Simulation Environment for Traffic Control Systems Targeting Mixed Autonomy Traffic Scenarios

Christopher Link[1], Kevin Malena[1], Sandra Gausemeier[1] and Ansgar Trächtler[1,2]
[1]Heinz Nixdorf Institute, University of Paderborn, Fürstenallee 11, Paderborn, Germany
[2]Fraunhofer Institute for Mechatronic Systems Design IEM, Zunkunftsmeile 1, Paderborn, Germany

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Abstract: The development of autonomous vehicles and their introduction in urban traffic offer many opportunities for traffic improvements. In this paper, an approach for a future traffic control system for mixed autonomy traffic environments is presented. Furthermore, a simulation framework based on the city of Paderborn is introduced to enable the development and examination of such a system. This encompasses multiple elements including the road network itself, traffic lights, sensors as well as methods to analyse the topology of the network. Furthermore, a procedure for traffic demand generation and routing is presented based on statistical data of the city and traffic data obtained by measurements. The resulting model can receive and apply the generated control inputs and in turn generates simulated sensor data for the control system based on the current system state.

1 INTRODUCTION

Traffic control is a vital part of road mobility, especially in urban areas. It is required for an efficient use of the given road network and often has a direct impact on the traffic situation. Current means of traffic control e. g., traffic light systems (TLS) or dynamic speed limitations on selected roads are key to improve the traffic flow and are therefore currently subject to optimisation. However, a major drawback of those systems is their cost and the need for additional infrastructure, like traffic detectors, to acquire an accurate picture of the traffic state. TLS, for example, can achieve significantly better performance if the traffic situation in their vicinity can be observed and used to determine the most suitable control input to handle the current situation (Malena et al., 2022).

The current developments in autonomous and connected vehicles offer a great potential to remedy these limitations and to integrate these vehicles as agents in traffic control systems themselves. Modern vehicles monitor their own position and speed continuously and could share this information using Car2X technology. Moreover, autonomous vehicles are dependent on the constant observation of their environment in real-time to be able to drive without assistance of a person. For a central traffic control system this data can give valuable insights in the local traffic situation close to the respective vehicles. Additionally, the current road infrastructure already integrates detectors, like induction loops or radar detectors, which can provide traffic data on stationary locations of varying quality. The incorporation of all these local data sources into a central control system can be used to obtain a comprehensive and up-to-date picture of the traffic network's state, even if only a small share of the road users is able or willing to participate in data-sharing.

Our goal, based on these considerations, is to develop such a traffic control system for future traffic scenarios and to utilizes the capabilities these systems would enable. A real-time picture of the traffic state can further improve TLS performance and enable route optimisation or rerouting suggestions for vehicles on the road. Furthermore, cooperative autonomous vehicles could be used to adapt the traffic flow speed in order to reduce congestions or stop-and-go traffic on road sections ahead. The framework development requires a suitable simulation environment since the traffic composition, as described above, and the means for data-sharing currently do not exist to the required extent.

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In this paper, we present a simulation environment and its components that is the foundation of such a system. In section 2, a literature overview is given to set a baseline for the presented research. An overview over the system and its structure is presented in section 3. Section 4 comprises the modelling of the road infrastructure as well as the traffic demand. Finally, in section 5 the conclusions are drawn, and the next steps are formulated.

2 LITERATURE OVERVIEW

Modelling a traffic environment and the associated control system are comprehensive tasks that include several aspects. In this section, a selective overview is presented due to the limited scope of this publication. There are many approaches and tools resulting from previous research. In (Lopez et al., 2018), the microscopic traffic simulation tool *SUMO* and its framework is presented which is used in this research. By employing the open-source software it is possible to model and simulate traffic scenarios in a realistic way. However, to reproduce the behaviour of a real traffic system, the mobility demand must be approximated realistically. An overview over methods for activity-based demand generation is given in (Schweizer et al., 2018). Depending on the available data, the desired output and the scope of the simulation, different methods can be pursued. Usually, the approaches derive the traffic demand from data about the population and its behaviour in the regarded area. Other structural information, e. g., the location and size of schools can also impact the simulated traffic situation, as investigated in (Ma et al., 2020). In that research, *SUMO* was used in combination with the tool *Activitygen* to simulate a realistic traffic environment and the results were compared to real traffic data. An alternative approach is used in (Maiorov et al., 2019) by splitting a large traffic region in multiple sections. Applying a gravitational model and incorporating structural data of the region, origin-destination (OD) matrices describing the traffic flows between the sections are created and used for route generation. In (Lobo et al., 2020), a method is presented to create a traffic model of an urban area using *SUMO*, *Activitygen* and an iterative routing approach. This is based on real traffic measurements and includes realistic programs for some TLS.

To obtain the road network, data from *OpenStreetMap* (OpenStreetMap contributors, 2022) can be imported and converted to the *SUMO* standards. A topological analysis of such a road network based on graph theory was performed by (Henning et al., 2017). Using several metrices, e. g., *Betweenness Centrality* and *Closeness Centrality*, a topology-based method was applied to identify important roads of the network. The results of such an analysis can be used by control systems or traffic planers to improve the traffic situation. A similar graph-based approach was taken by (Ahmadzai et al., 2019) to rate a city's road network.

The components of the planned control system are also based on prior research analysing different aspects. In (Farrag et al., 2020), information about the simulated traffic obtained via Car2X technology is used to identify and react to local traffic incidents (e. g., blocked lanes). Using this information subsequent vehicles can reduce their velocities which leads to a reduction in time loss. This demonstrates both, the potential of sharing traffic information and the capabilities of velocity control. This assessment is supported by the results of (Guo et al., 2020) who consider a mixed autonomy traffic situation. They show that through speed harmonization on roads leading to known bottlenecks, a better traffic flow can be achieved, provided there is sufficient sensor coverage in these areas. In (Malena et al., 2021a) and (Malena et al., 2021b), we present a validated method to obtain the traffic state of a real-world traffic area in real-time using stationary detectors. Using this approach, we were able to control multiple TLS in the regarded area and to integrate a more suitable target phase selection for the current traffic situation (Malena et al., 2022). However, this approach was limited to a city district of Paderborn and required the integration of additional sensor systems.

Finally, the subject of vehicle routing is important for the planned system since it is a key part of the desired real-time control system, and it is required for the initial route allocation as well. In (Lazar et al., 2021), a deep reinforcement learning algorithm is used for cooperative routing of the autonomous vehicles in a mixed autonomy environment while human-driven vehicles rely on selfish route choice. The research shows that a cooperative approach can lead to a reduction of travel times even if it is only applied to a fraction of the vehicles. Similar results were achieved by (Krichene et al., 2016) indicating that even a small share of controllable vehicles can be used to achieve significant improvements. Furthermore, other possible solutions to remedy the inefficiency of selfish, non-cooperative routing are summarised, like pricing congestion or the allocation of road capacities.

The traffic control system and the simulation environment presented below are based on the research presented here, combining and extending it. The *SUMO*-based simulation is complemented by new models of sensor systems and TLS. Also, a routing system was developed including results from topological analysis and real traffic data.

3 SYSTEM OVERVIEW

In order to describe the simulation model, it is necessary to understand how it is embedded in the control loop and to formulate the requirements it has to meet.

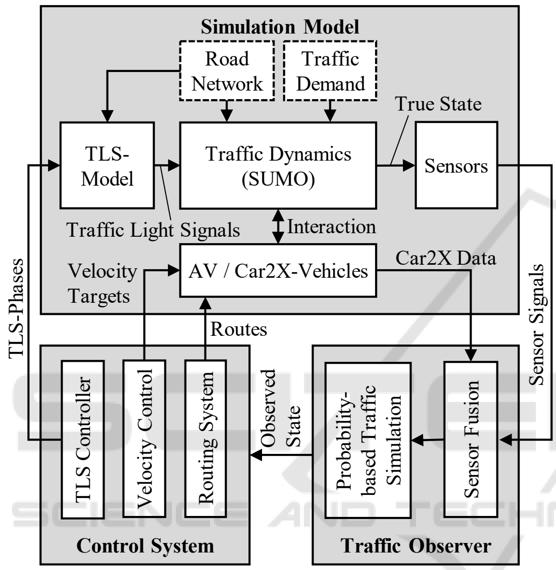

Figure 1: System overview.

The structure of the system which is being developed is depicted in figure 1 and consists of three major components: A simulation model, a traffic observer, and a control system. The latter two serve as the information processing unit which receives simulated sensor data from the model and in turn provides appropriate control inputs. In contrast to that, the simulation model is a substitute for a real traffic environment and is used to test the control system. Therefore, it has to encompass all relevant components which have a meaningful influence on the system's behaviour. It must be able to receive and apply the given control inputs and generate the required sensor data based on the system's state. The controller provides three means to interact with the traffic system:

A routing system utilizes the knowledge of the system state to dynamically find optimised paths to the given destinations. Such a system must weigh between multiple criteria, such as route length, expected travel time, traffic density etc. and suggest a route-change for compatible vehicles. It is assumed that autonomous vehicles follow these suggestions while the drivers of other Car2X-equipped vehicles can reject them which can be modelled using a probability-based approach. Other vehicles cannot be controlled by this system directly, however by easing traffic demand on critical road sections they are also expected to experience an indirect positive effect.

The second mean of control is also aimed at Car2X-equipped vehicles and utilizes the ability to send them respective target velocities for the road sections they are located on. If the estimated target velocity is below the current traffic flow speed it can be enforced by autonomous vehicles and cooperating human-driven vehicles. Using consensus algorithms for a purely autonomous traffic showed that it is possible to achieve a more homogenous traffic flow and to reduce undesirable effects like stop-and-go traffic if the target velocities are chosen appropriately (Mertin et al., 2020).

Since TLS have a great influence on the traffic flows, the final control structure is a system to optimise their performance. Based on the estimated traffic state on the roads in the vicinity of each TLS, the waiting times of the affected vehicles and their vehicle types (if known), a target phase and the desired switching time is to be calculated and applied to the traffic system. In our prior research, we have developed an approach based on Model Predictive Control (MPC), which is able to improve the performance of TLS significantly compared to control systems currently in use (Malena et al., 2022). An integration of this control approach is therefore planned for this system as well.

All those presented control systems prerequisite a comprehensive and up-to-date knowledge of the current system state in order to provide effective control inputs. To achieve this, an observer is currently under development, which processes and utilizes the data obtained by various sources in the simulation model. A probability-based traffic simulation is used to extrapolate the estimated system state and is continuously updated and corrected by the incoming sensor data. The accuracy of the estimated system state of certain areas of the road network therefore depends on the availability of recent sensor data. Further details about the observer are subject for a future publication as soon as implementation and further tests are completed.

Based on these interactions with other system components, it is possible to formulate several requirements for the simulation model: The road network has to be selected and provided to the various system components. The vehicle dynamics must be modelled containing relevant functions like car-following-models or lane-change-models. Also, the behaviour of the different vehicle types has to be specified, especially the behaviour of autonomous vehicles. This includes means to set the desired target velocities and routes. TLS must be integrated in the road network and the respective controllers must ensure that the given target phases are applied in a realistic way. Additionally, the sensors have to be modelled to generate the required data for the traffic observer. To test the system under realistic conditions the traffic demand must be determined and used to generate appropriate trips which in turn are the basis to calculate realistic initial routes for the vehicles in the simulation. In the following section, the simulation model is described in detail.

4 MODELLING PROCESS

In this section, the simulation environment and its relevant components are addressed and discussed, beginning with the selection of the road network and the model basics. Subsequently, the modelling of the traffic infrastructure is presented and followed by the method used for traffic demand generation. The simulation environment is built on the traffic simulation software *SUMO* which is an open-source tool maintained mainly by the German Aerospace Center. It is based on a microscopic traffic model and includes several sub-models e. g., for lane-changing, car-following behaviour or the reaction of the drivers to TLS. Therefore, it provides a suitable and extendable base to meet the requirements listed above. The system components rely on multiple data

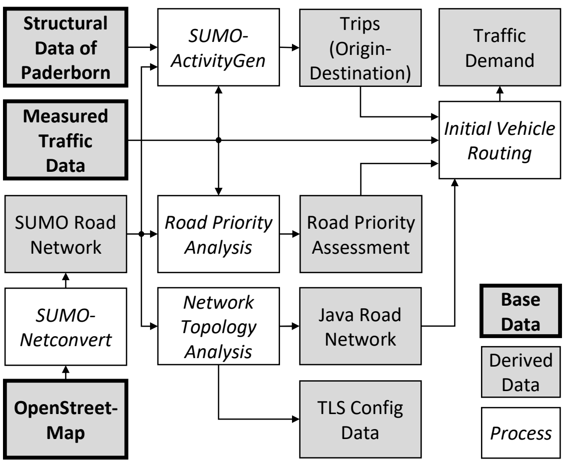

Figure 2: Data processing for the simulation model.

sets to perform their respective tasks. An overview over the processes needed to generate these data sets is depicted in figure 2 and will be referred to in the following sections.

4.1 Traffic Infrastructure

4.1.1 Road Network

The simulation model is based on a real-world traffic environment to demonstrate the applicability of the control system to existing road networks. The city of Paderborn, Germany, and parts of the surrounding area (see figure 3) serve as a template for the model. It includes over 960 km of roads (counting both directions separately) and consists of a wide variety of road types, from an Autobahn (highway) to residential streets. Also, there are 137 TLS in the network which are also considered for the simulation. Some roads are exclusively for public transportation and authorities.

The foundation of the road network was imported from *OpenStreetMap (OSM)* using the import tool *Netconvert* provided by the *SUMO* toolkit. Although it provides a useful basis for the model it is far from being directly deployable for simulation and requires extensive manual corrections to compensate for incorrect data. This especially applies to junctions and the correct definition of the lane connections indicating which target lanes can be reached from which origin lanes.

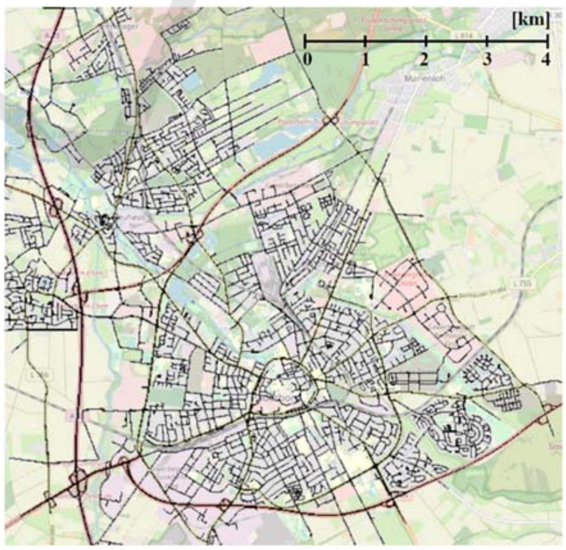

Figure 3: Extract of the selected road network of the city of Paderborn over the corresponding *OSM*-map layer (OpenStreetMap contributors, 2022).

In order to provide topological network information to the components of the system (i. e., the observer and the controller), a tool was developed to analyse the resulting *SUMO* road network file and to create a corresponding graph-representation. This includes the identification of areas of influence (e. g., for TLS based on the distance to them) as well as the identification of parallel and counter-directional roads since these are relevant for the control system design. Another field of application for topological network information is to integrate the TLS, which is described below.

4.1.2 Road Priority Assessment

The road network encompassed by the simulation model has an extensive expanse, however many roads lead through residential areas, the town centre, industrial areas, or other regions which are not intended to be a central vein of transportation. Especially for the routing-based control system it is important to consider this since extensive routing through these areas might cause problems or discontent among the residents. The importance of a road is represented by *OSM* in a priority class which is based on its role (e. g., highway, federal road), the number of lanes, etc.

On the other hand, it is important to identify which roads are most valuable for the traffic system due to the location or connections to other roads. A mean to incorporate this is to introduce a numerical priority rating for each road section as a combination of several criteria. An established method to rate the importance of a node in a graph is the *Betweenness-Centrality*. It is an indicator of how often a given node is part of the least costly connection between any two nodes in the graphs. To apply this to the road network, it is converted to a line graph that allocates a node to each road. The connecting edges are created based on the reachable follow-up roads at each junction. The cost associated with each edge is set using two different attributes of the roads. This leads to two independent graphs: One weighed with the length of the respective roads and the other with the free travel time on them (i. e., the length divided by the speed limit). These attributes were selected because both play an important role for drivers' route decisions and should therefore both be regarded. Consequently, the *Betweenness Centrality* is calculated for both cases.

To combine the priority rating $r_{prio,\tau}$ for road τ from *OSM* with the values obtained by the graph analysis using *Betweenness Centralities* based on distance and travel time $(r_{BD,\tau}, r_{BT,\tau})$, an optimisation problem is formulated. The goal is to find the weighting $w \in \mathbb{R}^3$ for the different rating approaches that minimizes the quadratic deviation between a linear combination of the ratings and actual traffic data v_τ for n measurement locations available in Paderborn with

$$w = \underset{w \in \mathbb{R}^3}{\operatorname{argmin}} \sum_{\tau=1}^{n} \left(v_\tau - \begin{bmatrix} r_{BD,\tau} \\ r_{BT,\tau} \\ r_{prio,\tau} \end{bmatrix}^T \cdot w \right)^2 . \quad (1)$$

In Paderborn, these measurements were acquired by a traffic count from 2018 and include the vehicles detected per day at about 300 locations within the network. The resulting weighting w is used to calculate a single value in the range 0 to 1.

4.1.3 Traffic Light Systems

As stated above, TLS are a key part of urban traffic environments since they exert an immediate influence on the traffic flows. *SUMO* supports the integration of TLS and the simulated traffic participants abide to the signal lights. However, it is up to the user to ensure that the TLS behave as expected. This is not limited to the selection of the TLS-phases (which is the responsibility of the control system) but also to the way they are implemented, e. g., regard the minimum green durations and transition times and avoid incompatible signal combinations. Depending on the junction's geometry and the desired phase transitions these details can have a significant impact on the transition times and therefore should not be neglected. To ensure that TLS in the simulation comply with, the official guidelines for TLS in Germany, *RiLSA* (RiLSA, 2015), a controller was developed that commands the signal lights based on the current TLS state and the desired target phase. It ensures the adherence to the yellow signal change time, the minimum green time and red clearance for conflicting signals. The basics of the underlying controller logic applied to each signal of a TLS are depicted in figure 4.

Each TLS-signal may control multiple lanes, but a lane is not limited to a single signal. E. g., a right-turning lane can be released by the 'main' green light or by a right-arrow green signal provided it has no dedicated red light. Depending on the current state of each signal and the selected target phase, a series of checks is performed to decide whether a state transition is permitted or must be postponed. This might even result in an active signal to be turned to red temporarily in order to allow a dependent signal to switch to green. The mutual relationships and dependencies of the signals depend on the geometry and conflict areas of the intersection. Lanes with no conflicting points and active signals can be controlled independently. They impose no restrictions for the controlling signals while lanes from a crossing street must not receive green if there are any conflicting areas.

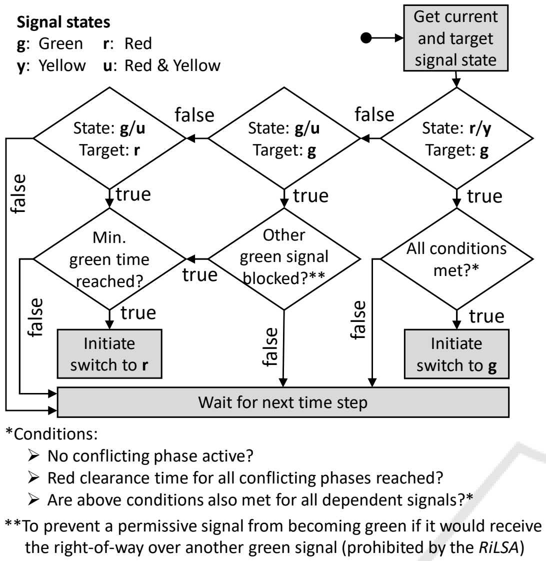

Figure 4: TLS controller logic (Malena et al., 2022).

An automated analyses is performed for each junction comprising TLS which generates plausible datasets to setup the simulation and the controller based on geometrical features. Depending on the incoming and outgoing lanes and the connections between them, a TLS setup is selected, and matching signals and phases are generated. Also, restrictions like minimum green times and transition times are set based on that. For TLS with unusual setups or to incorporate actual phase plans the configuration datasets can be adjusted manually to ensure a realistic behaviour.

4.1.4 Traffic Sensors

In a real-world scenario, the sensors are a vital part of the traffic control system since they are the only source of information about the current traffic state. To test the developed system under realistic conditions, it is therefore required that suitable data packages are generated by 'virtual' sensors based on the known system state of the simulation model. In this research, there are five different sources of information modelled. They vary in terms of the provided data as well as the time at which the data is shared. The sensor types with the corresponding information they provide are listed in table 1.

Table 1: Simulated sensors and their provided information.

Data Source	Transmitted Information
Car2X-equipped vehicles	- Own position - Own velocity - Own route (if available) - Own vehicle type
Autonomous vehicles	- All Car2X-vehicles' data above - Nearby vehicles' positions - Nearby vehicles' velocities - Nearby vehicles' types
Induction Loops	- Time of detections - Current occupation status
Radar Detectors	- Time of detections - Detected vehicles' velocities - Detected vehicles' types
Aggregated data sources	- Average traffic density over a given time span (delayed)

Induction loops are placed at the stopping lines of each incoming lane at a TLS. Furthermore, for TLS containing multiple lanes per direction, additional induction loops are set up to 40 meters ahead of the junction, as this is a common setup in Paderborn. Induction loops are prone to errors especially if crossed by small vehicles which do not inflict a huge impact on the inductivity of the sensor. To model this, a vehicle type-dependant probability is defined to determine if the crossing of a road user is actually registered by the sensor. Radar detectors are also stationary and placed manually on the road network. They are intended to augment the data collection efforts on road sections which do not feature induction loops but exhibit a sufficiently high traffic volume that would justify an installation of such a device. Radar detectors provide more reliable measurements than induction loops. Also, they are able to gather additional information like the crossing vehicles' velocities and vehicle types (which is also affected by a type-dependent misclassification probability). To generate the sensor data packages, the set $L_{z,k}$ containing all vehicles i on lane z at the current time step k is considered. For each vehicle being on the lane for one of consecutive time steps, i. e., $i \in L_{z,k} \cup L_{z,k-1}$, the following cases are checked using the vehicles' positions $x_{i,k}$ on their respective lane and the positions p_z of the lanes' respective sensors:

$$\begin{gathered}(i \in L_{z,k}) \wedge (x_{i,k} \geq p_z) \wedge (i \notin L_{z,k-1}) \\ (i \in L_{z,k}) \wedge (x_{i,k} \geq p_z) \wedge (x_{i,k-1} < p_z) \\ (i \in L_{z,k-1}) \wedge (x_{i,k-1} < p_z) \wedge (i \notin L_{z,k}).\end{gathered} \tag{2}$$

If any of the three conditions apply, a sensor crossing was determined. Consequently, the corresponding data is read from the known true simulation state and modified based on the misdetection and misclassification probabilities according to the type of sensor. The data package is provided to the traffic control system without additional delay since the transmission time is neglectable compared to the simulation step size ($\Delta t = 1\ s$) when using a suitable transmission protocol.

Due to the usage of Car2X communication technology by some traffic participants, these can be utilized as moving data sources. It is assumed that they share their current position, velocity, and the route they are on, if set. Additionally, autonomous vehicles provide information which they gather from their environment. Thus, the position, velocity and type of nearby vehicles are transmitted as well. Especially at junctions this can concern vehicles on multiple lanes, therefore a comparison of the state of the current lane is not sufficient. To preselect the vehicles which might be in range of autonomous cars, the road network is divided into a grid with several 100m-by-100m fields. Each vehicle is allocated to the corresponding field using its coordinates once per time step. Thus, to determine the nearby vehicles it is sufficient to check the distance to the vehicles in the current grid-field and all neighbouring fields. This reduces the number of checks to be performed significantly. Similar to the stationary sensors it is assumed that the data packages from Car2X-equipped vehicles are gathered each time step with no additional delay.

The final method to get information about the traffic are sources that aggregate data using different sensors before sharing it. These do not provide data of individual vehicles but instead estimate the traffic density on road segments of the network. Data like this can be gathered by using cell phone information e. g., via navigation apps or detecting and counting nearby Bluetooth devices. The aggregated data is not available in real-time but can still be important for a traffic control system, especially for routing purposes and areas of the network without a great sensor coverage. While the collection methods are not modelled in detail, the aggregated traffic density over a certain time period is modelled using a moving average of the vehicle count for each lane and delaying it further.

4.2 Traffic Demand

The fixed road infrastructure and the sensor systems are the base of the simulation model. However, to perform simulations the traffic itself has to be modelled as well. This includes the definition of the vehicle types and their respective behaviour as well as the generation of the traffic demand to fill the road network in a plausible way.

In the *SUMO* traffic simulation eight different vehicle types are used, e. g. passenger-cars or busses. Additionally, there are autonomous variants of most of the types. For human-driven vehicle types the parameters are configured to randomly deviate from an ‘ideal’ driving behaviour. This may result in divergences from the speed limits, not keeping a sufficient distance to the preceding vehicle, or an impatient behaviour at junctions regarding the right-of-way. For autonomous vehicles these deviations are disabled since a computer-driven car would not deliberately violate the traffic rules and cannot be distracted. Moreover, autonomous vehicles can be controlled by the traffic control system to some degree.

4.2.1 Trip Generation

The goal of the traffic generation is not to recreate the exact traffic which is present in Paderborn on a given day (this would require to monitor each traffic participant individually), but to create a plausible traffic situation that resembles the real traffic. The first step is to generate the trips that are to be carried out during the simulation. A trip defines the origin and the destination a vehicles’ route has to connect as well as the departure time. Therefore, the entirety of all trips represents the demand for mobility in the network without prescribing how it is realized. The (initial) routes the vehicles should take are determined in a subsequent step (see section 4.2.3). *SUMO* already includes the application *Activitygen* to generate trips based on a given road network and additional information about the environment which must be provided externally. These include statistical data about the population in Paderborn, like population count, demographics, employment rate, car ownership rate, etc. Also, information about the number of incoming and outgoing commuters as well as an approximate distribution of the usual working hours are given. This information was mainly obtained by publicly available data published by the City of Paderborn.

Furthermore, information directly related to the road network was provided that includes the position and size of schools in the regarded area, since they are a common destination for many trips at certain times of the day. Also, the main roads leading in and out of the road network were specified including the number of vehicles traveling on them each day. For most of the relevant roads this information could be obtained from the traffic count mentioned above. The traffic which is generated from and to a certain road is dependent on the number of residents that live there, and the number of workplaces located nearby. This is not uniform for all roads and can vary significantly depending on the location. As there are more than 40,000 road sections in the road network, a manual setting is not practical, and an alternative method was used.

To more efficiently allocate numerical values to the different road edges an image-based method was developed. It uses the RGB colour channels of a new layer which is added to the map displayed in figure 3 to encode the required information. Consequently, areas on the map can be marked according to their position and function with different colour intensities. A transformation function is used to map each network coordinate to the corresponding pixel of the image. Thus, for each road edge a central coordinate is determined, the corresponding pixel is selected, and the respective value is read based on the red component of its RGB value using a conversion factor. Note that this is a relative value and the total number of workers and inhabitants to be allocated is calculated based on the statistical data mentioned above. Since there is no data available for Paderborn that shows the population density or the density of workplaces in the level of geographical detail required, the areas on the map are marked based on their urban development and function. Residential areas receive a higher-than-average rating for the number of inhabitants while exhibiting only a limited number of workplaces. For industrial areas on the other hand an inverse structure is defined, and the city centre exhibits high values in both regards. Using this input data *Activitygen* creates a set of trips which is subsequently used as basis for the routing algorithm presented in the next section to generate the actual initial traffic.

4.2.2 Routing

The routing process determines how the OD pairs defined in the trips are connected. Note that this initial routing is performed for all generated trips, however the planned control system can allocate new routes for autonomous vehicles and cooperating Car2X-equiped vehicles online once it is integrated. The routing can be done by representing the road network as a graph and applying a pathfinding algorithm. Unlike the line graph used in the road priority analysis, here the junctions are represented by the nodes and the roads are modelled by the edges. This enables a direct connection between the cost and the associated attributes of the roads. However, a simple distance or time-based allocation would be unsuitable here, because in a road network the shortest way might lead through the city core or residential areas which is not desirable. Also, such a method would not consider the actions of other road users and could lead to smaller roads experiencing more demand than they could handle while better developed roads might not use their full capacity during critical traffic situations. In addition, a traffic scenario shall be simulated that resembles the real traffic situation in Paderborn, which therefore must be taken into account during the routing process. Based on these considerations, the usage costs for each edge i comprise of three cost components and are recalculated for each trip:

1. Expected travel time ($J_{TT,i}(n)$)
2. Road priority assessment ($J_{pri,i}$)
3. Real traffic data ($J_{m,i}(n)$)

The vector n contains the number of routes that includes the respective edge i and the vector r represents the weighting factors for the cost components. The resulting costs for crossing edge i are therefore:

$$J_i(n) = [J_{TT,i}(n) \quad J_{pri,i} \quad J_{m,i}(n)] \cdot r. \qquad (3)$$

The expected travel time is a major influencing factor for drivers' routing decisions and must be considered. It can be estimated using the length l_i of the considered road section and the expected travel speed on it. Under ideal circumstances (no other traffic present) this is equal to the speed limit $v_{max,i}$ on this road. With increasing traffic demand n_i on this road the expected speed decreases which is modelled by the monotonously falling function $f(n_i) \in (0,1]$ and leads to

$$J_{TT,i}(n) = l_i \cdot \left(v_{max,i} \cdot f(n_i)\right)^{-1}. \qquad (4)$$

The second cost factor $J_{pri,i}$ is based on the results of the road priority assessment and depends on the importance of the road for the network. More important roads are associated with lower costs while lower rated roads result in higher costs. In this case, a linear relation to the priority value was selected.

In order to match the recreated traffic according to the real traffic measurements, a third cost factor $J_{m,i}(n)$ is introduced for roads with available measurement data. This factor adds additional costs to these roads if the current number of routes containing this road n_i exceeds the number of vehicles $n_{m,i}$ recorded by the measurements. Since the latter value refers to a whole day of measurements, it is corrected by the share of all allocated routes related to the number of all recorded vehicle crossings on all observed roads resulting in

$$J_{m,i}(n) = \max\left(0, n_i - n_{m,i}\frac{\sum_j n_j}{\sum_j n_{m,j}}\right). \quad (5)$$

The total costs for a route are calculated by adding up the costs $J_i(n)$ of all contained edges i. To estimate the best route between the given origin and destination of a trip Dijkstra's algorithm is applied to the graph which is guaranteed to find the connection with the lowest associated costs. As the initial routing is performed prior to the actual traffic simulation there is no need to use a faster but less reliable algorithm. Also, the order in which the trips are processed is selected randomly and not chronologically by their departure time which is intended to further diversify the routes connecting different parts of the road network. This way alternative route options for similar connections are possible from early on and not after a certain simulation time to reach the threshold to switch to another route option (e. g., when the estimated traveling time-related cost increases for a road section due to the increased number of routes).

In figure 5, the number of allocated routes for each road section is depicted on the left side. To better illustrate the differences on lower frequented roads a logarithmic colour coding was used. Generally, it can be seen that Paderborn's main roads have a greater number of routes allocated to them while roads in residential areas or the city centre exhibit much less demand, which is realistic. To compare the accordance of the generated routes to the measurement data, at each available measurement location the share of realized detections it calculated ($n_i/n_{m,i}$). The average share for all sensor locations equals to 100,3% with a variance of 7,3%. An overview over the deviations of the number of routed vehicles from the measured data is depicted on the right side of figure 5. The number of detected and routed vehicles at the sensor positions are generally similar although locally the number can deviate slightly in both directions. A reason for that might be that not all features of the road network could be modelled for the *Activitygen* application, e. g., companies with many employees outside dedicated industrial areas or shopping centres which would have exceeded the limits of this research.

To show the temporal distribution of the traffic demand, figure 6 includes the cumulated detection rates at multiple sensor locations. This is compared to the cumulated crossing rates resulting from the generated routes at these positions. There is a good accordance between both datasets. Both, the morning and afternoon rush hours are clearly visible and the values generally match. Slight deviations e. g. at 3:00 and 17:00 are most likely caused by the probability-based approach for trip generation. Note, that all crossings registered for a route are allocated to its departure time on the horizontal axis which explains the small offset e. g. at 7:00.

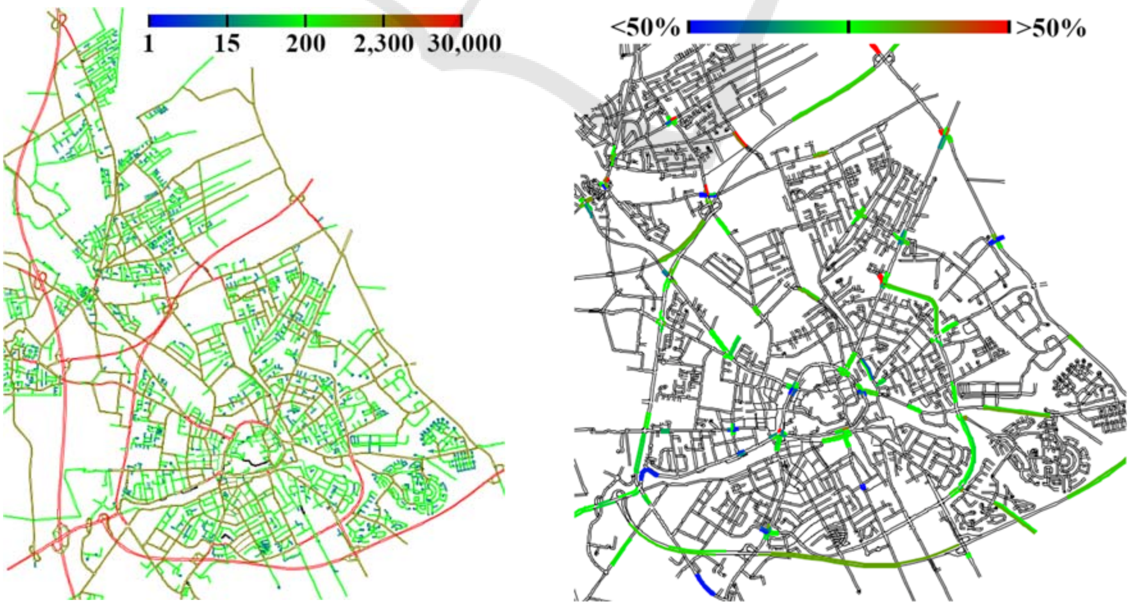

Figure 5: Left: Number of routes for each road section (logarithmic) / Right: Deviation routes count from measurements.

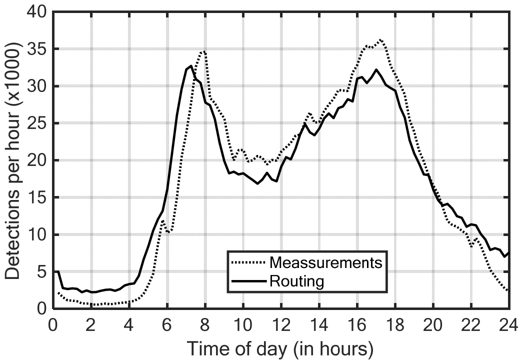

Figure 6: Comparison of the measured detection rates and the generated routes for a whole day at 54 locations.

5 CONCLUSION

In this paper, the modelling of a simulation environment based on the city of Paderborn for a future traffic scenario was presented. The simulation model is built on the software *SUMO* which handles the basic vehicle dynamics and is extended by multiple components. The road network was imported from *OSM*, revised manually, analysed, and converted to a graph representation. Based on that, a road priority analysis is preformed using different metrics as well as real traffic data in order to rate the different road sections' importance for the whole system. The results are used in the routing process and are also useful for the traffic control system currently in development. To accurately reproduce the influence of TLS and ensure that they obey the guidelines and restrictions of the *RiLSA*, a controller was designed to implement a given target phase selected by the control system. Using geometrical features of the road network, signals, phases, and additional configuration data were generated automatically for the TLS. Also, different sensor types were modelled which support both, stationary and mobile data collection in order to provide realistic information to a traffic observer system. To populate the simulated roads, multiple vehicle types were created for human-driven and autonomous vehicles. Based on the road network, statistical and structural data of Paderborn, trips were generated containing the desired origin and destination as well as the departure times of vehicles in the system. Finally, to create realistic routes, a pathfinding method utilizing a dynamic cost estimation method was applied.

The next step is the integration of the mentioned traffic observer to reconstruct a picture of the current traffic state based on the gathered sensor data. An observer is currently under development and relies on a probability-based approach to describe the vehicles' positions. Key of such a system is the handling of uncertainty due to incomplete sensor coverage and a realistic extrapolation of the vehicles' behaviour. An in-detail description and evaluation of this system will be subject for a future publication. Also, the development and integration of the traffic control system is due for the future.

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