are done in the microscopic simulation environment Aimsun. Aimsun is representing the real ideal world. Aimsun is extended (API), to model the predictive controller, and to be able to disturb the perfect simulation data.

5.1 Junction configuration and demand scenario

The approach is applied to a four-legged junction with configuration as displayed in Figure-3. The lanes are long enough, such that there is enough storage space for each direction and there is no spill-back to the network entrances. Two different demand scenarios are chosen, representing the under-saturated and saturated case. The saturated case (I/C=0.8) will probably be the most interesting, since errors in the input quantities of the controller can result in insufficient green times resulting in a collapsing system with high delays. The under-saturated case is chosen for comparison purposes, to see if the control is indeed most sensitive in saturated cases. The demand scenarios are simulated for 30 minutes (time-step 0.2sec). The arrivals are randomly distributed following an exponential arrival pattern with a constant mean (see Figure-3 for demand per movement). Each demand scenario is frozen to one repeatable realization.

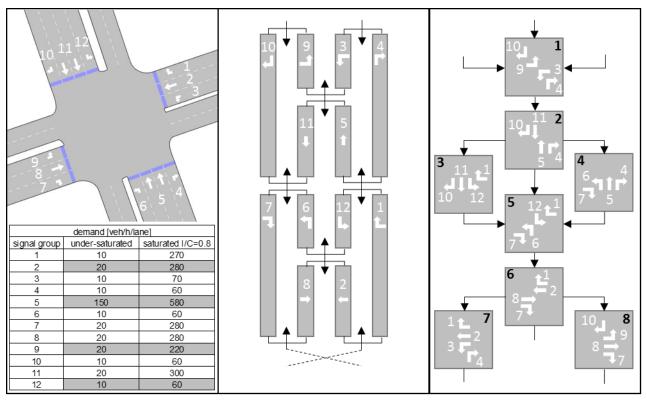


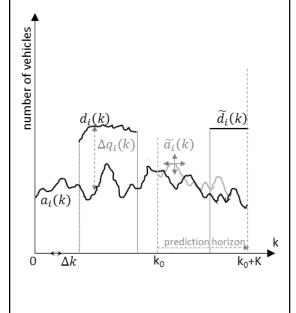
Figure 3: Junction configuration (left), signal groups (middle), phase structure (right)

5.2 Predictive phase-based controller

The sensitivity analysis is performed for a phase-based predictive controller. The basic structure of the controller is depicted in Figure-3. The possible phases and phase-transitions are pre-defined. The free control parameters, green times of the phases and underlying signal groups, are optimized based on a prediction of the traffic conditions. The cycle time differs per cycle resulting from the optimized green-times. The phase-based predictive controller is based on a rolling horizon approach. Each control interval (5sec), the control sequence is updated real-time considering a new planning horizon (30sec).

The objective of the controller is to minimize the total delay over the upcoming planning horizon, based on the current state (queues) and a prediction of the upcoming demand (arrival pattern). In the ideal simulation world, assuming perfect knowledge on the upcoming traffic situation, the expected delay could be determined by playing the simulation fast-forward for each candidate controller. However, to save computation time, a tuned vertical queuing model is used instead to approximate this situation (see Figure-4). In the queuing model, the predicted arrivals a(k) are perfectly known beforehand in the simulation environment. The non-delayed arrivals are stored and considered as the perfect predicted arrival pattern. The current state (queues q(k)) is also perfectly known in the simulation environment. The predicted departures d(k) are approximated by estimating vehicle passages through green, based on the state of the candidate control scheme and an approximation of the saturation flow-rate. The saturation flow-rate is tuned to come as close as possible to the situation as if playing the simulation fast-forward (0.45veh/lane/sec).

disturbance of number of arrivals: $\widetilde{a}_i(k) = a_i(k) * \left(1 + \varepsilon_i(k)\right) \ \forall k \ \forall i$ OR disturbance of arrival times: $\widetilde{a}_i(k) = a_i \Big(k + \varepsilon_i\left(k\right)\Big) \ \forall k \ \forall i$ with random error $\varepsilon_i(k) \sim \Phi(\mu, \sigma) \ \forall k \ \forall i$



$$min_{\{s_i(k)\}} \sum_{i} \sum_{k=k_0}^{k_0+K} q_i(k) * \Delta k$$

with queue q_i per signal group i defined as: $q_i(k) = q_i(k-1) + \Delta q_i(k) \quad \forall k \; \forall i$ $\Delta q_i(k) = a_i(k) - \widetilde{d}_i(k) \quad \forall k \; \forall i$

with arrivals a_i and departures d_i per signal group i, where

 $\widetilde{d}_i(k) = \begin{cases} r_i * \Delta k & \text{if } s_i(k) = 1 \text{ (green)} \\ 0 & \text{if } s_i(k) = 0 \text{ (red)} \end{cases} \forall k \; \forall i$ with saturation flow rate r_i and signal state s_i

such that general control equations are satisfied: signal states $s_i(k) \in \{0,1\} \ \, \forall i \, \forall k$ phase states $p_j(k) \in \{0,1\} \ \, \forall j \, \forall k$ signal equals phase state $s_i(k) = p_j(k) \quad \forall i \in I(j)$ one phase green $\sum_i p_i(k) = 1 \ \, \forall k$

and phase transitions are respected: $p_{\tilde{j}}(k+1) = 0 \quad \forall \check{j} \notin J(j) \quad \forall j : p_{j}(k) = 1$ with $J(\check{j})$ the set of possible phase transitions from \check{j}

Figure 4: mathematical programming formulation

The mathematical programming formulation of the controller is given in Figure-4. The control sequence is expressed in states (green/red) of the signal groups. The objective is to minimize the total delay over the planning horizon (as specified by the queuing model), subject to constraints on the controller (predefined phase-transitions). The mathematical programming problem is solved following a branch-and-bound approach using decision trees.

5.3 Sensitivity Analysis

The sensitivity of the phase-based predictive controller for errors in the predicted quantities is addressed by following the approach as described in Figure-2. In the sensitivity analysis, the perfect arrival pattern a(k) is disturbed by adding a prediction error (as explained in Figure-4). The influence of the disturbed predicted arrivals $\tilde{a}(k)$ on the performance of the controller is measured. Note that the current state, as initial state for the prediction, is assumed to be perfectly known, only the prediction is disturbed. The predicted arrivals are disturbed in two ways, the number of vehicles a(k) is disturbed by adding a relative error (percentage), and the arrival time-step k is disturbed by adding a time-shift. Both influences are measured separately. For now, it is assumed that the prediction method of the arrivals is biased (but no additional random noise is considered, σ =0). For each signal group and time interval, there is an equal

^{*}Although not included in the formula, loss times (clearance times and reaction times) and constraints on minimum and maximum green times are taken into account as well.

structural error ϵ expressed by the bias parameter μ . For both error types, the bias parameter μ is increased, and the performance of the controller is measured. Additionally, the relation between the performance and the horizon length is analyzed for the different error levels.

Figure-5,6 show the results of the sensitivity analysis for the predictive controller in the under-saturated and saturated scenario. Figure-a,b depict the experimental relation between the structural error (in number of arrivals (a) and in arrival times (b)) and the performance of the predictive controller. Figure-c,d express the effect in control performance of increasing the prediction horizon under different error values.

In the under-saturated scenario, the controller turns out to be more sensitive for a shift in the arrival times, then a disturbance in the number of arrivals (Figure-5a,b). Since the arrival pattern is sparse, containing holes, it is more important when vehicles arrive then how many vehicles arrive to give green at the right moment. A shift in the predicted arrival times clearly influences the performance of the controller, however, prediction still makes sense (Figure-5d). Increasing the prediction horizon, increases the performance of the controller, even with an erroneous prediction. Looking ahead, still gives valuable information on the average number of arriving vehicles per signal group, which results in better green-splits, then only reacting on the sparsely arrived vehicles. However, the performance that can be reached is still best for the error-free prediction when green times can be matched to the actual arrivals.

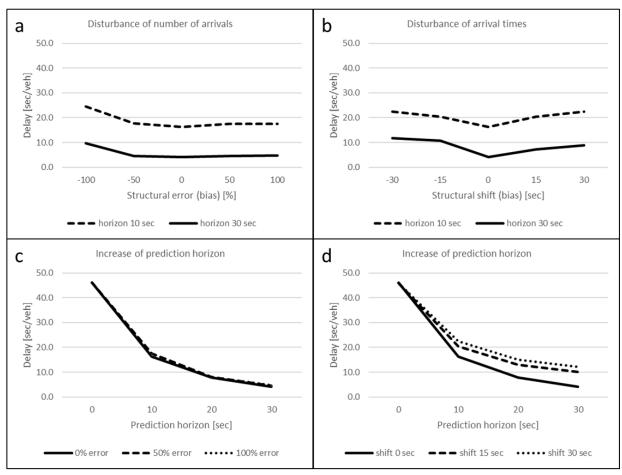


Figure 5: sensitivity of predictive controller in under-saturated conditions

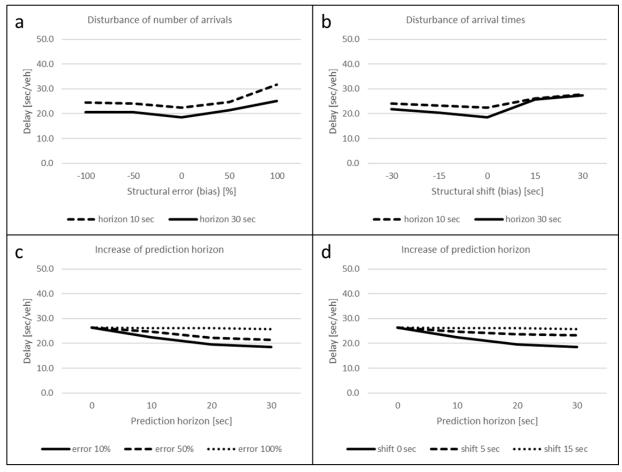


Figure 6: sensitivity of predictive controller in saturated conditions

In the saturated scenario, the controller is not only sensitive for errors in the arrival times, but also to errors in the number of predicted vehicles (since the arrival pattern is dense). Since queues are present in the saturated case, information on the current state seems most important. Prediction only gives an improvement, for the lower error levels. For increasing errors, prediction does not improve the delay anymore, and the performance of the predictive controller is equal to the performance of a controller that is looking at the current queues only, without any prediction (as shown in Figure-6c,d).

6 Conclusions and Recommendations

In this paper, an experimental framework is proposed to measure the sensitivity of signalized traffic controllers for disturbances in input quantities. The framework was illustrated for a phase-based predictive controller in under-saturated and saturated conditions. Experimental relations between increasing errors in the predicted arrival pattern and the decreasing performance of the controller were obtained. Additionally, the influence of the prediction horizon was analyzed for different error levels. In the under-saturated condition, prediction still improves the performance of the controller, even when

the prediction contains errors. For the saturated case, the benefit of a prediction disappears when errors increase. The outcome of the sensitivity analyses contributes in understanding the relations between information quality and the performance of signalized traffic control.

The final goal of future research will be, on the one hand, to decide how accurate estimation and prediction methods should be to be of added value for signalized traffic control, and on the other hand, to have guidelines for the development of signalized traffic controllers that are robust to input errors. To this end, more experiments in this framework need to be done to analyze the effect of errors in the estimated and predicted input quantities on the performance of the controller. The experiments will be extended by disturbing other quantities, like saturation flow-rates and estimated queues (current state), to see for which input quantities predictive control is sensitive. Other types of predictive control will be considered and compared, varying from cyclic control structures (less degrees of freedom) to structure-free control (more degrees of freedom). The experiments will be extended from the saturated to the over- saturated case, and from a single junction to coordinated junctions and finally a network context.

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