Calculating Average Driving Speeds of Emergency Vehicles by Road Type based on Emergency Call Data

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ABSTRACT

Emergency services provide essential and life-saving services, requiring prompt and reliable response times. Accurate travel time prediction is crucial for efficient dispatching and resource allocation, yet existing routing engines often rely on generalized speed profiles unsuitable for emergency vehicles. This paper presents an approach to derive average driving speeds for emergency vehicles on different road types. We combine an OpenStreetMap data-based route estimation with a linear regression model to analyze an ambulance dispatch dataset of over 97,000 calls from a large city in Germany. The results provide average ambulance driving speeds for seven road types. We compare results for six different daily time intervals, finding that high traffic indicators like rush hour times have a low impact on driving speeds, whereas driving during the night leads to a 22% speed reduction.

Keywords

Emergency service, driving speed, road types, linear regression, travel time prediction

INTRODUCTION

Emergency services provide essential and life-saving services to the population. Prompt and reliable emergency response is critical, especially for medical emergencies, where even small delays can affect patient outcomes. Rapid ambulance response is associated with higher survival rates (Mahama et al., 2018; Damdin et al., 2025), highlighting that accurately estimating response time is a key parameter for planning and operating emergency medical services (EMS) (Bürger et al., 2018).

In many countries, there are regulations for the maximum response time of emergency vehicles (EMV) (Cabral et al., 2018). In Germany, the recommended response time varies across each federal state (Reuter-Oppermann et al., 2017), while, for example, in New Zealand, the target depends on structural factors, such as whether the rescue scene is in an urban or rural area (Al-Shaqsi, 2010). Compliance with the response time is generally used as the main criterion for evaluating EMS quality (Ministry of the Interior and Local Government NRW, 2016) and for resource allocation.

Reducing response time is a priority for increasing survival rates, optimizing resources, and meeting local demand. Response time is defined as the interval between receiving an emergency call and the EMV arriving at the rescue scene (Reuter-Oppermann et al., 2017). This interval can be decomposed into three components: *processing time* of the emergency call (t_1-t_2), *turnout time* (t_2-t_3), where the rescue crew is alerted and boards the vehicle, and *travel time,* where the rescue crew travels to the rescue scene (t_3-t_4) (see Figure 1). The first two components do not vary a lot in time as they often follow standardized protocols. The most variable component is the *travel time*. Consequently, reducing EMV travel time offers the greatest potential to lower the response time, but this benefit depends on having accurate travel time prediction (TTP), which is the focus of our paper.

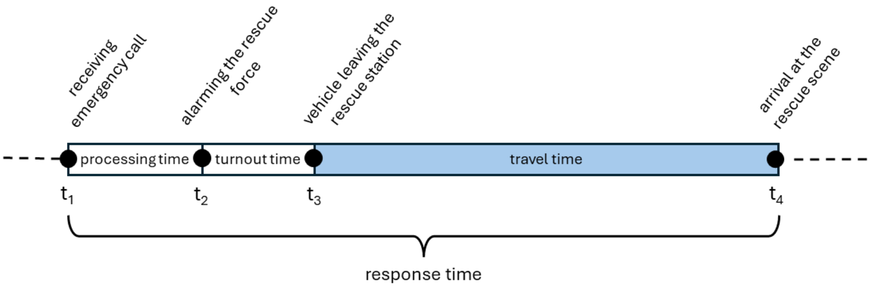

Figure 1 Elements of EMV response time (based on Reuter-Oppermann et al. (2017))

Accurate TTP is challenging, particularly in dense urban environments where traffic flows exhibit stochastic behaviors. Traffic dynamics are influenced by multiple interacting factors, including traffic volume, incidents, road works, and weather conditions (Lee et al., 2009). For EMV, the complexity increases further, as the vehicles operate partly outside traffic regulations, such as special right-of-way and exceeding speed limits (Abid et al., 2024).

Most routing engines estimate travel time by assigning average speeds to road segments based on vehicle and road type. Widely used platforms such as OpenRouteService and Valhalla rely on aggregated speed profiles to perform routing, accessibility analyses, and isochrone generation. However, their reliance on generalized or assumed speed values limits their suitability for modeling emergency vehicle operations. Poulton et al. (2018) show that Google Maps Distance API overestimates ambulance travel times in London by approximately 40%. Similarly, Lupa et al. (2021) demonstrate that ambulances operating with blue lights and sirens travel on average 56% faster than those without signals, highlighting that civilian-based speed assumptions are not transferable to emergency contexts.

Existing approaches to EMV-TTP can be categorized into four groups (Hao et al., 2024): I) model-based methods, which include statistic-based and machine learning methods; II) simulation-based methods with tools like SUMO; III) API-based methods with the acquisition of real-time data; and IV) novel approaches with UAV-based methods. Within the model-based methods, some studies rely on ambulance driving data, including GPS trajectories. For instance, Petzäll et al. (2011) and Torres et al. (2021), analyze recorded ambulance trips to estimate travel speeds and identify influencing factors. Lupa et al. (2021), Pappinen and Nordquist (2022), and Abid et al. (2024) similarly use historical GPS traces to derive segment-level speeds. Additionally, Poulton et al. (2018) propose a methodology for estimating ambulance speeds at a road-segment level by adopting a modified road network graph. A common characteristic of these approaches is their reliance on trajectory data, which enables reconstruction of the actual routes taken.

While these trajectory-based approaches provide detailed and empirically grounded speed estimates, they implicitly assume the availability of vehicle movement data. This assumption, however, does not hold for many EMS systems. For instance, in Germany, detailed GPS trajectory data for ambulances are hard to retrieve due to legal and privacy constraints. In fact, often only the starting rescue station, the incident location, and the total travel time are available. Moreover, prior studies (Sirenko et al., 2024; Lupa et al., 2021) demonstrate that response dynamics vary significantly between cities, making it difficult to generalize findings from one city to another. Consequently, despite the emerging body of literature available, a methodological gap remains whenever GPS trajectory data are unavailable for the city in question.

In this paper, we present a methodology for estimating the average driving speeds for EMV per road type when only dispatch data are available, i.e., no information on the actual route taken is available. The methodology includes a routing algorithm that determines the most probable route based on retrievable road network information. The estimated route serves as the basis for the linear regression model, which is used to calculate average speeds across different road types. We illustrate the method based on an extensive emergency dispatch dataset from one of Germany's five largest cities. For privacy reasons, the city name cannot be disclosed; however, it is known to the authors. We further validate the results to provide uncertainty metrics. Ultimately, the approach is designed to be easily transferable to other cities in order to help researchers and practitioners with more accurate routing analysis.

DATA

The emergency dispatch dataset is extracted from the dispatch center's control system, which manages the alerting and allocation of units to incidents. We use all ambulance dispatches within the city boundary from January 2023 to August 2023. The dataset consists of 97,834 data points, where each point includes: the geographic coordinates of the incident location and the starting station, whether the vehicle started from the home station, and whether the response was conducted using emergency right-of-way (sirens and blue lights). Furthermore, it includes the starting time of the vehicle and the arrival time at the scene (Table 1). These timestamps are manually set by the vehicle driver upon departure and arrival at the scene.

Table 1: Fictitious excerpt from the dataset

Call ID	Station	Starting time	Arrival time	Starting from the station	Sirens and blue light
1234	8	23-09-07 15:46:48	23-09-07 15:56:17	yes	yes
2345	3	23-09-07 16:21:54	23-09-07 16:26:18	yes	no
3456	7	23-09-07 17:34:41	23-09-07 17:41:11	no	yes

For the road network, we use OSM data (OpenStreetMap contributors, 2026). In Germany, OSM road data are characterized by their open accessibility and high degree of spatial accuracy (Fan et al., 2014; Mondzech & Sester, 2011). Each road segment is classified into one of 27 road types. Additionally, some segments contain speed limit information. Fire and rescue stations – used as starting points for the dispatches – are extracted from the OSM Points of Interest dataset. A comparison with official records confirms the accurate position of the stations. All OSM data is downloaded via geofabrik.de.

METHOD

The methodology is structured into four phases, namely, (1) data preprocessing, (2) estimation of driven routes between stations and incident locations, (3) calculation of the average travel times per road type for different vehicle types, and (4) comparison of the results with the existing travel times for model validation.

While the model can calculate average travel times for different vehicle types (fire trucks, police cars, etc.), in this work-in-progress paper, we illustrate the methodology and the results for the ambulance use case, since ambulances make the biggest share of all dispatches.

Preprocessing of emergency call data

Before the analysis, the data are filtered. We exclude all non-emergency calls, i.e., dispatches conducted without the use of blue lights and sirens. In addition, we exclude calls that do not start from a specific station. This occurs when the vehicle is dispatched while already on the road (e.g., on the way home from an emergency) and therefore starts from an unknown starting location.

The departure and arrival timestamps were recorded by the vehicle crew via manual status updates. This is susceptible to human error and leads to unrealistic travel times. We therefore discard trips with a travel time shorter than one minute or greater than 13 minutes. Furthermore, we only consider calls with turnout time between 0.5 and 2.5 minutes, as too short or too long intervals are possibly errors. We also estimate the route length to approximate the average driving speed per route. We then discard calls with an average driving speed (per route) below 25 km/h and above 75 km/h, as we they are unrealistically slow or fast. This exclusion accounts for roughly the top and bottom 10%. A random manual inspection of the excluded calls shows that we could exclude a satisfactorily high number of unrealistic outliers. Overall, we employ relatively strict filtering criteria. However, as a large number of calls is available and the amount of remaining data does not represent a limiting factor, we preferred a filtering strategy that is biased toward over-filtering rather than under-filtering.

Previous research suggests that ambulance driving speeds vary throughout different weekdays or hours of a day (Poulton et al., 2018; Lupa et al., 2021; Valentin et al., 2023; Petzäll et al., 2011; Westgate et al., 2016; Abid et al., 2024). To take into account this aspect, we use the average travel time per call, since the data does not provide information on average driving speed. It is worth noting that by using the average travel time, we can only approximate the driving speed, as travel time can be influenced by other factors like the number of ambulances available, which could, for example, influence the route length. A first analysis of the average travel time per call suggests that day vs night, as well as work day vs weekend, are influencing factors. On weekends, travel times are on average shorter compared to work days (Figure 2).

Another potential influencing factor is driving during rush hours, although its inclusion leads to varying results across various studies (for example, in Lee et al. (2009), Abid et al. (2024), Hao et al. (2024) and Westgate et al. (2016)). While Poulton et al. (2018), Abid et al. (2024) and Hao et al. (2024) find lower ambulance driving speeds during rush hours, Lupa et al. (2021) and Westgate et al. (2016) cannot detect such a strong influence. In order to include the potential influence of driving during rush hours, we decide to focus on work days and we divide the day in the following intervals: 18h-Day (6 am – midnight), 6h-Night (midnight – 6 am), Rush Hour (7 am – 9 am, 3 pm – 6 pm), Low Traffic Day (from 10 am – 2 pm), Low Traffic Night (10 pm – 6 am) and Whole Day (24 h) for comparison. We choose to divide in a 18h-Day and a 6h-Night interval as the latter is the quietest time of the day across all seasons. The Rush Hour, Low Traffic Day, and Low Traffic Night intervals are based on city-specific traffic overviews (TomTom International, 2026), to better account for high and low traffic volumes. To keep the results comparable, the number of calls for each time interval is reduced to 5470 dispatches, which is based on the interval with the lowest number of calls. This reduced dataset is then used to calculate the average driving speed by road type for each interval.

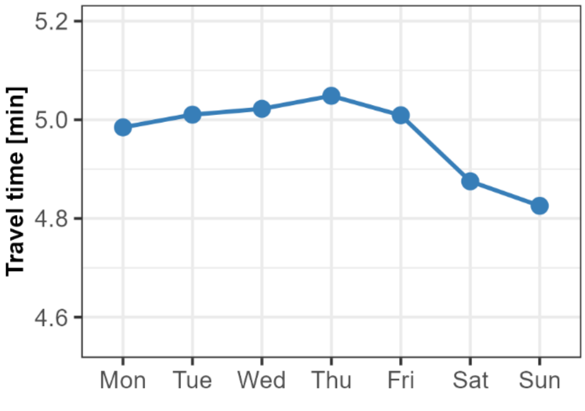

Figure 2: Average travel time of emergency calls per weekday

Preprocessing of the road network

The OSM road network serves as the basis for estimating the routes between the station and the scene of the emergency. Each road segment is assigned to one of the 27 road categories. We merge the "link" segment type with their respective parent categories (e.g., primary_link and primary) and exclude road types that are non-passable for emergency vehicles (e.g., footway, cycleway). The final network includes road types such as motorway, trunk, primary, secondary, tertiary, unclassified, residential, service, and living street. To make the road network routable, we assign a weight to each road type. This weight represents the time a vehicle needs to traverse a specific road segment from one end to the other. To do so, we use the maximum speed limits included in the OSM road dataset for around 40% of our road network. Since not all roads have speed limits assigned, we calculate an average maximum speed limit for each road type based on all segments where an explicit speed limit is provided, and assign it to segments without maximum speed limit values (Table 2). No maximum speed limit information is available for service and living street types, so they are defined by the authors based on visual inspection of the roads in satellite imagery and the OSM road type definitions. We assign 10km/h to living streets, which are roads where pedestrians are prioritized. Service streets are often not part of the public road network and are usually used to connect main roads to buildings, so we assume 15 km/h as the average driving speed. Together, the service, living street, and unclassified road types make up less than 3% of the actually used road network length. We therefore combine them into the new road type "other" to ensure enough samples for the later planned linear regression. It is worth noticing that these weights are based on maximum speed limits rather than on the average speeds typically achieved on each road type, and therefore, they might be unsuitable for a direct travel-time calculation. Nevertheless, they provide a relative weighting across the various road categories, which we exploit in the next step to estimate the routes that were actually traversed. Figure 3 shows the total distance by road type of the overall road network, next to the roads that were actually used by the ambulances.

Table 2: Average maximum speed per road type based on OSM data

OSM road type	Average maximum driving speed in km/h
Motorway	92
Trunk	58
Primary	48
Secondary	51
Tertiary	43
Unclassified	38
Residential	32
Service	15*
Living street	10*

* Defined by the authors

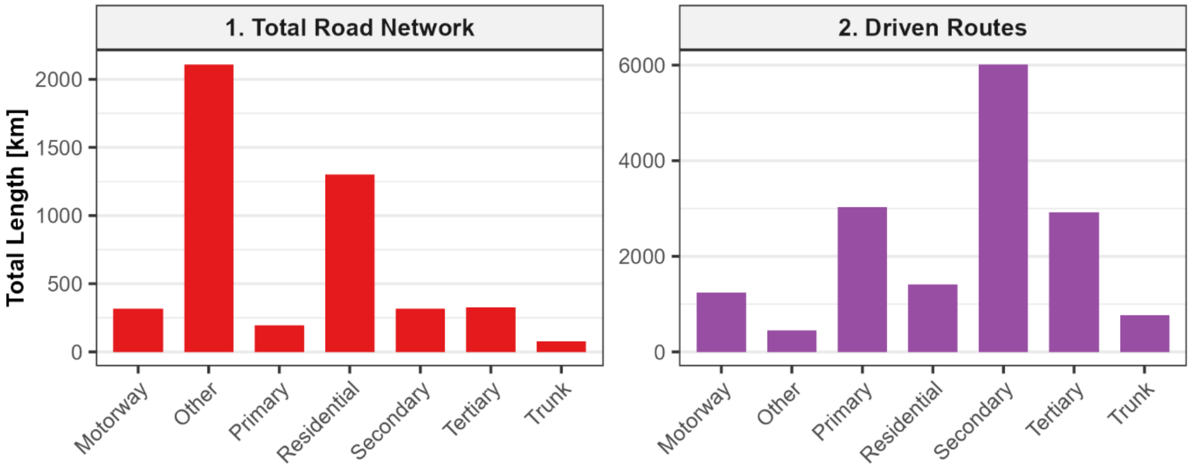

Figure 3: Comparing the length per road type of the total network vs. routes driven to all emergency locations (N=5470)

Estimation of routes taken by the ambulance

As already discussed, the dataset provides the starting station and the incident location, but it does not record the actual route taken by the vehicle. We therefore estimate the route an emergency vehicle took, based on the assumption that drivers will always choose the route with the fastest travel time. For this purpose, the preprocessed OSM road network is transformed into a routable network in R 4.5.1 using the sfnetworks library (van der Meer et al., 2024). Since travel times are computed between nodes, and some road segments in the raw data extend up to 3 km, the network is first decomposed into 20 m segments to enhance routing precision. The stations and incident locations are subsequently snapped to the nearest network nodes. The previously calculated average maximum speed limits are utilized to weight the road network. They provide a robust relative weighting of the road types against one another, allowing the algorithm to choose the shortest route based on the relative traversing time of each road segment. The routing procedure itself is based on Dijkstra's algorithm, which leverages these relative weights to approximate the presumed fastest route. For each of these estimated routes, the distances traveled across each road category, as well as the total route length, are subsequently aggregated. Each route is then associated with the actual travel time previously calculated from the dispatch dataset (Table 3).

Table 3: Extract of the input table for the linear regression (all values in meters, if not specified otherwise)

Motor-way	Trunk	Primary	Secondary	Tertiary	Residential	Other	Total Length	Actual travel time
0	863	0	3490	0	383	94	4,830	5.0 min
5694	1465	0	1852	928	276	94	10,309	10.2 min
0	0	0	3017	437	5	390	3,849	6.5 min

Calculation of the average travel times per road type

To derive the average driving speeds for each road classification, a multiple linear regression analysis is performed for each of the time intervals. After filtering and randomly excluding 500 dispatches for the following validation, 5470 calls remain for each regression analysis.

$$T_i = \beta_1 d_{i,motorway} + \beta_2 d_{i,trunk} + \beta_3 d_{i,primary} + \beta_4 d_{i,secondary} + \beta_5 d_{i,tertiary} + \beta_6 d_{i,residential} + \beta_7 d_{i,other} + \epsilon_j$$

The measured travel time of an emergency dispatch is modeled as the sum of the time spent on each individual road segment. T_i represents the total recorded travel time for dispatch i, d_i is the distance travelled on the specific road type, and β is the estimated "speed" coefficient, in minutes per meter, for each road type, while ϵ_i represents the error term. The intercept (β_0) was omitted from the model—forcing the regression through the origin—under the assumption that a route with zero distance requires zero driving time. The "speed" coefficients are then converted in order to calculate the final average emergency speeds in kilometers per hour. This statistical approach allows us to isolate the influence of each road type on the overall response time, effectively calculating specific speeds from aggregated dispatch data. The linear regression summary tables for every time interval are located in the appendix.

The suitability of the linear regression model was assessed through a suite of diagnostic tests. Multicollinearity was ruled out, as Variance Inflation Factors for all road types remained near 1.0, ensuring stable coefficient estimates for average speeds. Although a Breusch-Pagan test indicated the presence of heteroscedasticity (a common phenomenon in spatial routing data where variance increases with trip duration), the Ordinary Least Squares estimators remain unbiased. A visual inspection of the Q-Q plots confirms that residuals closely follow a normal distribution in the central quantiles, with deviations only appearing in the extreme tails. Given the large sample size, the Central Limit Theorem ensures that the parameter estimates are robust and valid for inferring average emergency vehicle speeds across the network.

Validation of average driving speeds

To assess the validity of our approach, we conduct a cross-validation experiment. In the first step, we generate a new routing-capable road network, which uses the newly calculated average driving-time values as edge weights. With this network, we compute travel times to a validation dataset of 500 incident locations that had not yet been included in any of the previous calculations. This validation dataset is chosen randomly from the pre-filtered call dataset. The resulting travel times are compared against the actual (real-world) travel times, which stem from the call data itself. To compare the predictive performance of our model, we compute the following error metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

PRELIMINARY RESULTS

The linear regression calculation provides average driving speeds for ambulances (Table 4) based on the 5470 calls that remain for each of the six scenarios after the extensive filtering. The results show motorways having the highest average speed, while road type "other" has the lowest. The relative ordering of the average driving speeds also mirrors the hierarchy of the previously calculated average maximum road speeds (Table 2), which we interpret as evidence that the computed values are fundamentally realistic. When comparing the different time intervals, a clear difference between day and night times becomes evident, with night times generating consistently and significantly lower driving speeds than the daytime intervals. Interestingly, the Rush Hour interval results in the highest driving speeds for motorways, trunk, secondary, and tertiary roads. The Whole Day scenario, on the other hand, displays the expected average of the other intervals.

Table 4: Average ambulance driving speed on different road types in km/h– coloring is applied horizontally per road type, red color indicates the lowest speed, green color the highest speed compared to all speed values of one road type

Road type	Whole Day	18h-Day	6h-Night	Rush Hour	Low Traffic Day	Low Traffic Night
Motorway	76.9	82.9	64.8	83.0	82.9	66.1
Trunk	49.8	45.7	50.1	52.8	50.2	48.8
Primary	43.3	46.2	34.2	47.8	50.8	37.0
Secondary	39.1	39.9	33.1	45.1	42.9	35.2
Tertiary	34.1	35.6	30.2	36.4	34.6	31.6
Residential	23.5	23.7	24.0	23.0	23.0	22.7
Other	20.8	22.1	19.2	20.1	19.8	21.7

Time intervals: Whole Day (24 h), 18h-Day (6 am – midnight), 6h-Night (midnight – 6 am), Rush Hour (7 am – 9 am, 3 pm – 6 pm), Low Traffic Day (from 10 am – 2 pm), Low Traffic Night (10 pm – 6 am)

The cross-validation, in which travel times for 500 incidents of the validation dataset were recomputed using the newly derived average speeds, yields satisfactory results (Table 5). The Whole Day results come with the highest error values, with a 24% higher MAE and a 20% higher MAPE than the other intervals. This shows clearly that average driving speeds have to be provided for different time intervals of a day, since whole day averages lead to higher errors.

Table 5: Error metrics for the linear regression model

Linear Regression	Whole Day	18h-Day	6h-Night	Rush Hour	Low Traffic Day	Low Traffic Night
RMSE	1.57	1.2	1.21	1.2	1.24	1.22
MAE	1.17 min	0.90 min	0.90 min	0.89 min	0.90 min	0.87 min
MAPE	23.30 %	18.70 %	18.70 %	18.80 %	18.70 %	17.80 %

Time intervals: Whole Day (24 h), 18h-Day (6 am – midnight), 6h-Night (midnight – 6 am), Rush Hour (7 am – 9 am, 3 pm – 6 pm), Low Traffic Day (from 10 am – 2 pm), Low Traffic Night (10 pm – 6 am)

DISCUSSION

This work offers a pragmatic first-step method to determine average speeds for EMVs on various road types, even when only the departure and arrival points of a trip are known. By estimating road-type-specific speeds, the resulting values can be fed into existing routing tools to produce preliminary travel-time estimates. Because such tools can be operated through standard GIS platforms such as QGIS, the availability of these speed figures broadens the accessibility of routing to a much wider range of practitioners.

Most routing engines already use average speeds from conventional vehicle profiles (e.g., car, truck) as a weighting factor for individual roads. However, the corresponding data for emergency vehicles is missing. Emergency vehicles, operating under blue lights and sirens, display fundamentally different driving behavior, which renders their travel times inapplicable to standard vehicle profiles (Poulton et al., 2018; Lupa et al., 2021). Consequently, road-type-dependent travel times for emergency vehicles are essential to conduct routing comprehensively and accurately. Since routing of emergency vehicles is a critical component for efficient dispatch to incidents, and for the planning of new ambulance station locations. Therefore, having reliable road-type-specific travel-time estimates is highly relevant to ensuring adequate service provision for citizens.

Our results show that, counterintuitively, the rush hour time interval (7 am – 9 am, 3 pm – 6 pm) actually leads to a slight increase in average driving speeds, suggesting that EMVs are not slowed by the possibly heavier traffic. This is aligned with the argumentation of Lupa et al. (2021) and Westgate et al. (2016), who conclude that the use of blue lights and sirens appears to be an efficient way for emergency vehicles to reduce the traffic impact. Another reason might be that not all roads taken during a trip are congested; for example, traffic jams are often limited to arterial roads and bottlenecks. In addition, ambulance crews might be able to avoid traffic jams, as they are usually familiar with their surrounding urban area. Our findings show an average speed reduction during the night, in both cases: the 6h-Night and the Low Traffic Night. With the highest difference between occurring for primary roads between the time intervals 18h-Day (46.2 km/h) and 6h-Night (34.2 km/h). We assume that this comes from a more defensive driving style during the night. Reasons for this might be the reduced visibility in the dark hours (especially when combined with weather effects like heavy rain or snow), or lower concentration capabilities of the driver (e.g., just awakened by an alarm, the last hours of 24 h shift, which usually start in the morning). Another interesting factor, which needs more investigation, could be that ambulances tend to switch off the sirens during the night to avoid disturbing residents. We assume that this leads to slower driving, since EMV drivers have to expect that other cars might not recognize them. Overall, our research shows that traffic appears to have only a little impact on the average travel time of ambulances. However, driving during the day and at night leads to significantly different driving speeds. In order to perform efficient routing calculations for ambulances, it is therefore advisable to use different values for day and night journeys. Based on our results, we recommend the values for 18h-Day and 6h-Night.

Our approach comes with some limitations. First, we estimate a single average speed for each of the seven road types, during each of the six pre-defined time intervals (Whole Day, 18h-Day, 6h-Night, Rush Hour, Low Traffic Day, and Low Traffic Night) (Table 4). These averages are, by necessity, only approximations of reality, because vehicles can travel at markedly different speeds even on roads of the same type. Furthermore, our approach estimates the taken routes based on average driving speeds estimated from OSM maximum speed limit data. This excludes situations where drivers chose different routes based on local knowledge, e.g., to avoid traffic or construction sites. To consider traffic congestion meaningfully, it would be necessary to include city-wide traffic data in the analysis, which is out of the scope of the present study. Similarly, local knowledge of ambulance drivers could be included in the analysis by conducting questionnaires in the future. The uncertainty that arises from these simplifications must therefore be taken into account when routing with average values. The MAPE values reported in Table 5 give an idea of this uncertainty.

Inspection of the raw data further shows that seemingly identical routes can produce different travel times, underscoring the inherent difficulty of travel-time prediction via absolute values. It is generally to discuss whether classical absolute travel-time estimates for specific points or isochrones with sharply defined boundaries for service areas can be truly realistic, or whether they might instead convey an unrealistic sense of precision. A possible approach would be to express travel times as a range (e.g., a destination is reached within 80 % confidence in 8–9 min) or to define a spatial envelope (e.g., the vehicle is located within an 80 % confidence region around an isochrone line). Such probabilistic or interval-based reporting could better reflect the variability observed in the data and provide a more nuanced basis for decision-making in emergency dispatch and service-area planning.

Our analyses are based on time stamps, which are manually recorded by the EMV crews, and are therefore subject to human error. We applied extensive filtering to remove implausible values, but residual measurement error may remain. In fact, this filtering strategy reduces the risk of unrealistic observations but may also exclude valid extreme cases. Manual random checks show that implausible values seem far more numerous than potentially excluded extreme values, and we also have a high number of data points; we believe this to be the more reliable approach.

Other studies claim that assessing EMS quality solely based on response time is too shortsighted: rescue teams might arrive in time at the rescue scene but still fail to treat the patient appropriately, thus measuring the performance of the EMS based on response time only might be misleading (Price, 2006; Al-Shaqsi, 2010). Nonetheless, we agree that response time influences the chances of success of EMS and should be considered as a relevant part, along with further criteria, e.g., appropriate treatment, quick relocation of a patient to the hospital, when assessing the performance and optimizing the resources of EMS.

We plan to extend our approach in the future. Several other approaches show that emergency call patterns can have significant differences between cities (Lupa et al., 2021; Sirenko et al., 2024; Sirenko et al., 2026). We therefore plan to extend our approach to other cities to investigate possible changes in the average road speeds.

Where legally permissible, limited GPS-based validation studies could help quantify the deviation between reconstructed and actual routes. This would allow a more precise assessment of the uncertainty introduced by our route estimation via, e.g., sensitivity analyses. It would further allow a more precise validation of the average driving speed results. Providing such GPS-based validation metrics would improve the usability of our results by practitioners, since the connected uncertainties would be more understandable.

Our results show lower driving speeds during the night. While we could identify possible reasons for these day and night differences, further research is needed to prove these assumptions. We therefore plan to conduct a survey with EMV drivers to gain more insights into actual driving behavior. GPS data could also be helpful to further narrow down driving time influencing factors.

While average travel times are crucial for routing engines, in certain cases, e.g., to improve ambulance dispatching, it is not necessarily relevant to know which route an ambulance takes. What is relevant is to predict how long it takes to arrive. We therefore plan to test further machine learning approaches and artificial neural networks to predict exact travel times between two points. This also allows to include further information, like the number of crossed junctions and traffic lights, or weather conditions.

CONCLUSION

This study demonstrates a method to derive average driving speeds of EMV for different road types, solely based on the starting and end location and time of the trip to an emergency, providing a transferable option that is not dependent on trajectory data. The road type-specific EMV speed results can be used as edge weightings in common and easy-to-use routing engines, making EMV-specific routing more accessible. In our showcase, we calculate average driving speeds for ambulances in one of Germany's largest cities (due to data privacy reasons, the city name cannot be published) based on a dataset of 97,834 dispatches from 2023. We use the OSM road network and average speed limits for nine road types to estimate the routes taken by ambulances between stations and the emergency locations. For each trip, the distance traversed on all of the seven road types is calculated. We use a linear regression analysis to derive average ambulance driving speeds per road type, based on the traversed distances and the total time needed for the trip. To cover several traffic and driving conditions, we repeat this process for various intervals: Whole Day (24 h), 18h-Day (6 am – midnight), 6h-Night (midnight – 6 am), Rush Hour (7 am – 9 am, 3 pm – 6 pm), Low Traffic Day (from 10 am – 2 pm), Low Traffic Night (10 pm – 6 am). The results show speeds between 83 km/h for motorways during rush hour and 19.2 for the road type "other" during the 6h-Night scenario. More importantly, the analysis shows that rush hour times do have a negligible impact on average ambulance driving speeds, whereas driving during the night leads to up to 22% reduced speed in comparison to daytime driving. Cross-validation on an independent sample of 500 incidents produced mean absolute errors of 1.17 min and mean absolute percentage errors of 23.3 % for the Whole Day set, improving by up to 24% when time-interval-specific speeds were employed. We conclude that specific road type-dependent driving speeds should be provided for day and night scenarios, as shown by our results (18h-Day and 6h-Night scenarios) for future use.

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APPENDIX

Linear regression summary tables

Whole Day

Road type	Estimate (min/m)	Std. Error	T-value	p-value
motorway	0.00078	0.00002	32.67563	< 0.001
trunk	0.00120	0.00005	25.21225	< 0.001
tertiary	0.00176	0.00003	65.81971	< 0.001
primary	0.00139	0.00002	59.67273	< 0.001
secondary	0.00153	0.00002	94.87809	< 0.001
residential	0.00256	0.00007	36.92174	< 0.001
other	0.00288	0.00019	15.28097	< 0.001

n = 5470 dispatches; R^2 = 0.9117; Adjusted R^2 = 0.9116

18h-Day

Road type	Estimate (min/m)	Std. Error	T-value	p-value
motorway	0.00072	0.00002	33.09425	< 0.001
trunk	0.00131	0.00005	28.04192	< 0.001
tertiary	0.00168	0.00003	63.88395	< 0.001
primary	0.00130	0.00002	60.05147	< 0.001
secondary	0.00150	0.00002	99.14354	< 0.001
residential	0.00253	0.00007	38.64315	< 0.001
other	0.00272	0.00018	14.80604	< 0.001

n = 5470 dispatches; R2 = 0.9136; Adjusted R2 = 0.9135

6h-Night

Road type	Estimate (min/m)	Std. Error	T-value	p-value
motorway	0.00093	0.00004	23.46797	< 0.001
trunk	0.00120	0.00007	17.11162	< 0.001
tertiary	0.00199	0.00004	49.96433	< 0.001
primary	0.00175	0.00004	49.37093	< 0.001
secondary	0.00181	0.00002	74.76806	< 0.001
residential	0.00250	0.00009	27.27394	< 0.001
other	0.00313	0.00031	10.04605	< 0.001

n = 5470 dispatches; R2 = 0.9288; Adjusted R2 = 0.9286

Rush Hour

Road type	Estimate (min/m)	Std. Error	T-value	p-value
motorway	0.00072	0.00002	30.19478	< 0.001
trunk	0.00126	0.00005	24.84823	< 0.001
tertiary	0.00165	0.00003	55.04083	< 0.001
primary	0.00114	0.00002	49.80797	< 0.001
secondary	0.00133	0.00002	79.67553	< 0.001
residential	0.00260	0.00007	35.74357	< 0.001
other	0.00299	0.0002	14.90943	< 0.001

n = 5470 dispatches; R2 = 0.8834; Adjusted R2 = 0.8833

Low Traffic Day

Road type	Estimate (min/m)	Std. Error	T-value	p-value
motorway	0.00072	0.00002	33.54536	< 0.001
trunk	0.00120	0.00005	24.45785	< 0.001
tertiary	0.00174	0.00003	63.80313	< 0.001
primary	0.00118	0.00002	54.13697	< 0.001
secondary	0.00140	0.00002	89.62011	< 0.001

residential	0.00261	0.00007	37.37932	< 0.001
other	0.00303	0.0002	15.34781	< 0.001
	n = 5470 dispatches; R2 = 0.9288; Adjusted R2 = 0.9286			

	Low Traffic Night			
Road type	**Estimate (min/m)**	**Std. Error**	**T-value**	**p-value**
motorway	0.00091	0.00003	35.15948	< 0.001
trunk	0.00123	0.00005	26.64405	< 0.001
tertiary	0.00190	0.00002	76.35444	< 0.001
primary	0.00162	0.00002	70.22980	< 0.001
secondary	0.00170	0.00002	107.70530	< 0.001
residential	0.00277	0.00006	44.22181	< 0.001
other	0.00265	0.00019	14.05886	< 0.001
	n = 5470 dispatches; R2 = 0.9298; Adjusted R2 = 0.9297			