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Analysis and modelling of road traffic using SUMO to optimize the arrival time of emergency vehicles

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Abstract: Traffic simulation tools are used by city planners and traffic professionals over the years for modelling and analysis of existing and future infrastructural or policy implementations. There are numerous studies on emergency vehicle (EV) prioritization in cities all over the world, but every area is unique and requires the data collection and simulation to be done separately. In this case, the focus area is the Mörfelder Landstraße in Frankfurt am Main, Germany, one of the busiest streets in this city. The study illustrates demand modelling, simulation and evaluation of a traffic improvement strategy for EVs. Vehicular traffic such as passenger cars and trams are simulated microscopically. To perform accurate traffic simulation, input data quality assurance and cleansing of Master Data is required. Therefore, the data is adapted to reproduce the real-world scenario and transformed into the readable format for the simulation model. Vehicular demand is calibrated by traffic count data provided by the Frankfurt Traffic Department. To model road traffic and road network, origin destination matrices using the Gravity Mathematical Model and Open Street Maps are generated, respectively. This process is time-consuming and requires effort. However, this process is critical to get realistic results. In the next step, the road traffic is simulated using SUMO (Simulation of Urban mobility). Finally, EV relevant key performance indicators (KPIs): total trip time and total delay time are derived from simulations. The real-world scenario is compared with five alternative scenarios. The comparison of the KPIs revealed that the real-world scenario results in longer travel times compared to the EV-prioritization scenario. In the least case, the overall travel times for EV has decreased significantly and, as we know, in the case of EVs, even a few seconds saved could prove crucial for a person in need.

Keywords: Demand Modelling, Origin Destination Matrices, Simulation, Emergency Vehicles, Traffic Improvement Strategy

1 Introduction

In the 21st century, high rate of urbanisation and the advancement in the transport sector has led to an increase in urban vehicular mobility. This resulted in people opting for a comfortable and luxurious life. But on the other hand, it has also negatively impacted the quality of life by increasing the potential for traffic problems such as traffic congestion, accidents, environmental issues for example, increase in greenhouse gases, carbon emission, particulate matter etc. To combat these problems traffic improvement strategies such as car pool lanes, public transport bus lanes, dedicated space for cyclists and pedestrians, to name some, are adopted. Testing and implementation of such strategies require prior investigation and analysis. Without these studies, the implemented strategies or policies could be unreliable and might end up costing even more in terms of infrastructure, time and in some cases even human life. To have a theoretical evaluation and predict the outcome of these strategies, traffic simulation plays a vital role.

For traffic simulation to be implemented properly numerous elements are needed but the following are the most important ones [1]:

- Network data such as roads, footpaths, tram routes
- Additional traffic infrastructure such as traffic lights, induction loops
- Traffic demand
- Traffic constraints e.g. speed limits, construction sites, bus lanes.

It is time consuming and requires effort to prepare a traffic simulation model using these elements. Therefore, many simulation tools provide ready to use simulation models so that the user can directly test their traffic improvement strategies and saves time and effort required for simulation [2].

One of the main motive of traffic simulation is to evaluate different traffic improvement strategies. This study shows another traffic improvement strategy based on emergency vehicles. *"An emergency vehicle is a vehicle that is used by emergency services to respond to an incident"* [3]. Even a small reduction in the arrival time of EVs (fire brigade, ambulance or police) can save lives of the people who need immediate assistance. To tackle such situations EVs have special rights such as violating red lights when approaching a traffic light junction (TLJ) or traveling in the opposite direction to reduce the arrival time. But this approach is not a full proof approach to optimize the arrival time. As, there are times when EVs are stuck in a long queue of vehicles in front of the TLJ or are stuck in a traffic congestion where there is no way to overtake.

The main objective of the study is to simulate the road traffic of the Mörfelder Landstraße in the Sachsenhausen area, Frankfurt am Main, Germany, followed by studying and evaluating different scenarios to optimise the arrival time of emergency vehicle which could help in combating the aforementioned situations.

This paper is structured as follows: Section 2 discusses in details about the master data, demand modelling and simulation process by elaborating on data pre-processing, network modification and traffic generation. Section 3 explains solution methodology, different case scenarios for EVs. Section 4 shows the result obtained from the case scenarios. Section 5 presents the conclusion and future work.

2 Master Data, Demand Modelling and Simulation

The data flow diagram based on Gane-Sarson methodology is shown in Figure 1. Master Data consists of the road network (supplemented with additional infrastructure and traffic constraints) and the aggregated vehicle count for 24 hours. The vehicular counts are provided in the form of shape file for the geographical location of the Sachsenhausen area in Frankfurt am Main and the road network is imported from Open Street Map [4].

A methodology named as Gravity Model [5] is used for calculating Origin Destination Matrices (ODMs). It is based on the principle of gravitation theory of Newtonian physics. With reference to the traffic planning, the Gravity Model theory states in [5] that: "the number of trips between two Traffic Assignment Zones (TAZ) will be directly

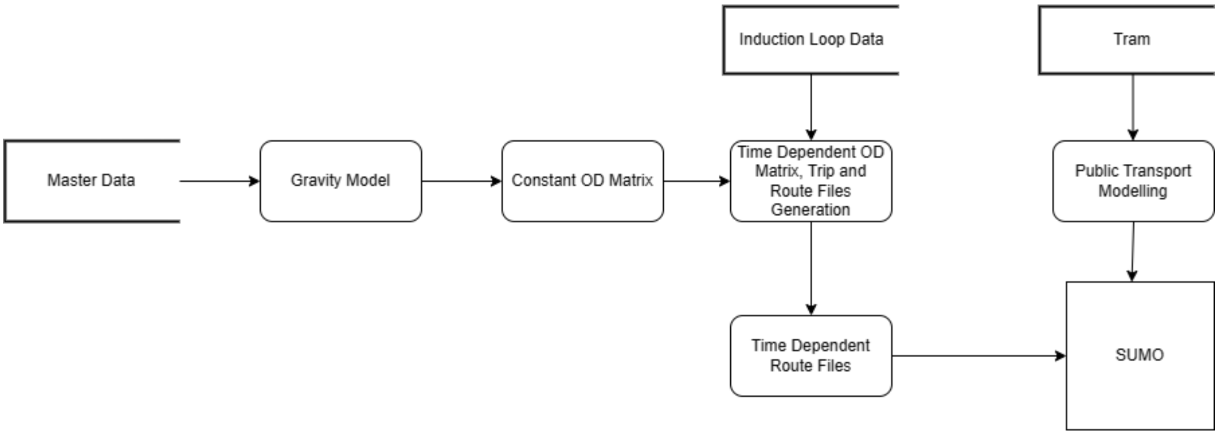

Figure 1. Data Flow Diagram, whereas Master Data comprises of additional infrastructure and traffic constraints

proportional to the number of productions in the production zone and attractions in the attraction zone. In addition, the number of interchanges will be inversely proportional to the spatial separation between the zones."

Mathematically, the Gravity Model is defined as [5]:

$$T_{ij} = P_i \left[\frac{A_j F_{ij} K_{ij}}{\sum_{k=1}^{n} A_k F_{ik} K_{ik}} \right], \tag{1}$$

with T_{ij}: number of trips from zone i to zone j, P_i: number of trips produced by zone i, A_j: number of trips attracted by zone j, F_{ij}: friction factor relating the spatial separation between zone i and zone j, K_{ij}: optional trip-distribution adjustment factor for interchanges between zone i and zone j, n: the number of zones.

The initial values of P_i and A_j are considered from the vehicular counts provided in the form of a shape file. The friction factor and trip distribution adjustment factor are not considered in this study as the only available data is traffic counts. Therefore, equation mentioned below is used for calculating the trip distribution:

$$T_{ij} = P_i \left[\frac{A_j}{\sum_{k=1}^{n} A_k} \right]. \tag{2}$$

Before applying this methodology, there are two assumptions made regarding the road network: First, the number of cars occupying the parking space and freeing the parking space are equal as in reality the difference is negligible compared to the normal traffic. Therefore it is not taken into consideration. The second assumption is that there is no generation or elimination of cars within the TAZ (conservative network). Additionally, the total number of cars generated at the entry points of the TAZ should be equal to the total number of cars eliminated at the destination points of the TAZ. This is known as "the closing condition at the edge" [6], also shown in equation 3:

$$\sum_{i=1}^{n} P_i = \sum_{j=1}^{n} A_j, \tag{3}$$

with P_i: number of trips produced by zone i, A_j: number of trips attracted by zone j, n: the number of zones [6].

If this closing condition is not met, which is shown in equation 3 then the balancing process is performed using equations 4 and 5. This process is adopted from [5] and is divided into two steps. Firstly, the balancing factor is calculated using equation 4. Secondly, the number of trips attracted by each zone is multiplied by this balancing factor calculated in step 1 to attain balanced number of trips attracted by each zones, shown in equation 5 and this leads to the fulfillment of equation 3:

$$Factor = \frac{\sum_{i=1}^{n} P_i}{\sum_{j=1}^{n} A_j}, \tag{4}$$

with $Factor$: balancing factor, P_i: number of trips produced by zone i, A_j: number of trips attracted by zone j and

$$A_j^{'} = Factor * A_j, \tag{5}$$

with $A_j^{'}$: balanced number of trips attracted by zone j.

Once the closing condition is met, the trip distribution matrix is generated using equation 2. The matrix balancing approach [6],[5] is carried out to ensure that the expected number of trips produced is equal to the calculated number of trips produced for all the zones. Similarly, the expected number of trips attracted is equal to the calculated number of trips attracted for all the zones. This is shown in equation 6 and 7. This is an iterative process, and it iterates until the calculated production and attraction is equal to the expected production and attraction i.e. $Factor_{Aj}$ and $Factor_{Pi}$ converges to 1. This process is implemented using a python script:

$$Factor_{Aj} = \frac{Given_{Aj}}{Total_{Aj}}, Factor_{Pi} = \frac{Given_{Pi}}{Total_{Pi}}, \tag{6}$$

with $Given_{Aj}$: expected number of trips attracted by zone j, $Total_{Aj}$: calculated number of trips attracted by zone j, $Given_{Pi}$: expected number of trips produced by zone i, $Total_{Pi}$: calculated number of trips produced by zone i and

$$D_{ij}^{'} = Factor_{Aj} * Factor_{Pi} * D_{ij}, \tag{7}$$

with D_{ij}: trip interchange calculated for each entry/exit zone.

Due to the numerical reasons, equation 6 and 7 do not converges to 1. To solve this issue, a heuristic approach is used where the study area is divided into 3 parts. This leads to the creation of 3 constant ODM. Hence section based demand modelling is performed. The study area for demand modelling is Mörfelder Landstraße. This stretch is around 3.3 km long, also highlighted in the Figure 2. A total of 21 entry/exit zones are present in the study area marked in red in Figure 2.

The calculated constant ODMs consist of aggregated count for 24 hours. Then the distribution of the counts over the period of 24 hours is done with the help of induction loop data. This data contains counts from June 2020 till March 2021 and each of this count is split with the time interval of 15 minutes starting from 00:00 until 23:57. With the combination of induction loop data and SUMO functionalities such as od2trips and duarouter, time dependent ODMs based route files are created. This acts as the input to SUMO to simulate the road traffic. In addition to the simulation of passenger cars, trams are also modelled with safety traffic lights at the tram stops. They are simulated using public transport model provided by SUMO. The frequency for the trams are set to every 10 minutes.

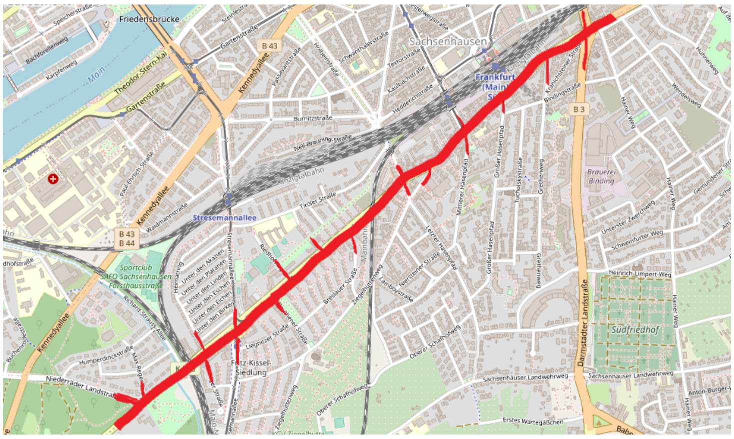

Figure 2. Study Area - Demand Modelling

3 Solution Methodology, Case Scenarios and Study Area

3.1 Solution Methodology

There are many studies carried out to optimize the arrival time of EVs such as optimization in routing and dispatching of EV which can led to faster routes for EV [7], ranking of alternatives for emergency routing [8]. However, behaviour of pedestrians, especially children is unpredictable, and even though SUMO can be used to model such patterns, but in the real world it does not function exactly in the simulation. In the case of re-routing an EV, the algorithm prioritizes the shortest route which is free of traffic. But the shortest route could include residential areas that consist of more foot traffic as compared to main streets. Thus, the preferred approach in this study is EV prioritization approach using V2X (Vehicle to Infrastructure) communication with TLJ. This approach is adopted from [9],[10],[11]. The basic approach is that as soon as the EV arrives at TLJ, traffic light is switched to green for the direction of EV trip and prioritizes the EV[9],[10],[11].

The following steps are performed for the EV prioritization application which is also known as the WALABI approach[9]:

- EV sends CAMs (Cooperative Awareness Messages) and route information
- Road side unit informs Traffic Management Center (TMC)
- TMC sets traffic lights on the route of the EV: green for the EV and red for all other traffic participants
- After the EV has passed the intersection normal operation continues.

For the aforementioned EV prioritization approach, the question arises what should be the optimal distance between an EV and the traffic light so that the traffic light should turn green. The study [10] shows that the EV is usually within the range of 300 meters from the TLJ and when EV enters this range, the traffic light is turned to green and when EV passes the TLJ the traffic light switches back to normal. Therefore 300 meters is considered as a threshold distance value for scenario 2 which is discussed in section 3.3.

There is a negative consequence of having this predefined value that is for the other vehicles who are waiting in front of the red signal. If the red phase on the traffic light increases then traffic congestion on the other side may also increase leading to more chaos and more time to diffuse the traffic congestion. Therefore to solve this issue, instead of taking a predefined value, it is calculated dynamically (dynamically calculating threshold distance). This threshold distance is calculated using the speed of the EV and the number of vehicles waiting in front of TLJ shown in equation (8) and (9). This approach is adopted from the study in [9]:

$$T_{free} = (N_{waiting} + 1) * t_B + t_{safety}, \tag{8}$$

with T_{free}: time which is needed to let the EV pass the traffic light, $N_{waiting}$: number of vehicles waiting in front of TLJ, t_{safety}: safety time which is 3 seconds, t_B: time required for one vehicle to pass the intersection which is 1.8 sec and

$$d = T_{free} * V_{EV}, \tag{9}$$

with d: distance of the EV to the intersection, V_{EV}: speed of the EV.

3.2 Emergency Vehicle Prioritization Study Area

The highlighted path shown in the Figure 3 is the route of EVs whose behaviour is evaluated in the simulations. The route length is approximately 1.5 km consisting of 3 major and 2 minor junctions of the Mörfelder Landstraße which are mentioned in Table 1.

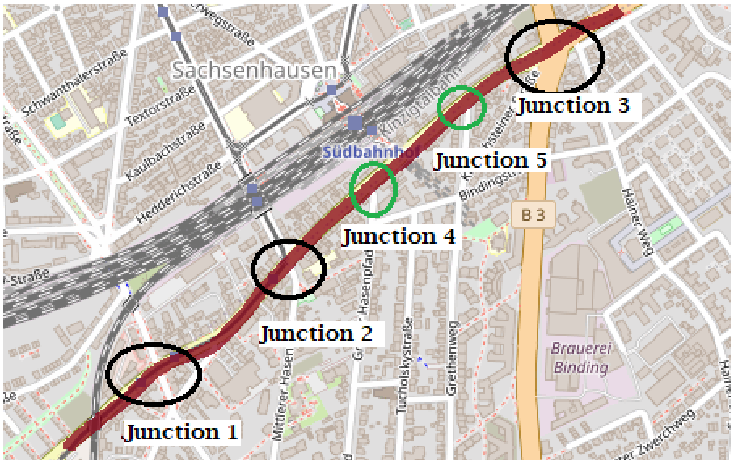

Figure 3. EV Study Area [4]

Table 1. Junction Details

Junction ID	Junction Name
Junction 1	Oppenheimer Landstraße and Mörfelder Landstraße junction
Junction 2	Schweizer Straße and Mörfelder Landstraße junction
Junction 3	Darmstädter Landstraße and Mörfelder Landstraße junction
Junction 4	Großer Hasenpfad and Mörfelder Landstraße junction
Junction 5	Grethenweg and Mörfelder Landstraße junction

3.3 Case Sceanrio

For each of the three scenarios which are considered for studying the behaviour for EVs, there are two cases considered. One is the usual traffic condition and other is the closed lane based on the assumption that only one lane stays available and all others are closed due to construction/incident reasons or by prioritizing these lanes for non car traffic. Hence making up a total of six scenarios.

1. Scenario 1: No-Priority for EVs i.e EV runs with their special rights such as violating red lights - Usual Traffic Condition (all available lanes are open)
2. Scenario 2: EV prioritization where prioritization starts at a pre defined distance i.e. 300 meters - Usual Traffic Condition (all available lanes are open)
3. Scenario 3: EV prioritization where prioritization starts at a dynamically calculating distance at run-time - Usual Traffic Condition (all available lanes are open)
4. Scenario 4: No-Priority for EVs i.e EV runs with their special rights such as violating red lights - Closed Lane (one or more closed lane present in the route of EV)
5. Scenario 5: EV prioritization where prioritization starts at a pre defined distance i.e. 300 meters - Closed Lane (one or more closed lane present in the route of EV)
6. Scenario 6: EV prioritization where prioritization starts at a dynamically calculating distance at run-time Closed Lane (one or more closed lane present in the route of EV).

In this study area, around 60% of the street has more than 1 lane. Figure 4 shows the setup of closed lanes where edges highlighted in red colour signifies that lanes are closed.

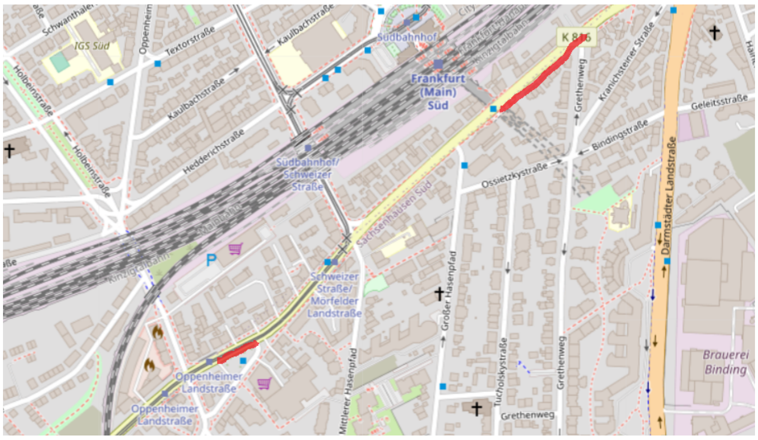

Figure 4. Closed Lane Setup [4]

To generate traffic in a realistic manner, induction loop data is used. This data of induction loops is cleaned, averaged out and normalised over the total number of cars which resulted in creation of traffic flow distribution over the course of the day. It is shown in Figure 5. The X axis represents the time of timeslice [hh:mm] and the Y axis represents the average rate normalised for the overall traffic per day. The maximum averaged, measured count per 3 minutes is observed around 8 am, which is 30 cars. It can be seen in the Figure 5 that the congestion in the morning from 7:00 am until 10:30 is the most on the street of the Mörfelder Landstraße and therefore that is the time range selected for testing the EV. A total of 10 EVs are run between this time range and their trip time and delay time are compared.

4 Results

This section explains the simulation results obtained for case scenarios discussed above. A total of 10 EVs (ambulances) are run. The departure time for each of these EV are 8:21, 8:36, 8:53, 9:06, 9:21, 9:35, 9:51, 10:06, 10:21 and 10:36 a.m. respec-

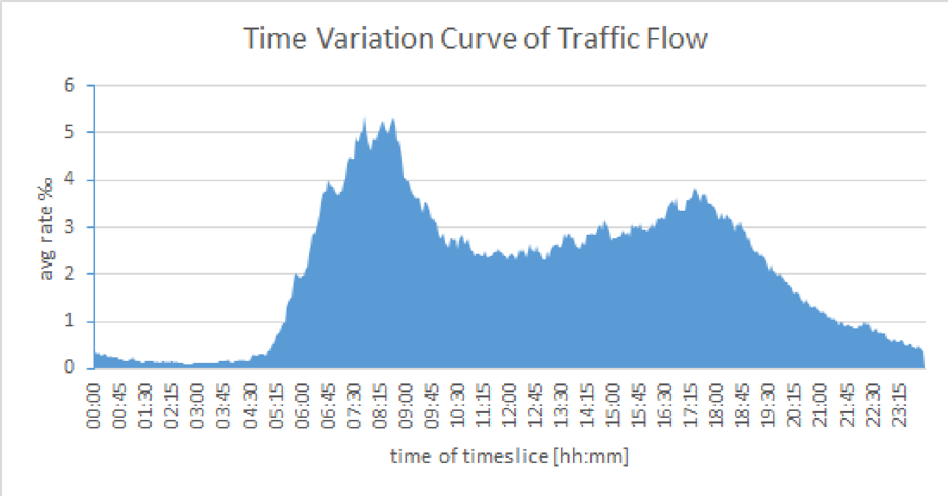

Figure 5. Traffic flow split of the 24 hour count for the Mörfelder Landstraße with timeslices of 3 minutes intervals

tively. The KPIs that have been considered are the total trip time (time required for the vehicle to finish the trip) and total delay time (time for which the vehicle travels below the ideal speed). For EVs, the speed is set 50% above the speed limit of the edge specified by the attribute ”speed factor” which is defined as 1.5 while configuring the EV in SUMO. This is adopted from the study [12].

4.1 Emergency Vehicle Behaviour - Normal Traffic Condition

Table 2 and 3 show the comparison of total trip time and total delay time for each of the EVs, where ”EV with No-Priority (Normal Traffic Condition)” scenario acts as the baseline reference for calculating the impact. For scenario 1, the trip time varies between 238 and 439 seconds. The average for scenario 1 is 315 seconds and empirical variance is 60.5 which is 19% of the average. This variance is almost the same for all other scenarios (20±3%). The first reason for this variance are the different traffic conditions such as traffic density. However, there are some specific events that have major impact on the trip time. In some simulations when a tram stops, the subsequent red traffic light led to a delay since the EV is not able to overtake the tram. This is also reflected in total delay time in Table 3 for e.g. ambulance with ID 6_Ambulance. For scenarios 2 and 3 the average trip time is 153 and 162 seconds respectively and average delay time is 82 and 91 seconds respectively.

Table 2. Normal Traffic Condition - Total Trip Time

Total Trip Time (seconds)	No Priority Scenario 1	With Priority Scenario 2	With Dynamic Priority Scenario 3
1_Ambulance	326	202(-38%)	210(-36%)
2_Ambulance	374	153(-59%)	122(-67%)
3_Ambulance	297	193(-35%)	216(-27%)
4_Ambulance	293	153(-48%)	146(-50%)
5_Ambulance	260	149(-43%)	163(-37%)
6_Ambulance	439	118(-73%)	141(-68%)
7_Ambulance	342	157(-54%)	181(-47%)
8_Ambulance	253	135(-47%)	131(-48%)
9_Ambulance	328	146(-55%)	155(-53%)
10_Ambulance	238	127(-47%)	152(-36%)

Table 3. Normal Traffic Condition - Total Delay Time

Total Delay Time (seconds)	No Priority Scenario 1	With Priority Scenario 2	With Dynamic Priority Scenario 3
1_Ambulance	255	131(-49%)	139(-46%)
2_Ambulance	303	82(-73%)	52(-83%)
3_Ambulance	226	123(-46%)	145(-36%)
4_Ambulance	222	82(-63%)	75(-66%)
5_Ambulance	195	78(-60%)	93(-53%)
6_Ambulance	368	48(-87%)	71(-81%)
7_Ambulance	272	86(-68%)	110(-59%)
8_Ambulance	182	64(-65%)	60(-67%)
9_Ambulance	258	75(-71%)	84(-67%)
10_Ambulance	167	56(-66%)	81(-52%)

4.2 Emergency Vehicle Behaviour - Closed Lane Scenario

Table 4 and 5 show the comparison of total trip time and total delay time for each of the EVs (Closed Lane), where "EV with No-Priority (Closed Lane)" scenario acts as the baseline reference for calculating the impact. For scenario 4, the trip time varies between 242 and 469 seconds. The average for scenario 4 is 344 seconds and empirical variance is 70.2 which is 20% of the average. The variances of the scenarios 4, 5 and 6 are almost the same as scenarios 1, 2 and 3 which is (20$\pm$3%). The reasons for the variances are the same like in section 4.1 but the occurrences of these special events happened in different time intervals. This is also reflected in total delay time in Table 5 for e.g. ambulance with ID 2_Ambulance. For scenarios 5 and 6 the average trip time is 183 and 191 seconds respectively and the average delay time is 112 and 117 seconds respectively.

Table 4. Closed Lane - Total Trip Time

Total Trip Time (seconds)	No Priority Scenario 4	With Priority Scenario 5	With Dynamic Priority Scenario 6
1_Ambulance	291	268(-8%)	225(-23%)
2_Ambulance	467	159(-66%)	182(-61%)
3_Ambulance	397	214(-46%)	230(-42%)
4_Ambulance	302	164(-46%)	178(-41%)
5_Ambulance	375	209(-44%)	238(-37%)
6_Ambulance	258	169(-34%)	190(-26%)
7_Ambulance	349	197(-44%)	206(-41%)
8_Ambulance	356	133(-63%)	153(-57%)
9_Ambulance	399	178(-55%)	146(-63%)
10_Ambulance	242	140(-42%)	157(-35%)

Table 5. Closed Lane - Total Delay Time

Total Delay Time (seconds)	No Priority Scenario 4	With Priority Scenario 5	With Dynamic Priority Scenario 6
1_Ambulance	220	197(-11%)	154(-30%)
2_Ambulance	396	88(-78%)	111(-72%)
3_Ambulance	326	144(-56%)	160(-51%)
4_Ambulance	231	93(-60%)	107(-54%)
5_Ambulance	305	138(-55%)	167(-45%)
6_Ambulance	187	98(-48%)	120(-36%)
7_Ambulance	278	126(-55%)	108(-61%)
8_Ambulance	285	63(-78%)	82(-71%)
9_Ambulance	328	107(-67%)	75(-77%)
10_Ambulance	171	69(-59%)	86(-50%)

4.3 Threshold Distance

In Scenario 2 and 5, the threshold distance is constant i.e. 300 meters. In contrast for scenario 3 and 6, the threshold distance is calculated using equation 8 and 9. Table 6 and 7 show this distance for all major junctions. The variance of these distances is due to the change in the number of vehicles waiting in front of the TLJs and the speed of the ambulance when entering the study area. The velocity used in these equations are derived from initial calculated speed of the ambulances after entering the study area. It ranges between 36 and 55 km/h.

Table 6. Normal Traffic - Dynamic Distance

Dynamic Distance (Normal Traffic)	Junction 1	Junction 2	Junction 3	Junction 4	Junction 5
1_Ambulance	263	201	97	222	118
2_Ambulance	87	253	182	111	134
3_Ambulance	139	230	139	121	67
4_Ambulance	211	156	432	101	239
5_Ambulance	334	236	358	138	65
6_Ambulance	394	179	340	179	72
7_Ambulance	397	261	451	126	72
8_Ambulance	196	60	60	105	60
9_Ambulance	276	250	457	146	69
10_Ambulance	83	218	240	105	60

Table 7. Closed Lane - Dynamic Distance

Dynamic Distance (Closed Lane)	Junction 1	Junction 2	Junction 3	Junction 4	Junction 5
1_Ambulance	261	119	47	47	47
2_Ambulance	312	232	526	152	178
3_Ambulance	220	91	188	91	91
4_Ambulance	375	101	348	101	320
5_Ambulance	231	183	207	111	64
6_Ambulance	369	142	142	67	92
7_Ambulance	397	126	208	181	72
8_Ambulance	118	65	100	47	136
9_Ambulance	258	71	205	71	98
10_Ambulance	117	179	283	76	76

4.4 Aggregated Results

Table 8 shows the average impact for EVs under ”Normal Traffic” condition where the number in parenthesis gives the average of the absolute impact and the percentage gives the average of the relative impact compared to the baseline reference. The scenario ”EV with No-Priority” is the baseline reference. Table 9 shows the average impact for EVs with ”Closed Lane” condition. Here, the scenario ”EV with No-Priority (Closed Lane)/Scenario 4” is the baseline instead of ”EV with No-Priority/Scenario 1”. Moreover, Table 10 ”Baseline Comparison” shows the average increment in the travel time and delay time when the lanes are closed.

Table 8. Normal Traffic Average Impact

Normal Traffic	Baseline Reference Scenario 1	With Priority Scenario 2	With Dynamic Priority Scenario 3
trip time	315s	-51%(-162s)	-49%(-153s)
delay time	245s	-66%(-162s)	-63%(-154s)

Table 9. Closed Lane Average Impact

Closed Lane	Baseline Reference Scenario 4	With Priority Scenario 5	With Dynamic Priority Scenario 6
trip time	344s	-47%(-161s)	-45%(-153s)
delay time	273s	-59%(-160s)	-57%(-156s)

Table 10. Baseline Comparison

Base Line Reference	Normal Traffic Scenario 1	Closed Lane Scenario 4	Normal Traffic vs Closed Lane
trip time	315s	344s	+9%
delay time	245s	273s	+11%

5 Conclusion and Future Work

5.1 Conclusion

The optimization process used in this study involved data pre-processing. This includes improvement of master data quality which required network modelling and the creation of ODMs to make the models as realistic as possible. During the process of importing networks from OSM, the imported network contained a lot of errors due to the misalignment with reality such as errors in simple road links (lanes wrongly connected), classification of lanes etc. Therefore, network corrections were done using SUMO (SUMO's editing tool NETEDIT). ODMs were created by leveraging tools such as Python and Excel. These processes were time consuming but at the same time it was important for the execution of the models.

The simulation results in Table 8 and 9 show that the implementation of EV prioritization techniques results in a significant improvement of the KPI values. For "Normal Traffic" condition, the average trip time and delay time is dropped by 51% and 49%, 66% and 63% respectively. For the "Closed Lane" condition, increases in travel time and delay time was anticipated but the impact is lower than expected. The reason maybe that only 33% of the overall multi lanes were reduced to one lane. However, the average trip time and delay time is also dropped by 47% and 45%, 59% and 57% respectively. The maximum impact were seen on the scenarios where the tram stops ahead of the ambulance and the subsequent traffic light is switched to green. The model where threshold distance is calculated dynamically is not as good as expected. The reason is that the calculated distance is mostly lower than 300 meters for all major junctions which reduces the optimization of the travel time of the ambulances. Nevertheless, in all cases the travel time was reduced with the intervention into the traffic infrastructure. Therefore, it can be concluded that through the EV prioritization approaches using V2X communication, EVs can save precious seconds which could be the difference between life and death for a person in need.

5.2 Future Work

In future work, the impact of the length of the closed lanes on the arrival times of the EV should be investigated. Another interesting addition to the simulation would be to include foot traffic (pedestrians), buses and cyclists. The current model is used to study only one EV at a given instant during the simulation. Therefore, further studies could be implemented to handle multiple EVs at the same time. As SUMO is a continuously improving software and thus, for this model, there is still scope of improvement for lane changing functionalities e.g. overtake using the opposite lane. The traffic light control plans used in the study are edited as per demand model. Further work can be carried out to incorporate real world traffic control plans that could lead to even more accurate depiction of the real-world scenario. Since "Dynamic Priority" scenario calculates the threshold distance often less than 300m, delivering the results in the section 4, the parameters in the "Dynamic Priority" strategy needs to be optimized. Finally, this simulation needs to be redone with higher, post pandemic traffic rates.

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