A Realistic Trace-based Mobility Model for First Responder Scenarios

Matthias Schwamborn, Nils Aschenbruck, Peter Martini
University of Bonn - Institute of Computer Science 4
Römerstr. 164, 53117 Bonn, Germany
{schwamborn, aschenbruck, martini}@cs.uni-bonn.de

ABSTRACT

Realistic modeling of the nodes' mobility is essential for obtaining credible results from the simulative performance evaluation of wireless multi-hop networks. However, most of the mobility models in the literature have not been validated with real world movement traces. To overcome this issue, we follow a trace-based approach to mobility modeling, where movement traces from the real world scenario are statistically analyzed and used for parametrization. In this paper, we introduce and evaluate a new realistic mobility model for first responder scenarios based on such an analysis while also considering geographic restrictions by incorporating free publicly available map data.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design—*Wireless Communication*; I.6.5 [**Simulation and Modeling**]: Model Development

General Terms

Performance, Design

Keywords

Mesh Networks, Simulation, Trace Analysis, Mobility Model, First Responder

1. INTRODUCTION

Wireless multi-hop networks, such as Mobile Ad hoc NETworks (MANETs), mesh networks, and sensor networks, have been in the focus of mobile network research for the last few decades. MANETs [9] do not rely on infrastructure. The dynamic nodes in the network act as routers and communication end-points at the same time. They are very well suited for deployment in catastrophe scenarios or in the military domain. However, one major challenge in MANETs is robustness which is a key requirement in first responder scenarios. Mesh networks do also consist of static nodes which act as a wireless multi-hop backbone, thereby providing more robustness. Thus, mesh networks are deployed as first responder networks. As an example, we name the San Mateo Police Department in San Francisco (cf. [7]).

The biggest challenge within the research area of mesh networks — and of wireless multi-hop networks in general — is the efficient routing of messages. Therefore, the performance of routing protocols in these networks needs to be evaluated. Since real testbeds are expensive and lack scalability as well as reproducibility, simulation is the most commonly chosen technique for performance evaluation. However, the simulation results reflect reality only as much as the used models do. Thus, realistic models are a crucial factor for the credibility of the simulation results.

Mobility models have a significant impact on the performance evaluation results in wireless multi-hop networks (cf. e.g., [8, 10, 26]). Nevertheless, in most performance studies, synthetic random-based models such as the Random Waypoint (RWP) mobility model are used (cf. [20]). Common assumptions of these abstract models are unrestricted node movement and uniformly distributed selection of target positions. With these unrealistic assumptions, the movement characteristics of specific scenarios in general, and of first responder scenarios in particular, cannot be properly reflected.

Apart from abstract models, there are also a lot of synthetic scenario-dependent models (for an overview, see e.g., [3, 4, 8]). However, only a few of these have been validated with real world movement traces. Therefore, it is unclear to which amount these models reflect the characteristic movement patterns of the scenario they are based on. To overcome this credibility issue, a trace-based modeling approach can be taken: Traces are gathered from the considered real world movement scenario. These usually consist of positional data measured through some global positioning method such as the Global Positioning System (GPS), or connectivity data based on WLAN or Bluetooth. By analyzing these traces, more realistic mobility models can be developed. In the literature, there are studies available on trace analysis and trace-based modeling (e.g., [14,17,22,27]). However, they mainly focus on connectivity traces and campus scenarios.

In this paper, we present and evaluate a new realistic trace-based mobility model for first responder scenarios. The focus is on ambulances. The model considers geographic restrictions, such as streets and buildings, by incorporating free publicly available map data.

MSWiM'10, October 17–21, 2010, Bodrum, Turkey.

We structured the remainder of this paper as follows: Section 2 gives an overview of related work. Then, we describe the new mobility model (Section 3) and parametrize it based on the trace analysis (Section 4). An evaluation at mobility level is given in Section 5. We conclude the paper with a summary of the main results and identify topics for future work in Section 6.

2. RELATED WORK

One approach to realize geographic restrictions is using map data. Map-based approaches are similar to graph-based ones but maps offer much more detail and can therefore be of much use for bigger sized and detailed movement graphs. Representatives of this approach are Random Waypoint City (RaWaCi) [19], the mobility model described in [18], and Random Street (RaSt) [5].

RaWaCi takes the proprietary MapInfo format as input, creates the corresponding movement graph and computes the routing tables according to mean speed values included in the data. The node movement is an adapted RWP movement, where the nodes take the fastest route to the random destination and pause at every crossing (graph node). In [18], a mobility model is presented that supports OpenStreetMap as well as GPS trace data. The mobile nodes move on the computed graph based on random decisions concerning pause times, speed, and the edges to move on, i.e., there is no target destination. RaSt makes use of a location-based service to compute optimal routes from start to destination and therefore does not need to pre-compute a movement graph. The movement pattern is motivated by RWP.

The CORPS mobility model [15] is an event-driven model for first responder scenarios, but — in contrast to our model — it focuses on the mobility of the first responders on-site of the place of operation. It consists of an FR, event, and interaction model. The FR model describes the first responders' (FRs') attributes, e.g., agency, role, and coverage region. FRs with the same role form a group and can perform group movement. The event model maintains and schedules events. Based on the event type, FRs are attracted to the event or they avoid the corresponding region. The interaction model takes care of the movement by letting the FRs interact with the events, i.e., by taking the event type into account.

In conclusion of this section, none of the described mobility models is suitable for modeling ambulance movement. The map-based models are too general and lack the ability to coordinate the nodes which is crucial for the timely arrival of the ambulances at the accident site.

3. DISPATCHED AMBULANCE MODEL

In this section, we describe the new map-based mobility model for first responder scenarios. The new model realizes the movement of ambulances by modeling the dispatch process. Therefore, we call it the Dispatched Ambulance (DiAm) model. The structure of this section is as follows: First (Section 3.1), we introduce the dispatch process which is incorporated by the DiAm model. The algorithm for generating the ambulances' movement is introduced in Section 3.2. In Section 3.3, we describe the different model parameters.

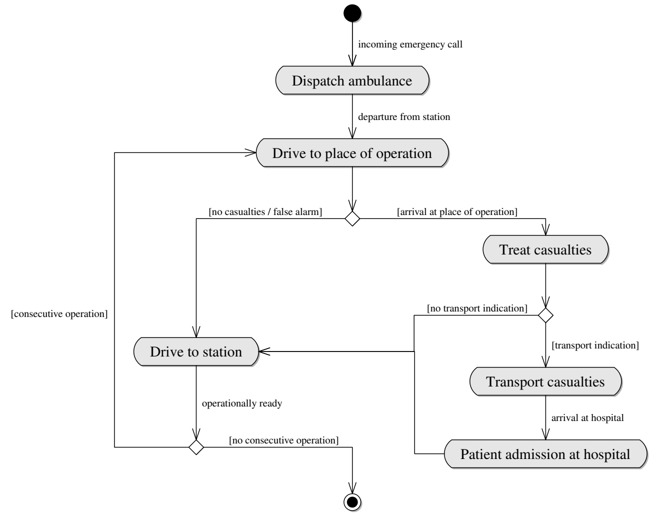


Figure 1: Activity diagram of the dispatch process

3.1 Dispatch Process

First responders try to keep the response times, i.e., the time span between answering an emergency call and the arrival of an ambulance at the corresponding place of operation, as low as possible. Therefore, an efficient way of coordinating the ambulances is required, which is achieved by the dispatch process (cf. [12, 13]).

Fig. 1 shows the different actions of the dispatch process in an UML activity diagram. The process starts with an incoming emergency call in the emergency dispatching center. In this call, among others, the place of accident (place of operation) is communicated. With this information, it can be determined, which operationally ready ambulance is nearest to the place of operation at this point in time. Here, the typical metric of choice for the distance calculation is the Euclidean distance. Then, the dispatched ambulance drives to the place of operation on the fastest route.

If there are no casualties or it turns out to be a false alarm, the ambulance is immediately considered as operationally ready and returns to its home station. Otherwise, after the arrival at the place of operation, the casualties are treated. If a transport of casualties is necessary, they are brought to the next hospital with free capacity. In rare cases, casualties are driven to a special surgery or even to their home. After the casualties have been delivered to the transport destination, the dispatched ambulance returns to its home station.

If there is a consecutive operation, the ambulance is dispatched on the way back to the station and drives to the new place of operation right away. Otherwise, the ambulance arrives at its home station and is idle until the next operation.

3.2 Movement Generation Algorithm

The DiAm mobility model realizes the dispatch process as follows (cf. Algorithm 1): At the beginning of the simulation, each ambulance (mobile node) starts at its previously designated home station (line 3). After an emergency call idle time $ECall\_IDLE$, a place of operation with coordinates within the simulation area is generated (ll. 5-6). Then, with respect to a given metric, an ambulance with minimal distance to the place of operation is chosen (l. 7).

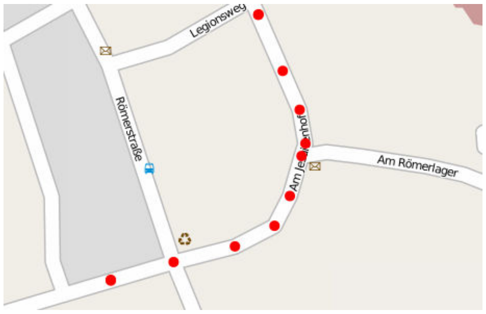


Figure 2: Segments approximating the course of the street

Algorithm 1: Pseudocode for DiAm

`/* initialization: */`
1 $t \leftarrow 0$;
2 **forall** *mobile nodes* i **do**
3 $\quad \vec{p_i}(t) \leftarrow$ `homeStation(`i`)`;

`/* main loop */`
4 **while** $t < T$ **do**
5 $\quad t \leftarrow t + ECall\_IDLE$;
6 $\quad \vec{p_O} \leftarrow$ `generatePlaceOfOperation()`;
7 $\quad i \leftarrow$ `getNearestReadyAmbulance(`$\vec{p_O}$`)`;
8 $\quad W_O \leftarrow$ `computeOptimalRoute(`$\vec{p_i}(t)$, $\vec{p_O}$`)`;
$\quad$ `/* ` i ` drives to place of operation */`
9 $\quad$ `addRouteWaypoints(`i, W_O`)`;
10 $\quad t \leftarrow t_O + PlaceOfOp\_IDLE$ with arrival time t_O at $\vec{p_O}$;
11 $\quad$ **if** `rand()` $\leq p_{CasualtyTransport}$ **then**
12 $\quad\quad$ **if** `rand()` $\leq p_{TDisHospital}$ **then**
13 $\quad\quad\quad \vec{p_{TD}} \leftarrow$ `getNearestHospital(`$\vec{p_O}$`)`;
14 $\quad\quad$ **else**
15 $\quad\quad\quad \vec{p_{TD}} \leftarrow$ `generateTransportDestination()`;
16 $\quad\quad W_{TD} \leftarrow$ `computeOptimalRoute(`$\vec{p_O}$, $\vec{p_{TD}}$`)`;
$\quad\quad$ `/* ` i ` drives to transport destination */`
17 $\quad\quad$ `addRouteWaypoints(`i, W_{TD}`)`;
18 $\quad\quad t \leftarrow t_{TD} + TranspDest\_IDLE$ with arrival time t_{TD} at $\vec{p_{TD}}$;
19 $\quad W_H \leftarrow$ `computeOptimalRoute(`$\vec{p_i}(t)$, `homeStation(`i`))`;
$\quad$ `/* ` i ` drives to home station */`
20 $\quad$ `addRouteWaypoints(`i, W_H`)`;
21 $\quad t \leftarrow t_H$ with arrival time t_H at `homeStation(`i`)`;

This may be an ambulance waiting at the station as well as an ambulance on its way back from a previous operation. In case of multiple dispatch candidates, the ambulance with the lowest index is selected. Next, this dispatched ambulance drives to the place of operation on an optimal (fastest or shortest) route from its current position to the destination computed on the basis of the road network (ll. 8-9). We use OpenRouteService (ORS) [24] for the route computation (for details, see [5]).

When the dispatched ambulance has arrived, a pause of length $PlaceOfOp\_IDLE$ models the idle time (of the ambulance vehicle) at the place of operation (l. 10). Thereafter, a transport destination is selected with probability $p_{CasualtyTransport}$ (l. 11). This is a hospital with probability $p_{TDisHospital}$ and a randomly selected destination otherwise (ll. 12-15). We initially pull the positional data of all hospitals within the simulation area from OpenStreetMap (OSM) [11]. Based on this list of hospitals, we choose the one that is nearest to the place of operation according to an initially defined distance metric (l. 13). In the real world, the free capacity of the hospital is checked first, but we do not consider this in our model as the added complexity would outweigh the benefits. The selection of the destination is again followed by the computation of an optimal route and the drive to the transport destination (ll. 16-17). After the idle time at the transport destination, $TranspDest\_IDLE$, has elapsed, the dispatched ambulance returns to its home station (ll. 18-21). If a transport of casualties is not necessary (probability $1 - p_{CasualtyTransport}$), the ambulance directly drives from the place of operation to its home station.

From the time when the ambulance drives from the station to the place of operation until such time as it starts to return to the station (from the place of operation or transport destination), it is not operationally ready. Only operationally ready ambulances can be dispatched in case of an emergency. Therefore, a consecutive operation occurs if and only if the ambulance is on its way back to the home station and it is nearest to the place of operation corresponding to the new emergency call.

3.3 Model Parameters

With the general idea of the DiAm model described, we will now go into more detail by describing the different parameters of the model (for an overview, see Table 1).

The `EPSGCode` parameter specifies the European Petroleum Survey Group (EPSG) code (cf. [23]) of the input coordinates. These have to be based on a projected Coordinate Reference System (CRS) such as UTM, since the model assumes Euclidean distances.

As mentioned earlier, we use OSM as a source for map data. In order to select a specific area of the map, a bounding box has to be defined with the `MapBBox` parameter. Furthermore, this parameter expects a factor $\lambda \in \mathbb{R}_{\geq 0}$ that specifies the relative size of an extra margin. We use this extra margin to account for routes that, in part, lie outside of the bounding box. These can result from the optimal route computation, especially if fastest routes, e.g., main roads and highways, are chosen.

In the domain of first responders, the ambulances are assigned a home station where they idle until they are dispatched. The locations of the different stations within the considered part of the map can be specified with the `Stations` parameter. Furthermore, the number of ambulances, that are assigned to a station, is set with the `NumberOfAmbulances` parameter. If this parameter is not specified by the user, the total number of ambulances is shared equally by all stations.

On the route to the destination, the ambulance drives at a fixed speed for each street segment (cf. Fig. 2). The speed value is uniformly chosen from the interval $[speed_{min}, speed_{max}]$ which can be specified with the `Speed` parameter. The idea behind this speed selection is that in reality, an ambulance is usually prevented from driving at a constant speed due to congested traffic. Furthermore, we decided not to model pauses on the way to the destination, since this would also be unrealistic with respect to ambulance movement.

The position calculation of the place of operations can be either trace- or random-based, defined by the `PositionCalcMethod` parameter. In case of a trace-based calculation,

Parameter	Meaning
`EPSGCode`	EPSG code of the input coordinates
`MapBBox`	Coordinates of the bounding box; factor for extra margin due to routing
`Stations`	Coordinates of the stations
`NumberOfAmbulances`	Number of available ambulances for each station
`Speed`	Speed interval $[speed_{min},\ speed_{max}]$
`PositionCalcMethod`	Method for calculating place of operation positions
`ORSDistanceMetric`	Metric to use for route computation
`DispatchDistanceMetric`	Metric to use for distance calculation in the dispatch process
`ConsecutiveOperations`	Turn consecutive operations on or off
`MeshNodeDistance`	Distance of two neighboring mesh nodes on the grid

Table 1: Parameters of the DiAm model

this parameter expects a CSV file containing a list of coordinates. Based on this list, DiAm uniformly chooses a position for a place of operation. Otherwise, if the user sets the calculation to a purely random one, a position is uniformly chosen within the simulation area. Since we need a valid destination for ORS, i.e., a position in the proximity of a street, we draw a random position until we have one that fullfils this criterium.

ORS can compute a fastest or shortest route to the destination. In DiAm, this option is provided by the `ORSDistanceMetric` parameter. Furthermore, we utilize this distance metric for the calculation of the distances considered when choosing a nearest ambulance to be dispatched as well as when choosing the nearest hospital. Apart from these two, the third option for the `DispatchDistanceMetric` parameter is to use Euclidean distances which is also the metric used in real world ambulance scenarios. It should be noted at this point that `ORSDistanceMetric` and `DispatchDistanceMetric` are independent from each other, i.e., the latter is only used for choosing a nearest ambulance or hospital, not for route computation.

Further control of the ambulance movement is given with the `ConsecutiveOperations` parameter. As the name implies, this parameter toggles the use of consecutive operations. If enabled, ambulances on the way back to the station are dispatched directly from their current position if they are closest to the place of operation at the considered simulation time. As a result, other ambulances potentially wait longer at the station till their next operation.

If the simulation is supposed to realize a mesh network, the user can specify static mesh nodes in addition to the dynamic ambulance nodes with the `MeshNodeDistance` parameter. Even though the static nodes are not part of the movement scenario generation, we think this option could be useful, since these nodes do not need to be specified manually in the simulator of choice. The mesh nodes are placed according to a grid, where the parameter defines the distance between two neighboring mesh nodes. Kraaier et al. [19] proposed a method that strategically places the mesh nodes on street crossings. Using this method, the radio range of the mesh nodes highly depends on the considered road network. Other possible methods could minimize the number of mesh nodes by assuming a fixed radio range. Using a more efficient strategy to place the mesh nodes is part of our future work.

4. PARAMETRIZATION

In Section 3.2, we introduced some parameters which we now want to assign values to by statistically analyzing the trace data described in Section 4.1. Parameters to consider are the three different IDLE times which we cover in Section 4.2. In Section 4.3, we examine the remaining parameters, i.e., the probabilites concerning the transport of casualties.

4.1 Trace Basis

The real world movement traces, on which the DiAm model is based, were measured in Bonn, Germany. The district of Bonn measures about $140km^2$ in size and is inhabited by more than $317,000$ people. A total of 12 ambulances are assigned to four stations which are tactically distributed over the whole district.

The traces span from 2007/09 to 2008/10, i.e., we have a long time period of 13 months. The traces contain data sets for each first responder operation during that time period. An operational data set consists of the ambulance ID number, several timestamps for different operational statuses, and the global coordinates of the place of operation and transport destination, if applicable.

Obviously, using this data as a basis leads to a parametrization tailored to first responder scenarios in Bonn. But on the other hand, this way the model already includes a parametrization based on a thorough analysis. Furthermore, one does not have to bother with trying to obtain these data sets which are not available to the public.

4.2 IDLE Time Fitting

The simplest method for selecting values for the emergency call, place of operation and transport destination IDLE times ($ECall\_IDLE$, $PlaceOfOp\_IDLE$, and $TranspDest\_IDLE$, respectively) is to use the empirical distribution given by the operational data. But since we want our mobility model to be self-contained, i.e., independent of scenario-specific operational data, we use well-known distribution functions by performing a fitting of the IDLE times. For this purpose, we consider the time series

(i) $(ECall\_IDLE_i)_{1\leq i\leq I-1}$,

(ii) $(PlaceOfOp\_IDLE_i)_{1\leq i\leq I}$, and

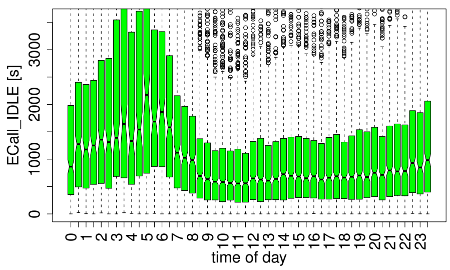
(iii) $(TranspDest\_IDLE_i)_{1\leq i\leq I}$,

where $I > 28,000$ denotes the total number of operational data sets.

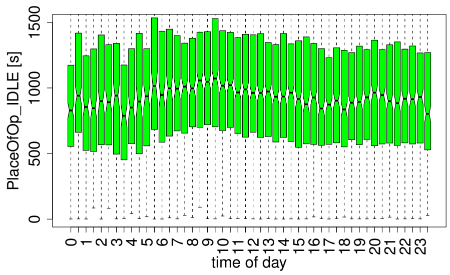
As already mentioned above, the operational data we use for our analysis was traced for a time period of 13 months. We use the first 11 months as a basis for the fitting and the last two months for validating the results of the fitting.

Stationarity and Independency

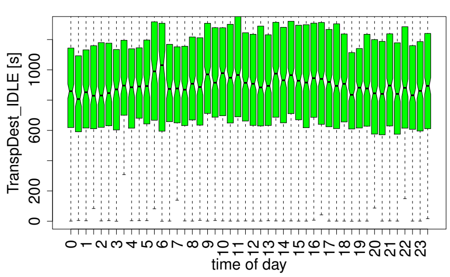
For the fitting, stationarity of the considered time series is a precondition. We are aware of the formal mathematical definition of stationarity. However, the time series we consider in this paper are non-stationary by their very nature, since they depend on the time of day. For the performance evaluation, high network traffic periods are typically the ones of interest. Thus, we need some kind of steady state for the performance evaluation during these periods. Therefore, we consider a weaker definition of stationarity: We sorted the



(a) $ECall\_IDLE$



(b) $PlaceOfOp\_IDLE$



(c) $TranspDest\_IDLE$

Figure 3: Boxplots of the IDLE time series

samples according to the time of day (scaled to $0.5h$) and show the corresponding boxplot. We consider a time series as stationary or steady state if the confidence intervals of the medians overlap and the interquartile ranges do not diverge significantly. Furthermore, we dropped outliers according to a threshold which we chose as a multiple of $3600s = 1h$ for the different time series.

None of the three different time series proved to be steady state over the whole range [0, 23.5] (see Fig. 3). Therefore, we extracted a time range for each time series that fulfills the above-mentioned critera and still contains as many samples as possible. Also, we tried to extract ranges that do not differ from each other too much. The results of this extraction are summarized in Table 2. The $ECall\_IDLE$ time series (Fig. 3a) shows significant differences between night- and daytime, i.e., at night, there were much less emergency calls. We extracted the interval [8.5, 22] and dropped samples with a value above $7200s$. The $PlaceOfOp\_IDLE$ time series (Fig. 3b) shows less fluctuation between day and

IDLE time series	**steady state interval**	**outlier threshold**
$ECall\_IDLE$	[8.5, 22]	$> 7200s$
$PlaceOfOp\_IDLE$	[10, 23]	$> 3600s$
$TranspDest\_IDLE$	[6.5, 18]	$> 3600s$

Table 2: Choice of steady state extracts

IDLE time series	**Distribution**	**MLE parameter**	**K-S distance**
$ECall$	exponential	rate = 0.001028745	0.0169
	log-normal	meanlog = 6.27694 sdlog = 1.326982	0.0671
	gamma	shape = 5.813777 rate = 0.01	0.2955
	weibull	**scale = 961.2075108** **shape = 0.9758523**	**0.0099**
$PlaceOfOp$	exponential	rate = 0.0009717898	0.2178
	log-normal	meanlog = 6.7441247 sdlog = 0.7418827	0.0715
	gamma	shape = 8.985656 rate = 0.01	0.1729
	weibull	**scale = 1156.293778** **shape = 1.827563**	**0.0300**
$TranspDest$	exponential	rate = 0.0009850198	0.2665
	log-normal	meanlog = 6.753413 sdlog = 0.742864	0.1176
	gamma	shape = 9.064934 rate = 0.01	0.1342
	weibull	**scale = 1139.126282** **shape = 1.973181**	**0.0561**

Table 3: Results of the IDLE time series fitting

night, but still we had to extract the time range [10, 23] and dropped samples with values $> 3600s$. Fig. 3c shows that also for the transport destination, the time of day does not have much influence on the IDLE time. Here, we chose the range [6.5, 18] and dropped all samples having a value $> 3600s$.

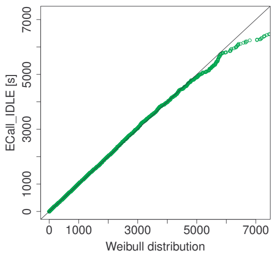
After checking for stationarity, we need to check the time series for independency. For this purpose, we checked the autocorrelations of the time series. The autocorrelation coefficient does not significantly deviate from 0. All of the three time series hold the independency property.

Fitting

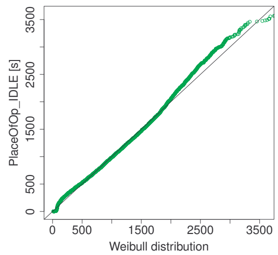
Both preconditions for fitting time series (stationarity and independency) have been checked. Now, we describe the fitting itself. We use the commonly applied Maximum Likelihood Estimation (MLE) (see e.g., [21]) for this purpose.

As candidates for the fitting, we chose the exponential, lognormal, gamma, and Weibull distributions. In order to decide which of the fitted distributions can represent the empirical data best, we also performed goodness-of-fit tests with the Kolmogorov-Smirnov (K-S) test (cf. [21]). The K-S test compares the Empirical Cumulative Distribution Function (ECDF) with the Cumulative Distribution Function (CDF) of the fitted distribution by calculating the maximal distance between the function values of the ECDF and CDF. This is called the K-S distance and the smaller this distance is, the better ECDF and CDF overlap and the better the fitting.

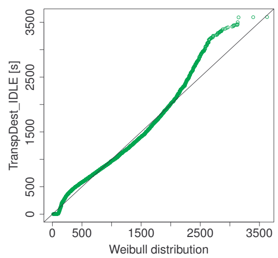
The results of the MLE and K-S tests are summarized in Table 3. For each of the three time series, the fitted Weibull distribution provides the lowest K-S distance. Apart from the K-S tests, we also evaluated the goodness of



(a) $ECall\_IDLE$



(b) $PlaceOfOp\_IDLE$



(c) $TranspDest\_IDLE$

Figure 4: Q-Q plots visualizing the goodness of the fitting

the fitting by visualizing it by means of Quantile-Quantile (Q-Q) plots (cf. [21]), shown in Fig. 4: Here, the quantiles of the fitted Weibull distribution are plotted against the quantiles of the corresponding empirical distribution. An ideal fitting would be a diagonal Q-Q plot (represented by the black reference line). Overall, the Q-Q plots prove that our fitting can represent the empirical data quite well. Only the tails of the plots differ significantly from the reference line. This is caused by the outliers present in the steady state extracts.

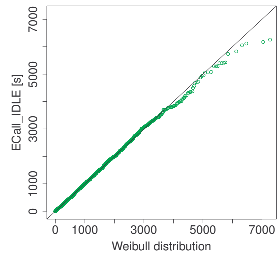
Validation

The purpose of the validation is to show whether the data used as basis for the fitting (first 11 months of the whole trace basis) is also valid for trace data obtained in the future. We compared the fitted Weibull distributions to the trace data of the last two months (2008/09-10). We used Q-Q plots, where the fitted distribution is shown on the x-axis and the empirical distribution based on the data of the last two months is shown on the y-axis (see Fig. 5). The plots prove that the fitting does not depend on the time period of the trace data it is based on and therefore is also valid for future traces.

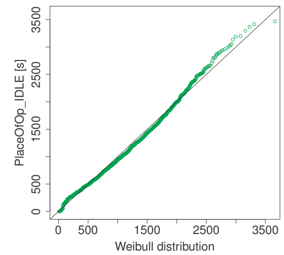
4.3 Deciding on Casualty Transport

Now we calculate values for the remaining parameters of the DiAm model, which are $p_{CasualtyTransport}$ and $p_{TDisHospital}$. The former one is the probability for the event that casualties need to be transported from the place of operation to some transport destination. We divide the number of operations with a transport by the total number of operations which yields

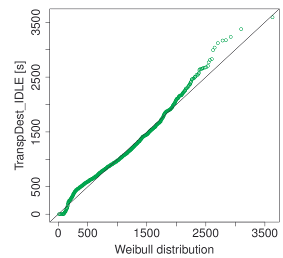
$$p_{CasualtyTransport} := 0.537234,$$



(a) $ECall\_IDLE$



(b) $PlaceOfOp\_IDLE$



(c) $TranspDest\_IDLE$

Figure 5: Q-Q plots for validating the fitting

Parameter	**Value**
`EPSGCode`	31466
`MapBBox`	(2572162.86193241, 5611326.02517925), (2585684.45650920, 5627251.16926147), 0.5
`Stations`	(2575916.82282699, 5623585.21380640), (2580549.34257569, 5623094.03460189), (2580788.77398661, 5617791.51749108), (2573965.80486246, 5620552.20755086)
`NumberOfAmbulances`	4, 3, 3, 2
`Speed`	[30, 120]km/h
`MaxPause`	7200s

Table 4: Fixed parameter values for Bonn scenario

i.e., about every second operation includes a casualty transport. The destination of such a transport is usually a hospital. How probable this case is, is defined by the $p_{TDisHospital}$ parameter. We divide the number of transport destinations in the trace data, which are hospitals, by the total number of transport destinations and obtain

$$p_{TDisHospital} := 0.953869,$$

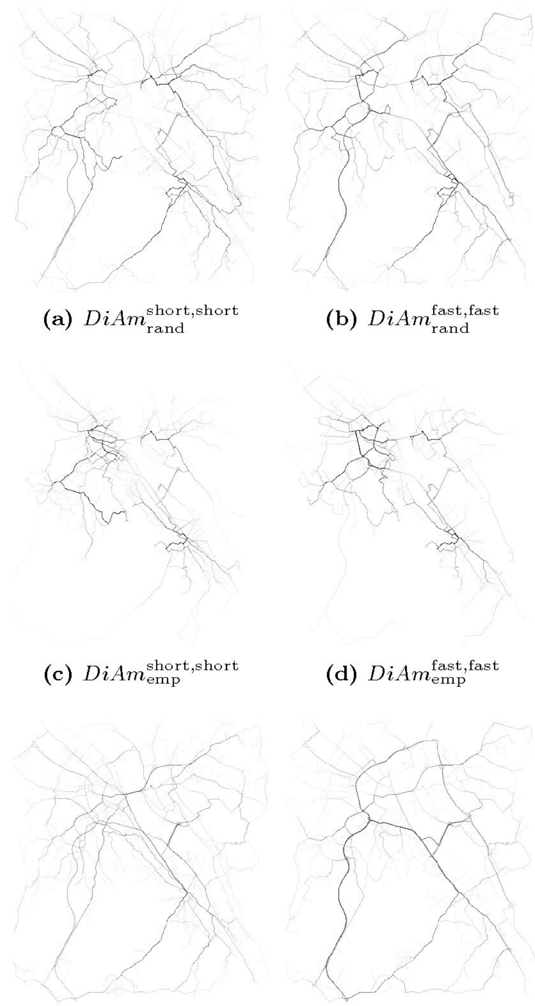
i.e., in 95% of all transport cases, the ambulance drives to the nearest hospital. Otherwise, a random transport destination is chosen.

5. EVALUATION

In this section, we evaluate and compare the DiAm model to RaSt [5] and RWP at the mobility level in order to show the impact of the new model by analyzing the movement traces. For this purpose, we implemented the DiAm model by extending the mobility scenario generation tool BonnMotion [1]. We chose RWP as a base line reference model and RaSt as a map-based variant of RWP. For similar conditions among the three models, we set the `MaxPause` value

Notation	Place of op. generation	CO	Routes	Dispatch metric
$DiAm^{\text{short,short}}_{\text{rand}}$	random		shortest	shortest
$DiAm^{\text{short,euclid}}_{\text{rand}}$	random		shortest	Euclidean
$DiAm^{\text{fast,fast}}_{\text{rand}}$	random		fastest	fastest
$DiAm^{\text{fast,euclid}}_{\text{rand}}$	random		fastest	Euclidean
$DiAm^{\text{short,short}}_{\text{rand,CO}}$	random	✓	shortest	shortest
$DiAm^{\text{short,euclid}}_{\text{rand,CO}}$	random	✓	shortest	Euclidean
$DiAm^{\text{fast,fast}}_{\text{rand,CO}}$	random	✓	fastest	fastest
$DiAm^{\text{fast,euclid}}_{\text{rand,CO}}$	random	✓	fastest	Euclidean
$DiAm^{\text{short,short}}_{\text{emp}}$	empirical		shortest	shortest
$DiAm^{\text{short,euclid}}_{\text{emp}}$	empirical		shortest	Euclidean
$DiAm^{\text{fast,fast}}_{\text{emp}}$	empirical		fastest	fastest
$DiAm^{\text{fast,euclid}}_{\text{emp}}$	empirical		fastest	Euclidean
$DiAm^{\text{short,short}}_{\text{emp,CO}}$	empirical	✓	shortest	shortest
$DiAm^{\text{short,euclid}}_{\text{emp,CO}}$	empirical	✓	shortest	Euclidean
$DiAm^{\text{fast,fast}}_{\text{emp,CO}}$	empirical	✓	fastest	fastest
$DiAm^{\text{fast,euclid}}_{\text{emp,CO}}$	empirical	✓	fastest	Euclidean
$RaSt^{\text{short}}$	-	-	shortest	-
$RaSt^{\text{fast}}$	-	-	fastest	-
RWP	-	-	-	-

Table 5: Parameter constellations of the models to compare



(a) $DiAm^{\text{short,short}}_{\text{rand}}$ (b) $DiAm^{\text{fast,fast}}_{\text{rand}}$

(c) $DiAm^{\text{short,short}}_{\text{emp}}$ (d) $DiAm^{\text{fast,fast}}_{\text{emp}}$

(e) $RaSt^{\text{short}}$ (f) $RaSt^{\text{fast}}$

Figure 6: Street distribution for DiAm and RaSt

of RaSt and RWP to the maximum over all IDLE times of DiAm. Since we consider the area of Bonn, we set the parameters accordingly (cf. Table 4). Note that the other parameter values for RaSt and RWP can be easily derived, e.g., the number of nodes is the sum of all ambulances and the simulation area has the same dimensions as the map bounding box. As mobility metrics are only useful if all nodes in the considered network are mobile and as the mesh nodes may influence the results unnecessarily, static mesh nodes are not part of this evaluation.

The factor for the extra margin (0.5) is based on an evaluation performed with RaSt. For different factors, we generated 10000 RaSt mobility scenarios with a simulation time of $2h$ each. A factor of 0.4 yielded at least one trespassing of the simulation area in 21.83% of all generated scenarios, whereas 0.5 yielded 1.24%. An increase of the factor to 0.6 did not improve this ratio significantly (1.07%).

For our evaluation, we examine the parameter space of the remaining DiAm parameters `PositionCalcMethod`, `ORSDistanceMetric`, `DispatchDistanceMetric`, and `ConsecutiveOperations`. All evaluation candidates and parameter constellations are listed in Table 5. Since we need a meaningful data basis for the evaluation and since the duration of the steady state intervals of the IDLE time series is around $12h$ (cf. Table 2), we generated mobility scenarios with a simulation time of $10 \cdot 12h$ for each constellation. Conventional mobility metrics such as average node speed [2], relative mobility [16], or the ones described in [6] cannot capture the special characteristics of the DiAm model. Therefore, we use specific metrics which are described below.

5.1 Street Distribution

The first metric we examine is the street distribution. For visualizing the distribution, we make use of alpha compositing (cf. [25]): The more often a street or path is used by the mobile nodes, the higher is its alpha value and the clearer it is visible. Suppose that n_S is the frequency a street S is used. Then, the alpha value $\alpha(n_S)$ is calculated as follows:

$$\alpha(n_S) := \begin{cases} \lfloor n_S \cdot \lambda \cdot \alpha_{max} \rfloor, & \text{if } n_S \cdot \lambda \leq 1 \\ \alpha_{max}, & \text{else} \end{cases},$$

where $\alpha_{max} \in \{0, 1, \ldots, 255\}$ is the maximal alpha value and $\lambda \in (0, 1]$ is a scalar. This results in a linear shade of the alpha values for $n_S \in \{0, 1, \ldots, \lceil \lambda^{-1} \rceil\}$. For the plots in this paper, we chose the values $\alpha_{max} = 255$ and $\lambda = 0.025$. Since the movement paths for RWP are used only once, it was not possible to find a parametrization that could visualize the distribution for DiAm, RaSt, and RWP equally well.

Fig. 6 shows the street distribution for DiAm and RaSt with routing/dispatch metrics "shortest" and "fastest" as well as empirical and random generation of places of operation. As expected, using random generation (Fig. 6a and 6b), the streets taken by the nodes are more evenly distributed within the bounding box than for the empirical generation (Fig. 6c and 6d). The empirical generation yields a street distribution that is concentrated in the city center. Thus,

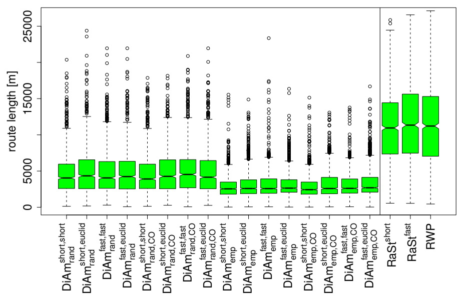


Figure 7: Boxplot of the route lengths

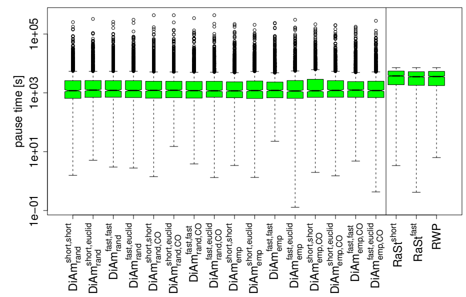


Figure 8: Boxplot of the pause times

the choice of the places of operation has a significant impact on the street distribution.

Comparing the different routing metrics, for RaSt it can be seen that in case of fastest routes (Fig. 6f), main roads and highways are used more frequently than others. In contrast to this, shortest routes (Fig. 6e) result in a more uniform distribution with more details in the city center. This effect cannot be seen as clearly for DiAm movement (compare Fig. 6a with 6b, and 6c with 6d). The dispatch process always chooses a node which is closest to the place of operation and therefore most routes taken are short. However, the impact of the "fastest" metric on the street distribution is only significant if the routes are long on average.

The main characteristic of DiAm can be observed if the street distribution, especially for the empirical generation (Fig. 6c and 6d), is compared to RaSt (Fig. 6e and 6f). In case of DiAm, the distribution has four centers which are the stations specified by the `Stations` parameter. The reason is that the dispatch process leads to routes that are mainly in the proximity of these stations.

5.2 Route Length

The route length is the total length of all street segments (cf. Fig. 2) from source to destination position. Fig. 7 depicts the distribution of the route lenghts in form of a boxplot for all parameter constellations. It confirms that, in general, the routes are shorter for DiAm than for RaSt and RWP. Obviously, the dispatch process effectively optimizes the distances. Furthermore, the empirical generation yields shorter route lengths than the random generation, which supports our observation in the last section concerning the street distribution.

5.3 Pause Time

Pause times of the mobile nodes give information about how long they idle at a position. Thus, long pause times indicate low mobility. The boxplot in Fig. 8 shows the pause time distribution for each parameter constellation using a logarithmically scaled y-axis. Two conclusions can be drawn from this plot: The different parameters of DiAm do not significantly impact the pause times. Apart from that, the pause times of the random-based models are consistently longer than for DiAm, which is due to the different distribution functions.

5.4 Generation Runtime

The final metric we consider in this paper is the runtime for generating mobility scenarios with BonnMotion. For this purpose, we created 100 replications with a simulation time of $12h$ each. We used Java 1.6 under Kubuntu 8.04 on a conventional PC with a Pentium IV 2.8GHz and 1024MB 400MHz DDR-RAM.

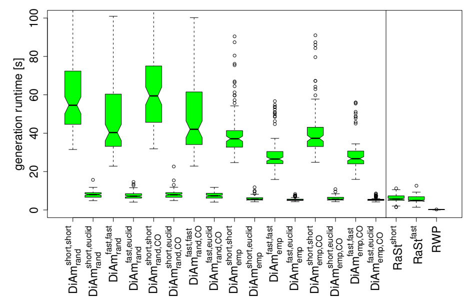


Figure 9: Boxplot of the mobility generation runtime

Fig. 9 shows a boxplot of the mobility generation runtime. On average, it takes less than a minute to generate a mobility scenario trace. The most significant impact can be observed for the dispatch distance metric. If the Euclidean distance is used, the runtime for DiAm scenarios is around $10s$. Otherwise, it is around 30 or 60 seconds, depending on the type of place of operation generation. This is the result of the distance computation for choosing an ambulance to dispatch, which has to be performed lots of times during the dispatch process. Every single distance computation based on the shortest or fastest route requires the sending of a route request to ORS which is located on a remote host. Since the dispatch distance metric does not have a remarkable impact on the other metrics examined above, we suggest to fix this parameter to Euclidean distance.

As we pointed out in Section 5.2, the average route length is shorter for empiric generation of places of operation. The time it takes to compute a shorter route is less than for longer routes. This is also reflected in the boxplot: The runtimes are shorter if the generation of places of operation is based on the empirical data.

Comparing to RaSt, the runtime overhead is negligible for Euclidean distance computation since RaSt also communicates with a remote host. RWP scenarios take around $0.2s$ to generate, yielding a DiAm runtime overhead factor of 50 (Euclidean distances). Clearly, this factor strongly depends on the latency of the network link to the ORS server.

6. CONCLUSION AND FUTURE WORK

In order to obtain credible performance evaluation results in the simulation of wireless multi-hop networks, it is crucial to model the mobile nodes' movement in a realistic way. In this paper, we have introduced the Dispatched Ambulance model, a new realistic mobility model for first responder scenarios. It is based on trace analysis and considers geographic restrictions with the help of free publicly available map data provided by OpenStreetMap. The characteristic movement pattern of ambulances essentially relies on the dispatch process which is the main part of Dispatched Ambulance. For computing optimal routes, we integrated the location-based OpenRouteService.

We further analyzed the operational data provided by the fire department of Bonn to parametrize the Dispatched Ambulance mobility model. This trace data includes data sets for each first responder operation within a time period of 13 months. Furthermore, it allows for the calculation and extensive fitting of different IDLE time series used in the model. With the resulting standard distribution functions of the fitting, the empirical distributions could be reflected very well and the model was enabled to be self-contained.

The evaluation of the impact on different mobility metrics has shown that the model in general yields significantly different movement traces compared to the random-based models Random Street and Random Waypoint. Also, its different parameters have shown a considerable impact on the mobility metrics. Thus, overall, the Dispatched Ambulance mobility model has proven to be valuable for modeling node movement in first responder scenarios.

For future work, we plan to refine the random generation of places of operation by considering arbitrary distributions. We also want to generate mobility scenarios for other cities to examine the general applicability of the model. Another aspect we plan to refine is the algorithm for placing the mesh nodes. Moreover, we want to perform extensive simulative performance evaluations using the Dispatched Ambulance model to substantiate its impact.

Acknowledgement

We wish to thank Pascal Neis and Alexander Zipf from the University of Heidelberg, Department of Geography, for providing their ORS as well as sustainable discussions and support. Likewise, we want to thank the fire department of Bonn for information and support.

7. REFERENCES

[1] N. Aschenbruck, R. Ernst, E. Gerhards-Padilla, and M. Schwamborn, "BonnMotion - a mobility scenario generation and analysis tool," in *Proc. of the 3rd Int. ICST Conference on Simulation Tools and Techniques, Torremolinos, Spain*, 2010, pp. 1–10.

[2] N. Aschenbruck, E. Gerhards-Padilla, M. Gerharz, M. Frank, and P. Martini, "Modelling mobility in disaster area scenarios," in *Proc. of MSWiM '07, Chania, Greece*, 2007, pp. 4–12.

[3] N. Aschenbruck, E. Gerhards-Padilla, and P. Martini, "A survey on mobility models for performance analysis in tactical mobile networks," *Journal of Telecommunications and Information Technology (JTIT)*, vol. 2, pp. 54–61, 2008.

[4] N. Aschenbruck, A. Munjal, and T. Camp, "Trace-based mobility modelling for multi-hop networks," 2010, submitted for publication.

[5] N. Aschenbruck and M. Schwamborn, "Synthetic map-based mobility traces for the performance evaluation in opportunistic networks," in *Proc. of the 2nd Int. Workshop on Mobile Opportunistic Networking, Pisa, Italy*, 2010, pp. 143–146.

[6] F. Bai, N. Sadagopan, and A. Helmy, "IMPORTANT: A framework to systematically analyze the impact of mobility on performance of routing protocols for adhoc networks," in *Proc. of INFOCOM '03, San Francisco, USA*, 2003, pp. 825–835.

[7] R. Bruno, M. Conti, and E. Gregori, "Mesh networks: commodity multihop ad hoc networks," *IEEE Communications Magazine*, vol. 43, no. 3, pp. 123–131, 2005.

[8] T. Camp, J. Boleng, and V. Davies, "A survey of mobility models for ad hoc network research," *Journal of Wireless Communications and Mobile Computing (WCMC): Special issue on Mobile Ad Hoc Networking*, vol. 2, no. 5, pp. 483–502, 2002.

[9] S. Corson and J. Macker, "Mobile ad hoc networking (MANET): Routing protocol performance issues and evaluation considerations," RFC 2501, IETF Network WG, 1999.

[10] M. Güneş, M. Wenig, and A. Zimmermann, "Realistic mobility and propagation framework for MANET simulations," in *Proc. of the 6th Int. IFIP-TC6 Networking Conference, Atlanta, USA*, 2007, pp. 97–107.

[11] M. M. Haklay and P. Weber, "OpenStreetMap: User-generated street maps," *IEEE Pervasive Computing*, vol. 7, no. 4, pp. 12–18, 2008.

[12] S. G. Henderson and A. J. Mason, "Estimating ambulance requirements in auckland, new zealand," in *Proc. of the 1999 Winter Simulation Conference, Phoenix, USA*, 1999, pp. 1670–1674.

[13] ——, "BartSim: A tool for analysing and improving ambulance performance in auckland, new zealand," in *Proc. of the 35th Annual Conference of the Operational Research Society of New Zealand, Wellington, New Zealand*, 2000, pp. 57–64.

[14] W. Hsu, T. Spyropoulos, K. Psounis, and A. Helmy, "Modeling spatial and temporal dependencies of user mobility in wireless mobile networks," *IEEE/ACM Transactions on Networking*, vol. 17, no. 5, pp. 1564–1577, 2009.

[15] Y. Huang, W. He, K. Nahrstedt, and W. C. Lee, "CORPS: Event-driven mobility model for first responders in incident scene," in *Proc. of the 2008 IEEE Int. Conference on Military Communications, San Diego, USA*, 2008, pp. 1–7.

[16] P. Johansson, T. Larsson, N. Hedman, B. Mielczarek, and M. Degermark, "Scenario-based performance analysis of routing protocols for mobile ad-hoc networks," in *Proc. of MOBICOM '99, Seattle, USA*, 1999, pp. 195–206.

[17] M. Kim, D. Kotz, and S. Kim, "Extracting a mobility model from real user traces," in *Proc. of INFOCOM '06, Barcelona, Spain*, 2006, pp. 1–13.

[18] J. Koberstein, H. Peters, and N. Luttenberger, "Graph-based mobility model for urban areas fueled with real world datasets," in *Proc. of the 1st Int. ICST Conference on Simulation Tools and Techniques, Marseille, France*, 2008, pp. 1–8.

[19] J. Kraaier and U. Killat, "The random waypoint city model - user distribution in a street-based mobility model for wireless network simulations," in *Proc. of the 3rd ACM Int. Workshop on Wireless Mobile Applications and Services on WLAN Hotspots, Cologne, Germany*, 2005, pp. 100–103.

[20] S. Kurkowski, T. Camp, and M. Colagrosso, "Manet simulation studies: The incredibles," *Mobile Computing and Communications Review*, vol. 9, no. 4, pp. 50–61, 2005.

[21] A. M. Law and W. D. Kelton, *Simulation Modeling and Analysis*, 3rd ed. McGraw-Hill, 2000.

[22] K. Lee, S. Hong, S. J. Kim, I. Rhee, and S. Chong, "SLAW: A mobility model for human walks," in *Proc. of INFOCOM '09, Rio de Janeiro, Brazil*, 2009, pp. 855–863.

[23] "EPSG geodetic parameter registry (version 7.4.2)," OGP Surveying & Positioning Committee, 2010. [Online]. Available: http://www.epsg-registry.org/

[24] "OpenLS route service with free OSM data," 2010. [Online]. Available: http://www.openrouteservice.org/

[25] T. Porter and T. Duff, "Compositing digital images," *SIGGRAPH Computer Graphics*, vol. 18, no. 3, pp. 253–259, 1984.

[26] P. Prabhakaran and R. Sankar, "Impact of realistic mobility models on wireless networks performance," in *Proc. of the 2nd IEEE Int. Conference on Wireless and Mobile Computing, Networking and Communications, Montreal, Canada*, 2006, pp. 329–334.

[27] C. Tuduce and T. R. Gross, "A mobility model based on WLAN traces and its validation," in *Proc. of INFOCOM '05, Miami, USA*, 2005, pp. 664–674.