Online State Estimation for Microscopic Traffic Simulations using Multiple Data Sources*

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Keywords: Microscopic Traffic Simulation, Online State Estimation, Mixed Road Users, Sensor Fusion, Integer Programming, Route Choice, Vehicle2Infrastructure.

Abstract: The online fitting of a microscopic traffic simulation model to reconstruct the current state of a real traffic area can be challenging depending on the provided data. This paper presents a novel method based on limited data from sensors positioned at specific locations and guarantees a general accordance of reality and simulation in terms of multimodal road traffic counts and vehicle speeds. In these considerations, the actual purpose of research is of particular importance. Here, the research aims at improving the traffic flow by controlling the Traffic Light Systems (TLS) of the examined area which is why the current traffic state and the route choices of individual road users are the matter of interest. An integer optimization problem is derived to fit the current simulation to the latest field measurements. The concept can be transferred to any road traffic network and results in an observation of the current multimodal traffic state matching at the given sensor position. First case studies show promosing results in terms of deviations between reality and simulation.

1 INTRODUCTION

In recent years, the evolution of Intelligent Transportation Systems (ITS) has been rapid due to constantly improving modelling software for traffic systems as well as the related sensor and computing technology. Depending on the different purposes of research and the wide range of data acquisition technologies there are several methods on how to reconstruct, analyze and improve the traffic state. The motives range from the strategic change of the traffic infrastructure or the recommendation of a certain route (e.g. navigation systems) to the improvement of the safety of road users. Another challenging aim is to control the traffic through its Traffic Light Systems (TLS). The stabilization of inner-city traffic with intelligent traffic controls offers a practicable and pleasant way of counteracting the problems of slow traffic and congestions at intersections. Therefore it is necessary to observe and approximate the current traffic situation in the surroundings of the TLS the best possible way. Based on these requirements to develop a fast reacting solution for the control of TLS, this paper formulates a novel approach on how to online-estimate the current traffic state by combining a microscopic traffic simulation model with real-time field measurements. The methodology is developed for a real road traffic system in Schloß Neuhaus (Paderborn, Germany), but also transferable to any comparable road traffic system. On top of conventional induction loops and telegrams for public transport (PT), i.e. vehicle-to-infrastructure (V2I) communication, the road network is equipped with further detectors. Their online measurements consist of the arrival time and the speed of each individual crossing road user. Working on basis of radar technology, these detectors immediately classify vehicle types compliant with data policies. This classification plays a central role in this approach because the extra information provides new possibilities for traffic estimation and forecasting since there cannot be a direct detection of individual

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*Research supported by the Ministry of Economy, Innovation, Digitalization and Energy of North Rhine-Westphalia, Germany.

Malena, K., Link, C., Mertin, S., Gausemeier, S. and Trächtler, A.
Online State Estimation for Microscopic Traffic Simulations using Multiple Data Sources.
DOI: 10.5220/0010414903860395
In *Proceedings of the 7th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2021)*, pages 386-395
ISBN: 978-989-758-513-5

vehicle routes by e.g. license plates (due to governmental restrictions in Germany). Thus, it is not possible to obtain complete and continuous information about the state of the complex traffic system. The simulation-based Dynamic Traffic Assignment (DTA) technique presented here estimates and predicts individual route choices for all road users in order to model the current traffic state. To overcome the difficulty of mutual interactions between road users and the traffic infrastructure such as TLS, a microscopic traffic simulation is used. This incorporation of a simulation offers a major advantage over a purely algorithmic information processing of the measured data. The concept attempts to solve the problem resulting from discontinuous, event-based and only locally recorded data by using route predictions to link past, current and future field measurements. All available data resources like the specially equipped radar detectors and the less informative induction loops can be combined in this versatile approach. In order to finally control the TLS optimally, the traffic has to be assigned dynamically using the online measured data. This requires a sufficient accordance of the real measured data with the data generated in the microscopic simulation. The resolution and accuracy of the simulation as well as the algorithmic efficiency are of particular importance. The microscopic level allows to distinguish between different vehicle types and enables the required online responsiveness of future TLS to individual road users. The needed fast responsiveness also implies short time intervals for the DTA algorithm. In order to remain efficient, the replicated simulation network itself has to be limited. It should only contain the main parts of the test area, i.e. solely the high traffic roads close to TLS and sensor locations. The traffic state reconstruction itself is formulated as an assignment problem. Based on the measurements of the mixed traffic of road users, the state description is mathematically translated into an integer linear programming problem for a predefined short time interval.

2 LITERATURE REVIEW

There are different purposes to estimate the traffic state within areas and therefore different ways to achieve the needed estimation. For example if cities want to improve their transport infrastructure, it is important to know which areas are usually loaded or free at what specific time. It is usually for such requirements that macroscopic statements on Origin-Destination (OD) flows, which have been determined offline solely on the basis of historical data, are sufficient to make the necessary conclusions (Osorio, 2019a; Osorio, 2019b).

In contrast to these applications, which do not need an online data processing, there are others which require the estimation of the traffic state almost immediately. Examples are navigation systems for route suggestions or TLS to cope with the current situation in the best possible way. The intention in this research is to deliberately influence the traffic flow through the area's TLS rather than the routes of the road users themselves. The more precise the road traffic model is, the more efficient the control strategy for the TLS can become. That justifies why this paper formulates an approach to maintain a well approximated traffic state that allows sophisticated signaling for the TLS optimization. In order to reach this aim, the simulation model needs to be adjusted with and to the data provided by the field measurements. There is already relevant literature like (Chen, Osorio, & Santos, 2019) which uses efficient Simulation-based Optimization (SO) algorithms to reduce travel times with signal control. However the control itself is mostly limited to a fixed-time strategy or there are no complex phases used, i.e. there is no lane specific release within the phases or the very important phase transitions are unattended (Kamal, Imura, Hayakawa, Ohata, & Aihara, 2015; Zheng et al., 2019). In addition, it is usually not shown how the traffic state was identified to determine the control. Therefore it is to be assumed that a perfect knowledge of the current traffic state is presupposed or this important step was not considered. On the contrary, (Wang, Wang, Xu, & Wongpiromsarn, 2013) are a positive example who disclose or at least name their data collection. The difficulty and novelty within this project is that not only green times or phase lengths for TLS are variable, but that the phase sequence itself with its complex phases should also be determined. This phase selection is based on the current traffic situation and thus in particular on the individual vehicles and their types considered in this estimation. Because of that, the traffic and especially the demand modelling is crucial. According to the guidelines for traffic simulation (Antoniou et al., 2014), the aim of the necessary calibration for microscopic simulation models is to close the gap between reality and simulation. The demand calibration is mentioned as basis for further steps such as car-following or lane-changing models. Most other research deals with driver behavior settings as calibration parameters (Paz, Molano, Martinez, Gaviria, and Arteaga, 2015). Their focus lies on the vehicle distribution at local detection positions and not on the route choice of individual vehicles to achieve those detections. This is a major difference to the research presented here. Their data bases mostly consist of complete pre-defined OD connections or the test area is as simple as a highway with off- and on-ramps, e.g., in the Kalman Filter based application in (Antoniou, Ben-Akiva, & Koutsopoulos, 2010). In a highway scenario there is no need for a complex route prediction since all detectors just have one predecessor and successor. The DTA concept presented in this paper is designed for a more complex urban network allowing vehicles to take routes to different subsequent detectors after a local detection. Therefore the selection of the individual routes can be considered as calibration parameters. In contrast to fully detected vehicle routes, field measurements just as the previous mentioned enhanced traffic counts (radar detections with vehicle type specification) are combined to estimate the most likely individual vehicle route. The combination of this data quality and the purpose to control an urban traffic network through its TLS is unique since also the online reaction time to estimate the traffic state has to be very short. For example in (Bierlaire & Crittin, 2004), the synthetic data have several minutes as time interval, which is not sufficient for this application. The desired choice of TLS phase sequences requires the reaction time of only a few seconds to adapt best to the current traffic.

3 PROBLEM FORMULATION

3.1 General Conditions & Idea

The concept of this DTA algorithm is to feed a microscopic simulation model with real-time sensor measurements to act as an (almost continuous) event-based observer for the current traffic state. Many operations can be performed offline in advance, but others like the processing of the measured data have to be done online whilst simulating the microscopic traffic scenario. The keyword real-time is crucial here, as there has to be sufficient computing time remaining for the prospective TLS control. In order to reconstruct the traffic situation between the local detector positions, predictive route choices have to link past and future measurements. The structure of the presented simulation-based method is sketched in Figure 1. The block diagram shows how the real world scenario interacts with the simulation and what kind of data is used for which purpose. As mentioned before, an essential aspect is the differentiation between the online and offline processing and calculations. There are several calculations which can be performed prior to the actual simulation as a kind of initialization process where for example average travel times for each vehicle type combined with the different traffic light states are computed. The intervals of other state estimators are relatively large (often minutes). The idea of adjusting a running simulation and the outsourcing of calculations are among others the reasons why very small update intervals (a few seconds) can be used for this online state estimation.

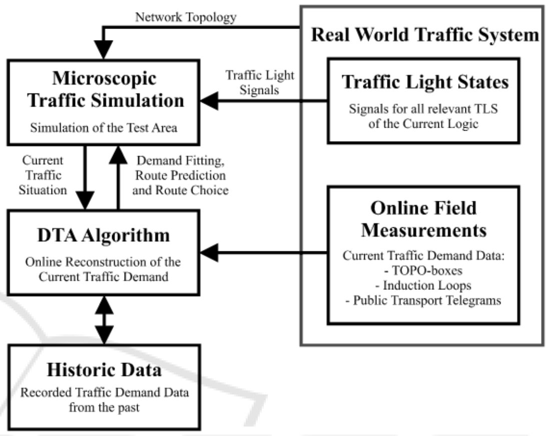

Figure 1: Block diagram of the presented DTA concept.

The main online field measurements in this research consist of superior traffic counts, i.e. not only a time stamp for crossing the detector, but also the vehicle type and the current speed are detected via radar technology. These detectors are so-called TOPO-Boxes and this kind of detection is necessary, because the future TLS control should contain a vehicle specific prioritization. Nevertheless, the concept is able to be enhanced by incorporating less detailed measurements of induction loops and/or PT telegrams (V2I communication type of specific PT buses and the TLS). These additional sensor information are inferior to those of the TOPO-Boxes and therefore result in different interdependent levels in the decision making process of individual vehicle routing. The vehicle types within this whole approach are generally classified according to the 8+1 class defined by the German Federal Road Research Institute (BASt) in (Bundesministerium für Verkehr, Bau und Stadtentwicklung, 2012). Thus passenger vehicles along with motorcycles, trucks, trailer etc. are taken into account. Additionally bicycles are detected so that the detection and the simulation are extended to the so-called ‘8+1+F’ classification (RTB GmbH & Co. KG, 2019).

Subject to the variety of available data sources, the algorithm has multiple routing levels. The most important source allows the differentiation between the above defined vehicle types. This is the reason why the next subsection describes the highest routing level in more detail (TOPO-Box Routing) and the last subsection is dedicated to the interaction of all considered and already mentioned levels.

3.2 TOPO-Box Routing

Since the TOPO-Boxes are mandatory due to their type differentiation and their positioning between successive TLS, this part of the paper dives deeper into the mathematical description of the respective dynamic problem. Some aspects of graph theory are used to illustrate and explain the methodology of this traffic estimation problem. Inspired by relevant literature like (Bierlaire & Crittin, 2004), the traffic network under research is modelled by a directed graph to process the simulated data. The graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$ is represented by its set of nodes $\mathcal{N}$ and its set of links $\mathcal{L}$. These nodes $\mathcal{N}$ can either be junctions or geometric points which meet the given traffic infrastructure. The geometric points are the discretization tool to model curves etc. which directly influence the simulation, e.g. in terms of possible speeds and accelerations. Streets of the complex traffic system are therefore modelled through the links $\mathcal{L}$. Special attention has to be paid to the TLS-nodes $\mathcal{N}_{TLS} \subseteq \mathcal{N}$, as they play a central role in controlling the system. In contrast to (Bierlaire & Crittin, 2004), the sensors monitoring the system are not directly represented by a subset of the links $\mathcal{L}$, but as geometric points $\mathcal{N}_{\mathcal{D}} \subseteq \mathcal{N}$. The graph $\mathcal{G}$ does only depend on the given infrastructure and not on the time and is therefore used to describe the empty traffic network. For all links $L \in \mathcal{L}$ the respective travel time to reach each detector $D \in \mathcal{N}_{\mathcal{D}}$ is calculated. For the presented approach it is important that these travel times are stored prior to the actual online simulation to determine the traffic state. Due to different traffic light states and system loads, the travel times will be modified over time. Any vehicle state at any time can be accurately transmitted to the data processing of the algorithm by the occupancy vector $\xi(t)$. It contains the vehicle type, the current speed and the current position on a specified edge of each single vehicle such that

$$\xi(t) \in \underbrace{\mathbb{N}^{|N_{veh}(t)|}}_{\text{vehicle type}} \times \underbrace{\mathbb{R}^{|N_{veh}(t)|}}_{\text{vehicle speed}} \times \underbrace{\mathbb{R}^{|N_{veh}(t)|}}_{\text{vehicle position}} \times \underbrace{\mathbb{N}^{|N_{veh}(t)|}}_{\text{vehicle's link}}. \tag{1}$$

The time dependent traffic state can be represented through this occupancy with $N_{veh}(t)$ being the current number of vehicles in the system and each vehicle type is associated with a different integer (first entry of each row of $\xi(t)$).

The aim of this theoretical construction is to help assigning individual vehicles within the simulation to specific sensors when there is a new measurement in reality. The basic idea for the decision whether or not a vehicle should be routed to a nearby sensor is to check if the vehicle ‘fits’ to the corresponding sensor measurement. The most important criteria to fit are the accordance of measured and simulated vehicle type and the needed travel time to reach the sensor. Since the simulation has to run in real-time, the simulation must be regularly adapted to the measurements so that the traffic state can be well estimated. Other criteria like the speed are less appropriate, as they can be very discontinuous due to curves, for example, and thus make the assignment process more difficult. But since the speed is measured, this information is used in a different way to predict the future vehicle situation the best way (explained later). It is a key aspect of the approach that each of the mentioned vehicle types is handled separately resulting in several subproblems. Obviously there are several situations in complex traffic systems where the route of vehicles has to be assigned in different ways. In this DTA concept each vehicle can be in any of the following positions to get routed, which can be determined depending on the current occupancy $\xi(t)$ and the current measurements. The first case is that the respective vehicles are not in reach of any sensor; i.e. the travel time to arrive at any of the specified sensors lies beyond a user-defined threshold of the algorithm. This means that those vehicle cannot fulfill any of the measurements. The second case is that vehicles are close to just one sensor. Here it is determined that if there exists a detection in the reality, the vehicle is routed towards this sensor to satisfy the measurement (i.e. ‘deterministic routes or vehicles’). The last scenario is that vehicles are able to reach multiple detectors due to their calculated travel time. Depending on the measurements of these sensors it is possible to construct an optimization problem which minimizes the travel time and maximizes the assignment of currently available vehicles simultaneously (so-called ‘flexible routes or vehicles’). The derivation of this binary optimization problem follows.

The time discretization of the problem is determined by the step size τ. Of particular importance for the construction of the online optimization problem is the difference between deterministic and flexible routed vehicles. The previous designation indicates that vehicles with just one reachable detector can be directly assigned to the respective detector, whereas the routes for vehicles in a 'flexible assignment area' are not predefined. The assignment of these vehicles to sensors that have current demand is subject of optimization. The complexity of this optimization problem depends on the number of vehicles n which are able to reach multiple detectors as well as on the number of reachable sensors q_i for each of these vehicles $i \in \{1, \dots, n\}$. Because not all vehicles are even within range of a single sensor it applies $n \neq N_{veh}(t)$. A flexible vehicle with its $\mathbb{N} \ni q_i \geq 2$ reachable detectors results in q_i binary optimization variables $x_{i,1}, \dots, x_{i,q_i}$ which determine whether or not a vehicle will be routed towards the respective sensor. The total number of optimization variables at the k^{th} step is

$$N(k\tau) = \sum_{i=1}^{n} q_i(k\tau). \tag{2}$$

Because each of the vehicles can only be routed once, the sum of all optimization variables for each of the n vehicles needs to be less than or equal to $b_{1,i} = 1$. This leads to the first n inequality conditions of the optimization problem for the k^{th} time step

$$\begin{gathered} A_1 x(k\tau) \leq b_1(k\tau) \\ \sum_{j=1}^{N} a_{1,ij} \cdot x_j(k\tau) \leq b_{1,i}(k\tau) = 1, \\ \forall i \in \{1, \dots, n\},\ k \in \mathbb{N}_0, \end{gathered} \tag{3}$$

where $a_{1,ij} \in \{0,1\}$ assigns the optimization variable $x_j(k\tau)$ to the vehicle $i \in \{1, \dots, n\}$. In order to route the exact number of detected vehicles in the corresponding time interval to the respective sensors, additional constraints are added to the problem formulation. These constraints are based on the number of sensors $S \mathrel{\widehat{=}} |\mathcal{N}_{\mathcal{D}}|$ and ensure that already assigned deterministic vehicles are considered. This second part of the restrictions yields to

$$\begin{gathered} \sum_{j=1}^{N} a_{2,ij} \cdot x_j(k\tau) \leq m_i(k\tau) - d_i(k\tau) \\ =: b_{2,i}(k\tau), \\ \forall i \in \{1, \dots, S\},\ k \in \mathbb{N}_0, \end{gathered} \tag{4}$$

with

- $a_{2,ij} \in \{0,1\}$ assigning the optimization variable x_j to the sensor $i \in \{1, \dots, S\}$,
- $m_i(k\tau) \in \mathbb{N}_0$ being the total number of measurements for sensor $i \in \{1, \dots, S\}$,
- $d_i(k\tau) \in \mathbb{N}_0$ being the number of already (in this time interval) deterministically routed vehicles to sensor $i \in \{1, \dots, S\}$,
- $b_{2,i}(k\tau) \in \mathbb{N}_0$representing the measurements still to be fulfilled for sensor $i \in \{1, \dots, S\}$.

If there are more vehicles that can be deterministically routed than measurements ($m_i(k\tau) < d_i(k\tau)$), the adjusted field measurements are set to zero, i.e. $b_{2,i}(k\tau) = 0$ and just the nearest $m_i(k\tau)$ vehicles are routed.

Through this inequality constraints the optimization problem can be formulated as

$$\begin{gathered} \min_{x \in \{0,1\}^N} f\big(x(k\tau)\big) \\ \text{subject to } \begin{bmatrix} A_1 \\ A_2 \end{bmatrix} x(k\tau) \leq \begin{bmatrix} b_1(k\tau) \\ b_2(k\tau) \end{bmatrix}. \end{gathered} \tag{5}$$

Just as already introduced, the objective $f\big(x(k\tau)\big)$ can be chosen to minimize the travel times of the vehicles to satisfy the detections and simultaneously maximize the number of assigned vehicles in the simulation. In this case the objective would be

$$\begin{aligned} &f\big(x(k\tau), t(k\tau)\big) \\ &= (w_t t(k\tau) - w_a) x(k\tau), \end{aligned} \tag{6}$$

where

- $t(k\tau) \in \mathbb{R}^N$ are the travel times for each vehicle to the respective sensors,
- $w_t, w_a \in \mathbb{R}$ describe weighting factors for travel time and assignment.

If the current demand of a specific sensor cannot be satisfied through the assignment of available vehicles, new vehicles have to be inserted into the simulation to fulfill the measurement, i.e. the inequality constraints in (4) are not met with equality. Notice that these insertions or spawns lead to a general consistency in terms of traffic counts and their equivalents in reality are incoming vehicles from unobserved side streets. Once a vehicle is assigned to a detector in the simulation, it cannot be reassigned until it reaches the desired detector. A follow-up destination is set for each vehicle assignment, i.e. a route prediction based on probabilities derived from historical data is performed. The details of this stochastic process will not be further discussed here. It closes the gap between the matching of a field measurement and the intrusion of a vehicle into an area for successive routing. Without the follow-up routes there would be no routable vehicles for the TOPO-Box Routing and all vehicles would have to be spawned or generated. The data processing of the historical 'offline' route prediction is done prior to the main simulation and updated frequently during the simulation. In doing so, a daytime-specific route can be assigned to the vehicles online. This route can be considered as less prioritized than the online route choice determined by the optimization. The routable vehicles for each vehicle type within the simulation can be derived from the current occupancy $\xi(k\tau)$ with an additional query whether the previous destination has already been reached. In the end of every simulation step there has to be a check if still routable vehicles are about to cross a detector. Since these vehicles were not assigned through the routing, a crossing is not justified and the vehicles need to be removed from the simulation to ensure the measurements of reality. In reality, these vehicles have entered unobserved roads or parking lots.

3.3 Interaction of Different Routings

The previous section points out the concept of the top level routing, but there are two more implemented levels which optionally help the traffic state estimation to be more accurate. It is clear that the more information and data the algorithm is capable of processing, the more precise the traffic estimation can become and the better the TLS-control can adapt to the current traffic. The second routing level affecting all types of vehicles is based on the induction loop data. As they are widely used nowadays, this information can complement the TOPO-Box measurements without the need to buy additional measuring equipment. For the purpose of controlling TLS they are extremely worthy since the radar technology is quite vulnerable in congested areas. Therefore, the TOPO-Boxes are not set up in the direct vicinity of an intersection. On the contrary, the induction loops are usually only to be found in these areas which is why the combination of data sources can be particularly profitable. The third and last data source uses V2I-technology, but exclusively for regularly driving PT buses. Those buses transmit their PT line number at specified locations within the system when approaching and leaving TLS. Right now it is already used to prioritize the PT, but in a way that has a strong negative impact on the other traffic and thus additionally leads to unnecessary congestion.

Because of that, the TOPO-Box Routing is extended in this approach with the so-called Induction-Loop Routing and the PT-Telegram Routing. The TOPO-Boxes are the most detailed and reliable data source in terms of detecting vehicles, but due to the relatively poor network coverage and the network complexity it is still hard to estimate the traffic state between measuring points. The induction loops are lane based, so better capable of detecting turning ratios at intersections and the PT telegrams directly offer the future route of the concerning bus since it is static. Figure 2 illustrates the algorithm's answer to the question how those advantages can be combined. It shows the mutual interaction (if allowed) of the different routing concepts according to the drawn arrows. All routing concepts have their own general spawn and routing strategies, which change based on the vehicles' previous assignments of other concepts.

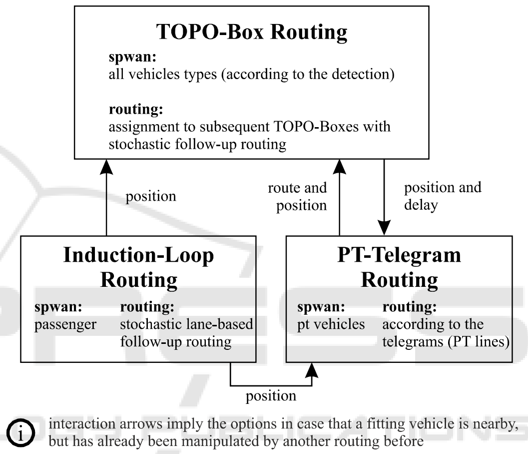

Figure 2: Methods and interaction of the different routing concepts.

To understand these interactions, it is important to recall the principle of the TOPO-Box Routing. Here, the vehicles (of all different types) get fixed routes until passing the detector. Afterwards they are equipped with flexible follow-up routes based on stochastic turning ratios, historical data, etc. This means that after crossing the aim detector an 'educated guess' is made how the vehicle will behave until a successive measurement that fits the vehicle comes up. As a consequence the routes of the non-assigned vehicles (not assigned to a consecutive TOPO-Box) can be manipulated to fit all different data sources e.g. those of the induction loops. In Figure 2 the boxes are divided into 'spawn' and 'routing'. This addresses exactly whether a corresponding vehicle in the vicinity of the sensor is available for this routing or not. The routing level interactions describe the vehicle handling depending on the previously used routing. An arrow from the

Induction-Loop Routing to the TOPO-Box Routing therefore implies the influence of the Induction-Loop Routing on vehicles which have already been assigned by the TOPO-Box Routing. As an example, if a truck is detected by a TOPO-Box with no truck in the vicinity of this sensor, a new one is spawned, routed to this sensor and provided with a stochastic follow-up route. Continuing this example, the truck enters an intersection after crossing the TOPO-Box with the desire to drive straight (derived from the stochastic follow-up route). Suppose an induction loop on the left turning lane is activated, then, as indicated in Figure 2, the position of the truck is changed and shifted to the left lane. Also, the route is manipulated in such a way that the vehicle turns left and approaches a destination in that direction. Otherwise, if the target TOPO-Box location is behind crossing the intersection straight, then the truck could not be used for the Induction-Loop Routing. This is because the left lane is not on the truck's route, so the change of position towards the induction loop indicated by the arrow cannot be applied. Depending on the absence of other vehicles a new one (passenger type) would have to be spawned to match the measurement. The usage of the PT telegrams is rather simple and therefore kept short, since for buses the educated guess can be swapped with the determined fixed routes known due to the PT lines information. After overwriting, the routes are fixed and the PT buses can only be delayed or repositioned.

4 ALGORITHMIC PROCEDURE

For the traceability of the algorithm a step-by-step guideline is presented in order to outline the interaction of the microscopic traffic simulation performed in SUMO (Lopez et al., 2018) and the algorithmic data processing in MATLAB. First the required traffic network for the simulation and the correct representation of the traffic infrastructure has to be built accurately in SUMO. This is a time-consuming process, but clear due to the unambiguousness of the infrastructure. The necessary communication of microscopic traffic simulation and data processing is realized with the interface TraCI4Matlab (Acosta, Espinosa, & Espinosa, 2015).A brief summary of the concept to reproduce the dynamics of the traffic system is as follows:

Step 0. *Pre-Simulation calculation of all necessary travel times. Loading and processing of historical data to assign prediction routes (follow-up routes). Initialization of the SUMO simulation.*

Step 1. *Change of the traffic lights according to the recorded data and adaptation of the travel times.*

Step 2. *Check of the current vehicle situation in the traffic system to decide their availability for the different routing concepts.*

Step 3. *TOPO-Box Routing.*
For each vehicle type: Solution of the integer linear optimization problem.

- *a.* *Generation of the inequality constraints using the current measurements and the simulation's vehicle states. Vehicles in areas with just one reachable sensor within the travel time threshold are assigned and given follow-up routes.*
- *b.* *Performing of the integer linear optimization.*
- *c.* *Assignment of the flexible vehicles resulting from the optimization with determination of consecutive destinations.*
- *d.* *If there is still unsatisfied demand (leftover detections), new vehicles of the respective type are created and added to the simulation at the required location with subsequent post-destination routes.*

Step 4. *Induction-Loop Routing.*

Step 5. *PT-Telegram Routing.*

Step 6. *Removal of vehicles that would cross the TOPO-Boxes unwanted (no detection recorded at this time) in the considered time interval.*

If the desired simulation period is covered, stop, otherwise return to step 1 for the next simulation step.

After this short overview some aspects will be described in more detail. Prior to the initialization step 0 the traffic network must be provided. Since SUMO is used as simulation tool, its own network editor NETEDIT (Lopez et al., 2018) is employed to prepare the test area usually using OSM-data like in (Feldkamp & Strassburger, 2014), but with the SUMO-internal program OSMWebWizard. Also the local sensors can be positioned here. To initialize the simulation, the net information is employed to create look-up tables including the travel times via TraCI4Matlab. These tables store the travel times depending on traffic light signals and vehicle types.

Since the road permissions for vehicles within the network vary with their types and the simulation also uses different general driving parameters, this calculation procedure has to be done for each of the vehicle types. A not further discussed offline-algorithm determines the probabilities for the follow-up routesup routes after reaching a destination in the third step and also for step 4 beginning from the induction loop lane. This algorithm tries to link traffic counts of different detectors based on measurements of the past creating routing probabilities. Even if no historical data is available, random follow-up routes can be assigned.

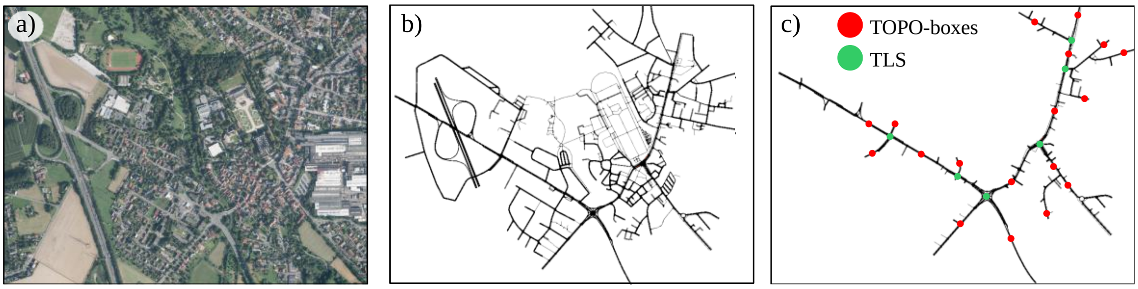

Figure 3: Transformation of the real test area in a) to the OSM-imported SUMO network in b) and its reduction to the ‘observable’ main roads equipped with the positions of TOPO-boxes and TLS in c).

After this preparation, the SUMO simulation can be started. SUMO is used to handle the driver specific behavior and mutual interaction between all vehicles of all types. Each simulation step begins with the setting of the current TLS signals and the query of the current vehicle state. Based on an implemented trigger, the routable vehicles with no fixed route are filtered (follow-up routes from previous steps). The filtering is followed by the different routing concepts ordered according to their priority and ability to interact with steps 3 to 5. Step 3 guarantees the satisfaction of the detected vehicle demand through whether deterministic, optimization based or necessary leftover routing. These routing types are superior to the follow-up routing after crossing a detector. The superiority itself is realized by overwriting the previous route. Since the TOPO-Box measurements also include the vehicles’ speeds, the velocity parameters of the routed vehicles are adjusted through a simple not further explained algorithm. For the removal of vehicles that do not correspond to a field measurement, the routing trigger and the distance to the upcoming detector is checked. If a certain distance is underrun, the vehicle is removed (step 6). As mentioned before, this corresponds to unobservable events such as stopping at parking lots or turning into unobserved roads or a false route prediction. The procedure for the reconstruction of the traffic state is highly sequential which is why certain modifications can have positive impacts in terms of efficiency. The removal of vehicles has to be performed every simulation step for each vehicle type whereas the vehicle assignment based on the real-time data can be split for the types and distributed on several seconds to increase the efficiency without losing the consistency with field measurements.

5 CASE STUDY

5.1 Test Area Setup

The chosen test area of the pilot project in Schloß Neuhaus (Paderborn, Germany) covers a total area of approximately 2 km^2 with multiple entries and exits. In the following Figure 3 a bird's eye view of the real road network in a) (Land NRW, 2019) is transferred via the import of OSM data (OpenStreetMap contributors, 2019) into a SUMO traffic simulation network in b). Besides some necessary manual adjustments, especially to replicate the real TLS and the multimodality of the road permissions, the import has been reduced by the unobservable roads (see c)). The final network consists of a total of 441 nodes (junctions and geometrical points) and 622 edges or links including six TLS which will be object of future optimization. These key numbers of the respective graph are a result of a post-import discretization to determine the travel times depending on the edges more correctly because their length is limited to a maximum of 40 m. This way, a more time-consuming online calculation can be avoided. The real test area is equipped with around 20 TOPO-Boxes, which are also shown in Figure 3 c). Those detectors are capable of measuring the current traffic for both directions of the road on which they are installed. For this reason, twice the number of sensors are inserted in the simulation at the corresponding positions. Concerning the other data sources, there are nearly 70 induction loops surrounding the six TLS controlled intersections and 60 notification marks of the pt telegrams. The TLS junctions are also illustrated in Figure 3 c). This system architecture enables the application of the routing without further adjustments.

5.2 Simulation Results

The approach was tested using several data sets from different days in the near past, i.e. selected days in October and November 2020 building various scenarios with different vehicle loads. For the following average data shown in Table 1, each of the scenarios included a 30-minute time slot.

Table 1: Average deviation between real-life and simulation measurements.

Total TOPO-Box Crossings	−1 %
Total Induction Loop Crossings	+20 %
Vehicle Speeds	−6 %

The exceeding of the induction loop counts is based on the lower priority of those measurements. The TOPO-Boxes are the most important and reliable data sources and therefore the Induction-Loop Routing is not able to change already assigned vehicle routes. Since Induction-Loop Routing itself tries to meet its unfulfilled measurements, the number of crossings is increased by 20 % because the rights to manipulate the vehicle routes are intentionally missing (see Figure 2). The vehicle speeds vary minimally dependent on the higher local occupancy of the system. Some intentional safety mechanisms in SUMO prevent the exact mapping of the set speeds to make the overall simulation more realistic. With this system setup, the average speed deviation of 6% corresponds to a difference of less than 1 m/s. If the induction loop measurements prove to be more reliable in the future, the occurring deviations can even be reduced by allowing more interactions towards the top level routing (see Figure 2 again). Generally it can be said that due to the design of the approach the TOPO-Box measurements are almost perfectly approximated. But in order to get a better temporal breakdown of the results as well as some explicit vehicle counts a specific example is given below in Figure 4. It illustrates exemplary measurements of the above mentioned time slots, where each slot and each sensor provides comparable results for each vehicle type. In the upper part of Figure 4, the crossings of the passenger vehicles are shown. The accordance of simulation and reality is easy to notice as well as the absence of settling processes. This is due to the fact that the time interval used for all test results shown in this paper is only 3 s. Additionally, the speeds for the corresponding vehicles are pictured in the lower part of the figure. The real average speed for this time slot is 10.30 m/s and the simulated average is 9.97 m/s.

The distribution of the induction loop crossings or counts is not shown separately here, as it is comparable to Figure 4 (with more deviation), but does not include the same information because no speeds are measured in reality. Due to the PT-Telegram Routing there is nearly no deviation of TOPO-Box crossings for buses ($\ll 1\,\%$) since the routes are fixed and the area coverage of the telegrams together with the TOPO-Boxes allows steady adjustments.

As a conclusion for the results, the estimation at the local detection points (TOPO-Boxes and induction loops) works very good and in combination with SUMO also the speeds can be simulated accurately.

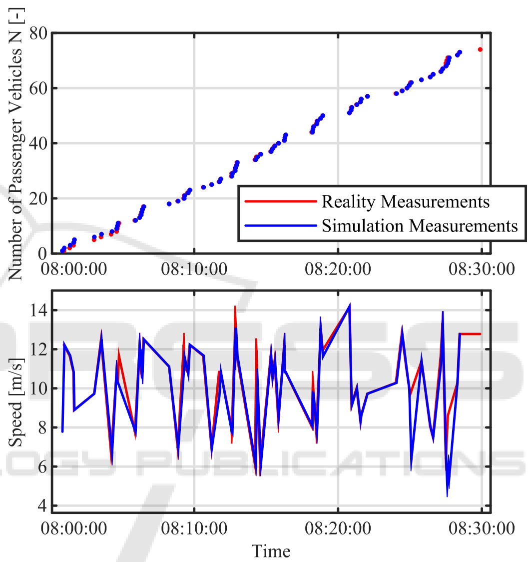

Figure 4: Comparison of the reality and simulation measurements for a single TOPO-Box regarding passenger vehicles.

6 CURRENT & FUTURE WORK

The individual routes are not directly necessary for the actual control of the traffic system. Since these traffic records are also very expensive and difficult to enforce in Germany, a simulated validation option is preferred. This is why currently an extensive validation study is performed using ground truth models and surrogate data as suggested in (Antoniou et al., 2014). First examples with some vehicle convoys show good results, as the system states can be estimated reliably, but the study still has to be extended to a completely realistic traffic.

In the future, the presented method will have to be improved while maintaining its generic character.

Within possible enhancements it is important to take note of an efficient implementation because of the real-time capability. Also, topics like the robustness to corrupted measurements have to be discussed more detailed. At the moment incorrect detections are compensated at the next sensor. In terms of sensor coverage, at least the main roads of the network have to be covered. Pedestrians are another aspect which will be added to the simulation based on their identification by pressing the corresponding push buttons at the intersection. This information will be taken directly from the TLS control unit.

In parallel, various TLS control concepts are currently under development, which have to be coupled with the presented traffic state estimator. This coupling will become very interesting, especially under the aspect of state estimations with deviations from reality.

The last future issue addressed here is that to reach the overall goal of controlling TLS in the field based on such a state estimation, some additional interfaces and latencies should be kept in mind. Especially their common standards, i.e. in this project the OCIT standard (OCIT Developer Group (ODG), 2019), have to be considered.

ACKNOWLEDGEMENTS

The authors would like to thank all participants of the *Pilot Project Schlosskreuzung* (PPS) for the provided data. This paper is part of the PPS and funded by the Ministry of Economy, Innovation, Digitalization and Energy of North Rhine-Westphalia.

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