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Modeling Civilian Mobility in Large-Scale Disasters

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ABSTRACT

When disasters destroy critical communication infrastructure, smartphone-based *Delay-Tolerant Networks* (DTNs) can provide basic communication for civilians. Although field tests have shown the practicability of such systems, real-world experiments are expensive and hardly repeatable. Therefore, simulations are required for the design and extensive evaluation of novel DTN protocols, but meaningful assertions require realistic mobility models for civilians.

This paper analyzes trace files from a large-scale disaster field test with respect to typical human behavioral patterns in a disaster area. Based on this, we derive a novel civilian disaster mobility model, encompassing identified behavior like group-based movement and clustering around points-of-interests like hospitals and shelters. We evaluate the impact of mobility on DTN communication performance by comparing our model against other established mobility models and against the trace file dataset in a simulative evaluation based on the field test scenario. In general, our mobility model results in a more realistic assessment of DTN communication performance in comparison to other mobility models.

Keywords

Civilian Disaster Communication, Delay-Tolerant Networks, human mobility, mobility models, disaster response, simulation

INTRODUCTION

Throughout the last years, an increase in the occurrence and devastation of natural disasters, such as extreme weather conditions or earthquakes, was observed and is expected to further increase in the future (Université catholique de Louvain (UCL) 2019; Toya and Skidmore 2018). These events often impair information and communication technologies (ICT), by either significantly damaging or destroying ICT infrastructure itself or by inhibiting critical infrastructure such as the power grid on which ICT infrastructure relies on. However, the subtraction of ICT is actively obstructing effective disaster relief efforts, for example, by rendering otherwise crucial means of communication for coordinating and informing affected civilians unusable (Mori et al. 2015; ICRC 2017).

Everyday mobile devices such as smartphones can provide basic, fast-deployable communication functionalities for civilians during disasters where the ICT infrastructure is unavailable, by creating *Delay-tolerant*

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Networks (DTNs) (Nishiyama et al. 2014; Álvarez et al. 2018; Lieser, Zobel, et al. 2019). In DTNs, ad hoc communication capabilities of mobile devices are used to directly exchange messages between them. However, the short communication ranges and the high mobility of devices leads to a frequently changing and highly partitioned network topology. Typical routing approaches, as used in pure Mobile Ad Hoc Networks (MANETs) are therefore not applicable. Instead, DTNs rely on the *store-carry-forward* principle, where messages are carried around by each mobile device in a digital backpack and exchanged with other devices when in range. Disconnected network partitions are unable to communicate with each other without this mobility. Hence, the communication performance of DTNs is directly linked to the mobility of civilians carrying these devices. Civilian mobility in disaster scenarios, however, is usually non-random and clustered around points-of-interests or localized social communities, which leads to increased contact times between specific users and lower mobility between separated network partitions (Álvarez et al. 2018; N. Richerzhagen et al. 2017). Therefore, a good understanding of civilian movement patterns in exceptional situations is crucial to fully evaluate the potential of DTN protocols and applications. However, data of civilian mobility in real disaster scenarios is scarce (Stute et al. 2017).

In this paper, we use the publicly available dataset[1] from a real-world field test to assess requirements for realistically modelling civilian mobility. This field test was conducted in Germany in 2017 with 125 participants to evaluate the capabilities of smartphone-based DTNs for civilian communication, coordination, and disaster response (Álvarez et al. 2018). In cooperation with experts from the German Federal Office of Civil Protection and Disaster Assistance (BBK), the German Federal Agency for Technical Relief (THW), local fire departments, and other NGOs, civilian disaster services were tested in a realistic environment with several scripted disaster events (Álvarez et al. 2018). Throughout the field test, user behavior and digital interactions were recorded in detail.

Although it is nearly impossible to recreate a real disaster with all its facets, the available dataset provides novel and valuable information. In this paper, we specifically focus on the dataset properties that provide unique conclusions about human behavior in disaster scenarios and the human factor on DTN performance in general. We use these insights to increase the expressiveness of simulative evaluation models of civilian DTNs based on smart mobile devices in disaster scenarios. Specifically, we make the following contributions that are relevant for the evaluation of DTN communication in disaster-related scenarios in general:

- We model civilians' mobility in large-scale natural disasters based on traces from a real-world disaster field test with civilian participants.
- We present a novel model for civilian mobility in disaster scenarios which is integrated in the discrete-event open-source simulation platform SIMONSTRATOR (B. Richerzhagen et al. 2015).
- We demonstrate the influence of human mobility on DTN communication performance and compare our model with other commonly used mobility models in a simulative evaluation based on the field test scenario.

The rest of the paper is structured as follows. In the next section, mobility models and related works are discussed. Afterwards, the field test trace files are analyzed with respect to participants' mobility. We present the civilian disaster mobility model in the subsequent section, which is then compared and evaluated to other models. Eventually, we conclude the paper and discuss further approaches for future work.

RELATED WORK

To assess the communication performance of Delay-Tolerant Networks (DTNs), real-world traces would be the most realistic approach. But they are often scarce due to missing records during or after a real disaster, or due to restrictions related to security or data privacy of users and mobile network operators (Stute et al. 2017; Álvarez et al. 2018). Additionally, they are also highly scenario-specific, which may decrease the expressiveness of results outside of that specific scenario (Krug et al. 2014). Other traces are derived from connectivity logs of, e.g., access points or Bluetooth devices, and thus, are imprecise with regard to the specific user location (Pelusi et al. 2006). Furthermore, obtaining traces requires elaborate preparation and may be subject to human, software, or hardware failures (Álvarez et al. 2018). Trace generators such as BonnMotion (Aschenbruck, Ernst, et al. 2010) can create additional trace files that are, for example, modeled after real firefighter traces and used to evaluate domain-specific applications for firefighters or first responders in disaster scenarios (Aschenbruck, Gerhards-Padilla, et al. 2009; Martín-Campillo et al. 2013; Krug et al. 2014). Trace generators, however, are unidirectional as they provide fixed movement without a real interaction between network and mobility. Hence, modeling reactions in the movement to

[1]Dataset available online: https://seemoo.de/smarterfield-test/ (last accessed 22.02.2021)

Figure 1. The field test area of approximately $2x5\,km^2$. Village outlines are shown in yellow. The main road connecting all three villages is marked in blue. Villages B and C were close to each other, around 1 km in distance or 20 minutes walking time apart. Villages A and C were farther away with around 5 km distance or 60 minutes walking time. (Álvarez et al. 2018)

events in the simulation is impossible with trace generators, but become possible with mobility models directly calculated in simulation time (N. Richerzhagen et al. 2017).

Simple and widely used mobility models include, for example, Random Walk, Random Direction, or Random Waypoint movement, in which mobility is computed based on random values for speed, direction, target location, and more. Node movement is often unrestricted, but more sophisticated versions also include map-based random node movement (Cerqueira and Albano 2015) or simple movement groups of multiple nodes (Hong et al. 1999). Nevertheless, such models do not take human mobility into account, which is usually not random or uniformly distributed. Therefore, simulated results of tested DTNs can usually not be used to determine the performance in real world scenarios. For that, more sophisticated approaches to model human mobility are created. An example is the SLAW mobility model (Lee et al. 2009) that initially defined abstract geographic constraints to mobility. Consequently, it was later-on enhanced to also include real-world map data (Schwamborn and Aschenbruck 2013). For mobile social applications, a mobility model based on map-based movement and public points-of-interest like cafés or parks (Stingl, B. Richerzhagen, et al. 2013) was extended to support complex human social ties and models user interaction by providing interactivity between mobility model and the networked application (N. Richerzhagen et al. 2017). In the scope of large-scale disaster scenarios, a complex simulation of different vehicles and pedestrians moving on a real-world map is available (Uddin et al. 2009), but the mobility is based on assumptions on human behavior in the specific scenario rather than on real-world traces. A similarly sophisticated simulation re-modeled a real-world disaster based on profound expert knowledge, providing many different roles such as civilians, emergency service members, and scientists moving throughout a large-scale disaster area. Node mobility was defined for each node by specific behavioral patterns and daily activities. However, the model lacked comparability to the real disaster as there were no movement traces available (Stute et al. 2017). In this paper, we specifically use real-world disaster movement traces to tackle realistic human mobility problems in such scenarios. In contrast to most related work, our model is modular and fully configurable, providing the possibility to evaluate a wide range of different scenarios and behaviors.

FIELD TEST MOBILITY ANALYSIS

The evaluation of DTN applications and approaches would be ideally performed in a real disaster situation, which is obviously not feasible. Instead, real-world simulations with staged disasters or field tests are used, but they require extensive planning and preparation. They are therefore also unfavorable for regular evaluation of applications and especially unreasonable for simply trying out new ideas and concepts. A significantly less labor- and cost-intensive option are simulation-based evaluations, which are mimicking disaster characteristics while providing a sandbox for the evaluation and testing of various approaches. However, extensive knowledge provided from real disasters or real-world field tests also allows the increase the realistic assessment within simulation-based environments.

To evaluate the capabilities of smartphone-based DTN applications for civilian self-coordination and communication, a large field test was conducted in 2017 at the military training area *Senne* near Paderborn, Germany (Álvarez et al. 2018). In cooperation with experts from the German Federal Office of Civil Protection and Disaster Assistance

(BBK), the German Federal Agency for Technical Relief (THW), local fire departments, and other NGOs, a large set of disaster services such as distress calls, I-am-alive-messages, and a resource market (Lieser, Alvarez, et al. 2017) was tested with 125 civilian participants. They were distributed in three villages with concrete buildings and provided with smartphones using the IBR-DTN protocol (Schildt et al. 2011) for DTN communication and the disaster services. Each participant received a set card, including social relations with other participants and a set of tasks for the field test, e.g., finding relatives or collecting batteries. Several points-of-interests like shelters, hospitals, and food distribution points were located inside villages and scripted events like multiple-casualty incidents were staged with professional actors to increase stress and encourage the disaster services usage. User behavior and digital interactions were recorded in detail and the dataset provides real-world mobility traces as foundation for further analysis with significant insight into human mobility in disaster scenarios.

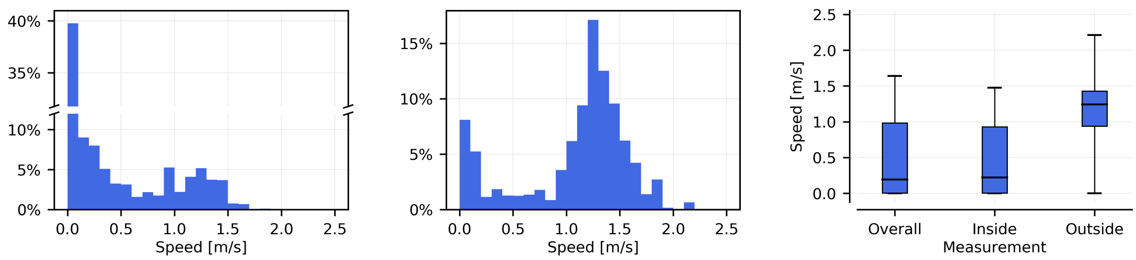
As analyzed by Álvarez et al., participants showed a high willingness to form groups and did not walk alone when moving between villages. Furthermore, group movement between the villages was scarce which negatively influenced message distribution. Participants stayed in villages most of the time and formed groups otherwise, therefore the average number of network neighbors was significantly higher than expected. However, due to the limited communication range of Wi-Fi, this also led to a high network separation with groups and villages forming distinct network partitions. As a result, message spread was slow or impossible between network partitions and resulted in only a small percentage of reached devices (Álvarez et al. 2018).

By analyzing the available dataset, our goal is to gain additional insights into human mobility in disaster scenarios. Metrics on digital interaction, but also participant behavior and the influence of weather and disaster events are already provided by Álvarez et al. Here, the goal is to combine this information with knowledge gained from the analysis, to be able to assess requirements for a realistic civilian mobility model in disaster scenarios. We incorporated the available mobility traces into the simulation environment Simonstrator (B. Richerzhagen et al. 2015), which allowed us to visualize and compare the device movement against other mobility models.

Typical for real-world measurements—and an additional reason why obtaining real-world traces is difficult—, parts of the trace files were lost due to hardware and software malfunctions, empty batteries, or wrong user interaction (Álvarez et al. 2018). Hence, just around 40% of the 125 traces cover the field test duration of 4.5 hours entirely. More than 30% percent of trace files cover less than 3 hours, with the shortest being only 32 minutes. On average, the trace files provide movement information of 70 participants with a minimum of 49 and a maximum of 94 participants simultaneously. Furthermore, jitter and inaccuracy of GPS locations and gaps in the GPS intervals have a significant influence on the trace file analysis. Dense vegetation—roads between villages run through dense forest—and occurring rainfall also impaired the GPS signal's accuracy. To cope with this problem, we smoothed the traces with a rolling average and allowed gaps between GPS measurements of up to 30 seconds. Larger gaps are treated similarly to impartial trace files, in these cases the respective nodes are removed from the simulation environment for that time until new location information may be available.

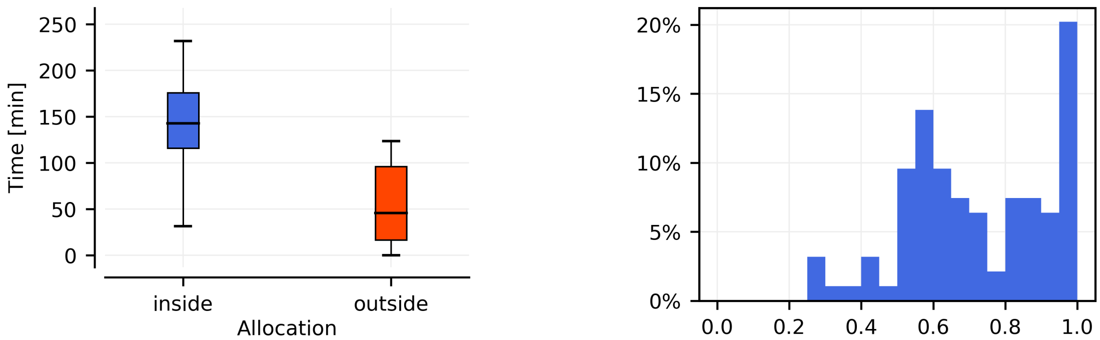
To understand human mobility, an analysis of the participants' mobility and its possible dependence on the respective location is required. The average walking speed of the participants was around $0.4\,\frac{m}{s}$. But more than 50% of the measurements are static or slower than the average. More than 15% are significantly faster with speed between $1.0\,\frac{m}{s}$ and $3.0\,\frac{m}{s}$. Therefore, the average seems to be not very expressive and this high deviation must be assessed. From a qualitative view on the traces, we saw significant behavioral differences inside and outside the villages. First, participants seem to roam through villages, often stopping close to other participants and gathering points—most probably for social interactions—, which conforms to the static behavior described in (Álvarez et al. 2018). Furthermore, we observed groups forming within villages, often remaining static for a short period inside the villages during the formation, and then heading out towards another village. Comparing the mobility behavior inside and outside of villages, groups' overall movement speed seemed faster when moving between villages. Second, mobility outside of villages also reveals social interactions between participants. When different groups met on their way, they often stopped for a few minutes. Sometimes, when a faster group caught up to a slower group walking in the same direction, they merged and moved together.

To better understand the mobility differences, we therefore conducted measurements of the participants' mobility on the available trace files and separated them for in and outside of the villages, as marked in yellow in Figure 1. As shown in Figures 2a and 2c, static or near static behavior was measured nearly 50% of the time inside villages, with most of the measurements being below $0.9\frac{m}{s}$. This corresponds to the qualitative assessment for the static behavior of participants inside of villages. In contrast, mobility outside of the villages was much more dynamic with the majority of measurements outside being within $0.9\frac{m}{s}$ and $1.6\frac{m}{s}$. These values are similar to the typical walking speed given by related work (Stute et al. 2017). Only 13% of measurements outside of villages showed static or near static behavior below $0.5\frac{m}{s}$, corresponding to pauses and roaming of groups when encountering each other. Significantly faster speeds above $2\frac{m}{s}$, for example when participants were running, were much rarer than static



(a) Speed distribution within villages. **(b) Speed distribution outside of villages.** **(c) Box plots comparing overall measurements against inside and outside measurements.**

Figure 2. Movement speed distribution of participants in the field test traces. Inside of villages, the movement was slower and very static, in contrast to faster mobility outside of villages.

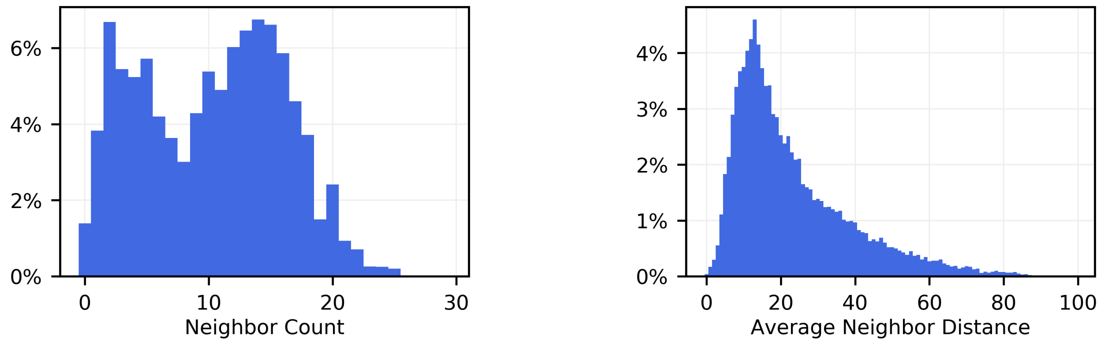


(a) Allocation total time. Colored boxes show 25th to 75th percentiles, whiskers 2.5th and 97.5th percentiles, respectively. Bold strokes denote median values. **(b) Distribution for participants inside villages respective to the available trace time.**

Figure 3. Total time for participant allocation and distribution of relative time inside of villages. Most of the time was spent within villages, but mobility between villages also required a considerate amount of time due to the long travel time.

behavior. Both match our initial observation of less static behavior and faster movement speed outside of villages. Therefore, it becomes obvious that there is a significant difference of the participants' mobility whether they are moving between points-of-interests or inside of villages.

In addition to speed, the allocation of participants for inside and outside of the villages is another issue for understanding the participants' mobility in the field test. Figure 3a depicts the total time of participants located inside or outside of villages, respectively. Participants spent significantly more time inside villages than outside, between approximately 2 and 3 hours. However, these total values must be taken with care due to the predominantly partial availability of traces. Thus, we also look at the share of each trace file that is spent inside villages, depicted in Figure 3b in combination with the allocation time in Figure 3a. For this we can deduct that nearly every trace file shows at least 50% allocation inside of villages, or 72% allocation inside on average, corresponding to approximately 3 hours. Furthermore, a total of 19 participants never left their starting village (w.r.t. to the trace file duration). An additional 9 participants were only outside for less than 25 minutes, which is just enough to make a single trip at walking speed between the two closest villages. Concerning the mobility between villages, the majority of participants that were outside for longer times moved towards or from the farthest Village A, which took around 1 hour in normal walking speed from Village C. Due to this long travel distance, most participants only performed one trip between Village C and A in either direction. Between the much closer Villages B and C, however, some participants moved multiple times back and forth. Regarding the overall time, around 50% of participants spent more than 50 minutes traveling. Only two participants spent more than 75% or 3 hours moving between villages. This generally low mobility between villages corresponds to the long delivery delays and low distribution rates of messages as described in (Álvarez et al. 2018).



(a) Distribution of the average number of neighbors of each participant.

(b) Distribution of the average distance to neighbors of each participant.

Figure 4. Participants were regularly highly clustered within a range of 10 to 20 meters, either in smaller groups of a few or larger groups of up to 20.

Another negative influence on the message distribution in DTNs is the natural behavior of humans to cluster around points-of-interest, form groups, and social interaction. Data transfer between DTN devices is usually significantly faster than the time social interactions take, for example when groups meet while traversing between villages. Therefore, pausing and talking to other groups delays the propagation of messages between villages. Additionally, a single device is sufficient to transport data between DTN partitions like villages. A group of devices with the same information moving at the same time to the same destination is, thus, in general less efficient than every single participant moving at a different time to different destinations would have been. For a realistic human-centric disaster scenario, group mobility and clustering of the network is a significant impact factor as the number of usable devices is often limited and movement is also restricted, e.g., due to blocked streets. Group formation usually happened within a village, starting by gathering at a location before leaving. On average, five groups moved between the villages simultaneously. The typical size of such groups was between two and six participants. When encountering each other, groups usually stopped between 1 and 5 minutes to talk to each other, but sometimes also just passed by. On some occasions, groups merged when moving in the same direction.

Besides short-term encounters of groups and long-term movement of groups between villages, network clustering typically happened within villages, predominantly around points-of-interest like the simulated hospitals. Figures 4a and 4b show the distributions for the number of neighbors in a 1-hop network neighborhood and the average distance to these neighbors, respectively. The distribution of the number of neighbors shows two summits around 2 to 5 neighbors, similar to the perceived group sizes, and around 10 to 16 neighbors, respectively. As detailed in Figure 4b, the average 1-hop distance is usually around 17 meters, and longer distances between neighbors are rarer, indicating a highly clustered network.

Despite clustering around several points-of-interests in the villages, the DTN was usually highly interconnected and short-range communication performed well (Álvarez et al. 2018). Even with a simple flooding-based approach, message exchange was fast and reliable. Utilization of the DTN's store-carry-forward principle was only required infrequently. However, inter-village communication performed significantly worse due to poor mobility and infrequent formation of groups in combination with the lack of faster, more frequent, and more efficient means of message distribution such as UAVs (Lieser, Zobel, et al. 2019; Álvarez et al. 2018). To conclude, the participants' mobility was the predominant influence factor on the overall communication performance. The dataset shows a high deviation in the mobility of participants when considering mobility in and outside of villages. A realistic model for civilian mobility and social interactions within a disaster scenario, as perceived in the field test, therefore has to incorporate the described features. Simultaneously, such a model must be adjustable for the simulation of alternative scenarios and the evaluation of DTNs under various circumstances.

CIVILIAN DISASTER MOBILITY MODEL

Based on the field test data (Álvarez et al. 2018), it becomes clear that civilian mobility in a disaster scenario has to be differentiated between individual mobility for short-distance movement around points-of-interests and group mobility for long-distance travel. In this work, we specifically focus on the representation of the available civilian mobility data from the field test (Álvarez et al. 2018), as a reference. However, one of our main objectives is to provide a modular and configurable model that can be adjusted to represent a wider variety of different scenarios and is not limited to the represent the specific scenario of the field test.

Our civilian mobility model for disaster scenarios (Civilian Disaster Mobility, *CDM*) is implemented as an extension to the discrete-event open-source simulation and prototyping platform Simonstrator (B. Richerzhagen et al. 2015), which focuses on the evaluation of networked mobile applications and services. In detail, mobility models are implemented within the PeerfactSim runtime environment (Stingl, Gross, et al. 2011), that already provides a broad range of models like simple Random Walk, map-based SLAW (Stingl, B. Richerzhagen, et al. 2013), or social graph-based mobility for networked social applications (N. Richerzhagen et al. 2017). Furthermore, it combines real-world OpenStreetMap[2] data with the offline routing library GraphHopper[3], allowing the deterministic reproduction of mobility experiments in a realistic setting under varying simulation parameters. Specific points-of-interests and surrounding areas can be defined as *attraction points* for mobility models in PeerfactSim, modeling parks, neighborhoods, or in case of disaster scenarios hospitals, shelters, and similar.

The *CDM* implementation is modular and extensible, comprising of distinct components for *individual mobility*, *group mobility*, *group formation*, and *group encounter behavior*, that model different features perceivable from the field test traces. *Individual mobility* and *group mobility* define separate mobility models for themselves, which are fully adaptable and exchangeable. The full model allows to portray a wide variety of scenarios and behaviors, and is therefore also applicable for various types of disasters. Furthermore, *CDM* could also be integrated into other network simulators like ONE (Keränen et al. 2009), if required properties such as attraction points and network and mobility simulation interaction are given. The components and their interaction are sketched in Figure 5 and described in detail in the following.

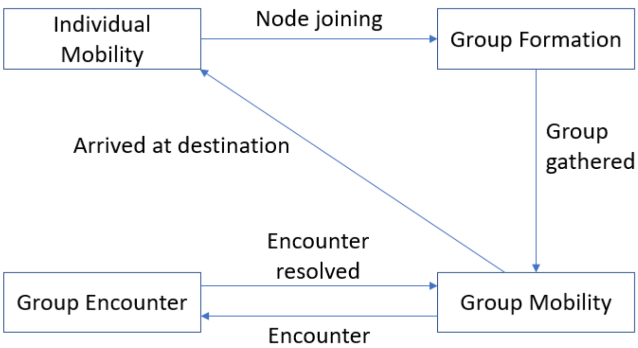


Figure 5. Components of the mobility model and their interaction with each other.

Individual Mobility

The *individual mobility* component specifies mobility for individual node movement within the area of attraction points, that is w.r.t. the field test mobility each of the villages. For our case, we use an adapted map-based random waypoint mobility model that represents the roaming of participants through the villages. Movement is restricted to roads and pedestrian walkways within the area of an attraction point, and therefore, this component cannot define mobility between different attraction points. Our model for *individual mobility* is defined by two distributions, which specify the speed of a node while moving on the one hand, and on the other hand the time a node remains static for social interactions or other activities. The pause time distribution can either be defined globally or for each attraction point separately. Since no significant differences could be perceived in the field test data, a uniform distribution in the range of 5 to 10 minutes is used for all APs to represent the field test. For the speed distribution, we approximated the results from the trace file analysis by a normal distribution using $\mu = 1.05\frac{m}{s}$ and $\sigma = 0.3\frac{m}{s}$. In general, however, this component can be exchanged with any attraction-based mobility model which is able to define individual node movement restricted to specific areas, like a more sophisticated model defining specific points-of-interest within the attraction point area itself.

Group Formation

When and how groups are formed is defined by the *group formation* component. In the field test, we see that after an initial burst of groups being created to explore the area, the number of groups was relatively stable around five.

[2]www.openstreetmap.org (last accessed 09.12.2020)
[3]www.graphhopper.com (last accessed 09.12.2020)

A new group formed approximately every 10 minutes, while others dissolved when arriving at their destination. Therefore, we used this as the range for another uniform distribution specifying the interval between group formation. The attraction point in which a group is formed is randomly selected from the set of attraction points, as there was no predominant variance in the field test data for the formation of groups in specific villages. The *group formation* process considers all nodes within that attraction point as potential candidates for the new group. In our case, we define a side-condition to exclude nodes that are currently less than 30 minutes within that attraction point, with regard to the analyzed traces. Furthermore, the group size is defined as a uniform distribution between 2 and 6 nodes, similar to the analyzed group sizes. The selection of group members is made randomly from the candidates, until the group size is reached, or no more candidates are available. In case the minimum size is not met, e.g., if there are no other nodes around the attraction point, the *group formation* process is repeated at another attraction point. The selection could also be made based on the time a node is already inside that attraction point. However, no clear evidence for such behavior could be found in the traces. After the group members are selected, a group head is chosen and its location used as gathering location. Using *individual mobility*, all members will then proceed to that location, before the *group mobility* component is applied.

Group Mobility

In contrast to *individual mobility*, *Group mobility* defines the movement behavior between separate attraction points for every group. It is applied after that group's formation until its destination is reached and the group is dissolved. Initially, one attraction point—different from the one the group is formed in—is chosen as the group's destination. In the field test, the smaller Village B is less frequented, and thus, defined to be also less likely (80% of the likelihood for Village A or C, respectively) to be chosen in this step[4]. The group head defines the general mobility of its group, on which we apply a map-based movement model (Stingl, B. Richerzhagen, et al. 2013) heading towards the chosen destination. The head's speed is approximated similar to the found results for speed outside of villages by a normal distribution using $\mu = 1.3\frac{m}{s}$ and $\sigma = 0.3\frac{m}{s}$. All other members are placed within 10 meters around the head corresponding to the average neighbor distance (c.f. Fig. 4b), but are similarly to the head restricted to roads and accessible pedestrian pathways. When outside of attraction point areas, the group may encounter another group and then switch to *Group Encounter Behavior*. When the group arrives at its destination, it dissolves and all nodes switch back to *individual mobility*.

Group Encounter Behavior

From the field test, we know that groups usually stopped and paused for several minutes (approx. 3 minutes on average) for social interactions when encountering each other outside of villages. The *group encounter behavior* component specifies such behavior by suspending *group mobility* on an encounter. An encounter is specified as when two or more groups have moved within 5 meters of each other. Social interactions may take some time, and this pause time is randomly chosen from a uniform distribution between 1 and 5 minutes. Other groups that arrive within that pause time will also stop for the remaining time. After this time is expired, the encounter is resolved and every group resumes their initial route as before using *group mobility*. Note, that our implementation also provides different possibilities for groups to partially or fully merge and a probability for groups to ignore group encounters. However, such specific behavior cannot be correlated with the traces and is therefore not used for depicting the field test, but rather left open for future work.

EVALUATION

In this section, we evaluate the Civilian Disaster Mobility (*CDM*) model and compare it to other prevalent mobility models. Additionally, we compare these models with trace mobility (*Trace*) to show similarities or differences and assess how realistic simulations with these models are in a well-known scenario. All experiments were performed using the SIMONSTRATOR (B. Richerzhagen et al. 2015) simulation platform with the modifications to the PEERFACTSIM runtime environment (Stingl, Gross, et al. 2011) as described in the previous section. Results are collected and aggregated over ten simulation runs with different random seeds. For analyzing the communication performance, we rely on the epidemic DTN protocol HyperGossip (Khelil et al. 2007), which is available in SIMONSTRATOR and very similar to IBR-DTN used in the field test (Schildt et al. 2011; Álvarez et al. 2018).

Specifically, *CDM* is compared with three other, commonly applied mobility models: (1) the Random Waypoint (*RWP*) mobility model where target waypoints are chosen randomly and nodes move there unrestricted in a straight line, (2) the map-based Random Waypoint (*RWP-MAP*) mobility model in which nodes still randomly choose waypoints but are restricted to roads and pedestrian walkways, and (3) an adaption of the *SLAW* (Stingl,

[4]Simonstrator defines weights for each attraction point

B. Richerzhagen, et al. 2013) mobility model. *SLAW* is similar to our approach such that it allows for the same map-based movement restrictions, the definition of attraction points, and the movement of single nodes between them. However, it does lack some possibilities, e.g., to form groups and specify different behaviors for inside and outside of attraction points. Each village from the field test is defined as an attraction point for *SLAW* and *CDM*. The most important environmental simulation settings are summarized in Table 1.

In this paper, we restrict parameters and components of the simulation environment to retain comparability between the simulated models and the field test traces. First, the number of simulated nodes is chosen to resemble the size of given traces and is required for a fair comparison in a same-sized scenario. Simonstrator, PeerfactSim, and the simulated mobility models are however not limited to a specific number of nodes. Second, we restrict node mobility to pedestrian movement only, since it was likewise restricted in the field test. Nevertheless, future work could include multiple forms of movement like bikes of cars in combination with pedestrian movement in the evaluation. We note that the realistic inclusion of different forms of movement may require detailed knowledge of each type and their possible interaction, similar as done for pedestrian movement for groups and single nodes in this work. Message sizes of 300 Byte and a rate of 6 generated broadcasts per minute are based on the average values in the field test.

Spatial Node Distribution and Mobility

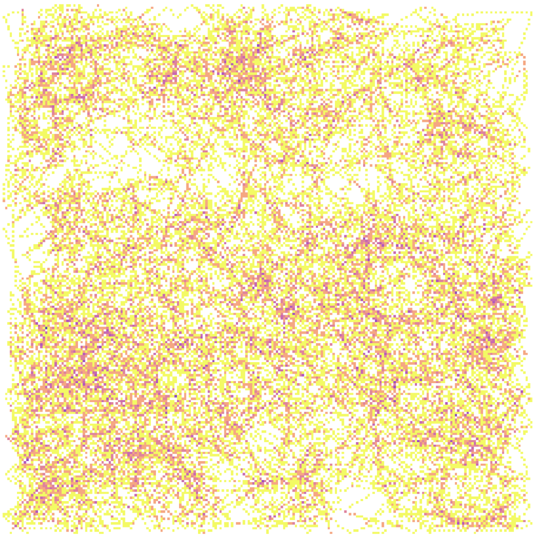
Typically, a DTN's performance is highly affected by both mobility and clustering of nodes. While communication within clusters is fast and performant, the communication between clusters usually relies solely on node mobility. Consequently, inter-cluster mobility over larger distances—as experienced in the field test—leads to slow and incomplete message spread and potential message drops due to the expiration of the Time-to-live (TTL) of messages. The mobility of nodes, their spatial distribution, and the amount of clustering in the network are therefore important factors influencing DTN communication.

For that, we visualize the spatial node distribution for *RWP*, *RWP-MAP*, *CDM* and *SLAW*, and *Trace*, respectively, in Figure 6. Node positions are sampled every 30 seconds and aggregated into grid cells of 20 m by 20 m size. The number of positions in a cell is denoted by a logarithmic color scale ranging from white over bright yellow to dark purple. Circles show attraction points areas for *CDM*, *SLAW*, and *Trace*.

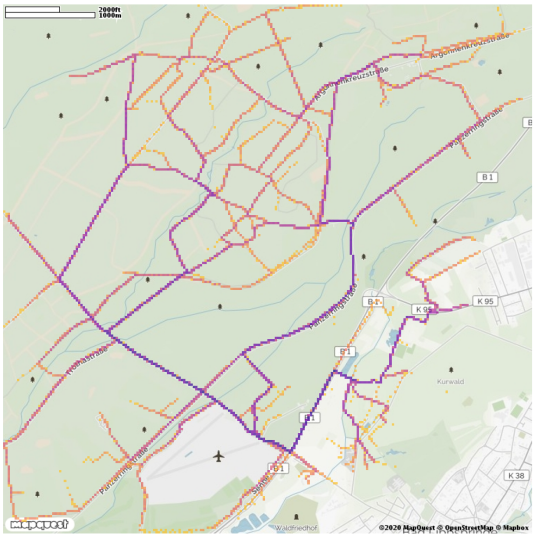
The random distribution of the *RWP* model can be seen in Figure 6a, with the restricted *RWP-MAP* model in Fig. 6b as a contrast. In the latter case, we see that the node distribution is significantly higher on the main roads, side roads and forest paths are less frequented. There are, however, no recognizable hotspots with node clusters in either case and a rather equated node distribution. Naturally, both models fail to mimic human behavior as seen in the field test. Figure 6c visualizes the node distribution for *CDM*. The map for *SLAW* shows only insignificant visual differences and was therefore not included. Although a similar spatial node distribution may suggest a high similarity between *SLAW* and *CDM* in general, later comparisons will better highlight their differences. Also note that measurements in Figure 6d do include GPS inaccuracies. Thus, some positions are scattered off the roads rather than on them, in contrast to simulated movement in Figure 6c. Another difference is best seen in Village A. The node distribution in *CDM* is relatively centered in the area. However, *Trace* shows several distinct hotspots primarily in the south of the village and a more evenly distribution as participants also moved cross-country. A more extensive

Table 1. Simonstrator Environmental Settings

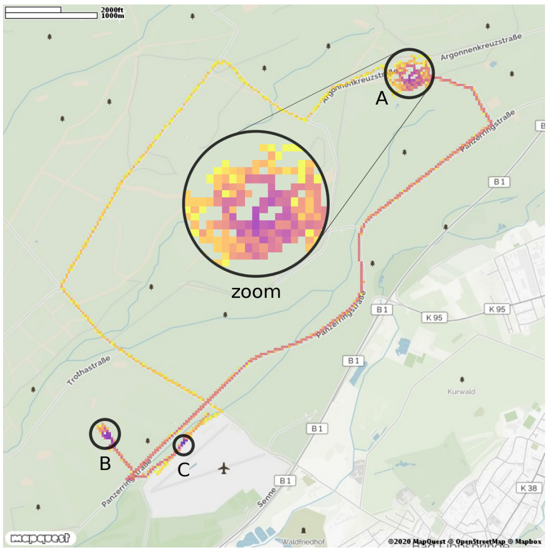
Scenario	Area	4,500 m x 4,500 m
	Map and APs	Field Test
	Duration	4.5 h
	Nodes	Trace, 70
Comm.	PHY	Wi-Fi (IEEE 802.11g)
	Range	approx. 90 m
	Data Rate	5 Mbit/s
DTN	Protocol	epidemic DTN (Khelil et al. 2007)
	Msg TTL	60 minutes
	Msg Size	300 Byte
	Msg Rate	approx. 6 per minute
Mobility	Model	Trace, RWP, RWP-MAP, SLAW, CDM



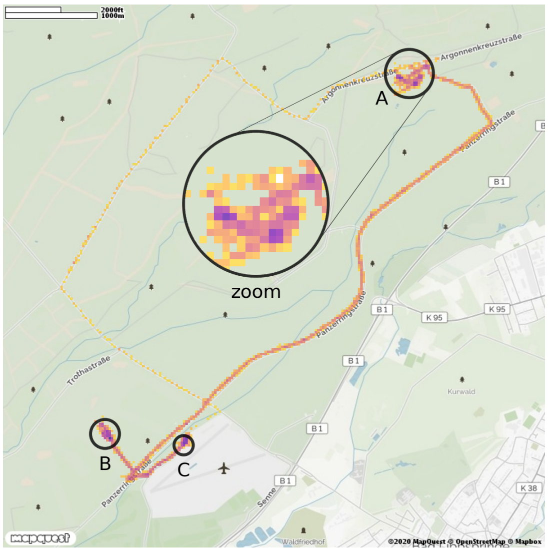
(a) RWP



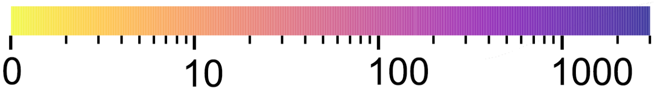
(b) RWP-MAP



(c) CDM (SLAW shows a similar node distribution)



(d) Trace (Álvarez et al. 2018)

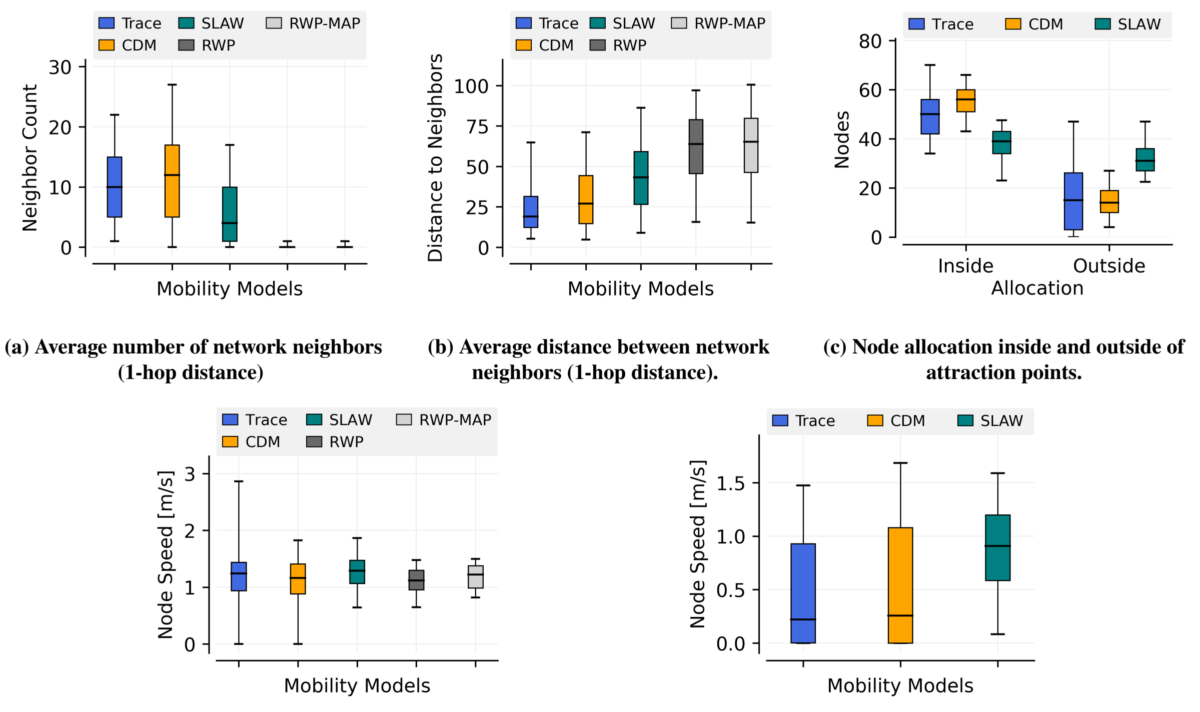


(e) Color code, node measurements per cell.

Figure 6. Collected spatial node distribution for mobility models (a-c) and trace files (d). Node positions are sampled every 30 seconds and aggregated in cells of 20 by 20 meters size. Circles denote attraction points used in mobility models. The color scale is logarithmic to highlight more frequented locations.

individual mobility could encompass this for *CDM* in future work, but within the size of the field test villages and the anticipated communication ranges we do not expect a significant difference for the DTN performance.

The amount of clustering in the network is an important factor influencing the quality of DTN communication. For that, we compared the number of neighbors (cf. Figure 7a) and the distance to that neighbors (cf. Figure 7b), respectively. Again, *RWP* and *RWP-MAP* cannot accurately depict reality with predominantly zero neighbors and—if there are any—large distances between them. Due to the incorporation of attraction points, results for *SLAW* are closer to reality than that of the random models. With an increased node count and shorter distances, the network becomes more clustered. But as visualized in Figure 6, nodes in villages are distributed more evenly in *CDM* and *SLAW*, and thus, the topology is less clustered than in reality. This results in more opportunities for nodes to be in range, but also a generally higher distance between nodes. Therefore, both models show a higher node distance in comparison to *Trace*. However, the single node movement between attraction points of *SLAW* has



(a) Average number of network neighbors (1-hop distance)

(b) Average distance between network neighbors (1-hop distance).

(c) Node allocation inside and outside of attraction points.

(d) Node speed outside of attraction points.

(e) Node speed inside of attraction points.

Figure 7. Network topology and mobility metrics, values are aggregated every 10 seconds.

a significant effect and reduces the average amount of neighbors to around half that of *Trace*. In contrast, with *CDM* the average neighbor count is only increased by two and the average neighbor distance increased by ten meters, respectively, due to the more evenly distribution. Thus, although not perfectly depicting the high degree of clustering inside villages, *CDM* provides a topology significantly closer to reality.

Additionally, the number of nodes inside and outside of attraction points is presented in Figure 7c. *RWP* and *RWP-MAP* were excluded as these models do not incorporate the attraction points. *Trace* has significantly larger deviations in the allocation compared to *CDM* or *SLAW*. We attribute this on the one hand on the changing numbers of available traces at a time, as described in the trace analysis. On the other hand, simulated models usually provide a much steadier and more even mobility, in contrast to sometimes bursty behavior in reality which may be impossible to integrate into mobility models. In direct comparison to *Trace*, the number of nodes inside of villages is higher for *CDM* and lower for *SLAW*. More importantly, however, *CDM* approximates the average outside allocation, which is more important for the overall communication performance because it determines the number of possible message transfers between large DTN clusters. Outside allocation in *SLAW*, on the contrary, is significantly higher due to an increased single node movement between attraction points.

The last assessed mobility metric is the node speed, separated for outside in Figure 7d and inside of attraction points in Figure 7e, respectively. Inside attraction points, *SLAW* results in much higher speeds due to the indistinction of mobility based on node allocation and the absence of behavioral models for social interactions. *CDM*, on the other hand, better approximates the trace files although not perfectly matching the real-world speed distribution. Outside of attraction points, however, the differences between the models are less. Although *RWP* and *RWP-MAP* show similar speeds, results for *RWP* are lower despite using same speed distribution, which might be a result of shorter travel times and thus more frequent pause times at arrival on a random waypoint. Because similar pause times are only tracked inside of attraction points for *CDM* and *SLAW*, their upper quartiles are significantly higher in comparison. However, both cannot incorporate infrequent faster speeds above 2 $\frac{m}{s}$ as seen in comparison to *Trace* in the upper quartiles, respectively. On the other hand, the lower quartiles of *CDM* suggest that the used *group mobility* component correctly resembles social interactions and group encounters outside of attraction points.

DTN Communication Performance

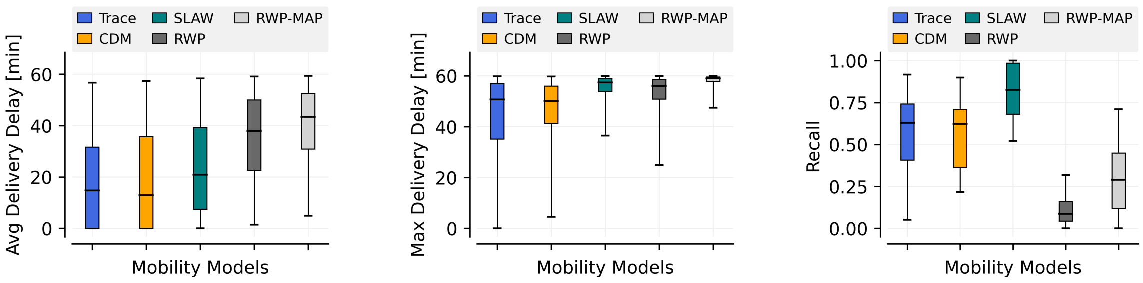
Eventually, the network topology and the mobility of nodes directly influence the performance of DTN applications. Thus, communication performance must also be evaluated to assess the expressiveness of mobility models. To this end, we focus on the two standard performance metrics *Recall* and *Delivery Delay*.

Recall is defined as the fraction of the total number of nodes that a message reached in the end, therefore denoting the spread of a message in the whole network.

Average Delivery Delay is defined as the average of every time delay a message required to be delivered to each reached node.

Maximum Delivery Delay is defined as the maximum out of every time delay a message required to be delivered, which is similar to the delay a message required from its creation until reaching the last node it reached.

All three metrics are required, because a low average or maximum delay does not necessarily denote a good performance in general. Since messages are spread quickly within a network cluster, e.g., at an attraction point, both average and maximum delivery delays will be very low—in range of seconds or less—if this message never spreads farther than just that cluster. In such cases, recall will also be low. With to a high *TTL*, however, a message can spread to more nodes after a significant time. In such a case, recall and the maximum delivery delay increases more significantly than the average delivery delay. Similarly, a high delivery delay does not implicate a high recall. Evaluation results for the DTN performance metrics are visualized in Figure 8.



(a) Average delivery delay. **(b) Maximum delivery delay.** **(c) Recall (message spread).**

Figure 8. DTN performance metrics. Box plots show the aggregated values over all messages.

Comparing the different mobility models in Fig 8c, we see that *RWP* has the lowest recall due to the low number of encounters. *RWP-MAP* achieves a higher recall due to the restriction of streets and thus more encounters. Both models, again, cannot depict reality accordingly. In contrast to low recall of the random models, *SLAW* performs significantly better with a recall of more than 0.5 for every message. Even more, 75% of messages achieve a recall between 0.68 and 1.0, resulting in an average recall of 0.83, which outperforms the both *Trace* and *CDM* by far. The single node movement between attraction points obviously also increases the capability of messages to spread in the network, which in turn also increases the delivery delays. The performance of *CDM*, on the other hand, is much better resembling that of the real-world traces. Around half of all messages have a recall between 0.4 to 0.74 in *Trace*, while *CDM* gives a slightly lower recall between 0.36 and 0.71. Together with slightly increased delivery delays, we see that *CDM* underestimates the civilian mobility between attraction points, as similarly seen for the speed distribution in Figure 7d. Additionally, the lower percentile of *Trace* also shows that some messages could not spread at all, which is not incorporated by *CDM*. Furthermore, *Trace* provides a faster dissemination for around a quarter of messages (cf. Fig 8b). All of this can be attributed to two different issues. Firstly, an increased participant movement between the closer villages, which is not exactly modeled by the chosen weights in the weighted target selection in *CDM*'s *group mobility* component. And secondly, some traces are fragmented which results in these nodes being removed during the simulation. Thus, messages on that node are not distributed further, which reduces the communication performance and explains the lower recall and maximum delivery delay of *Trace* approximating zero, respectively.

Nevertheless, the most important conclusion is the significant difference between *Trace* and *CDM* compared to *SLAW* (cf. Fig. 8). Such high recall values—some messages even achieved a full network spread—were neither achieved in the field test nor with the simulated traces or our mobility model. The single node movement of *SLAW* outperformed the real-world trace message spread by an average of around 20%, and therefore, overestimates the capability of the simulated DTN. *CDM*, at the same time, resembles the real-world performance much better than other state-of-the-art mobility models with a slightly worse performance of around 4% on average. Overall, this evaluation highlights the direct impact of mobility models on DTN performance as expected and with that outlines the necessity for more realistic mobility models such as *CDM*.

CONCLUSION

The application of Delay-Tolerant Networks for civilian disaster response using everyday smart mobile devices shows great potential to provide communication when ICT infrastructure is completely unavailable. Evaluating such applications requires complex simulations, since real-world testing is expensive, time-consuming, not repeatable under the same conditions, and does not scale. However, simulation models have to reflect reality to gather expressive results. As presented, modeling human mobility is a highly complex topic with numerous approaches for various applications and scenarios.

In this paper, we used recorded trace file data of a real-world field test to analyze the mobility of civilian participants. Based on this analysis, we created a Civilian Disaster Mobility (*CDM*) model that uses group-based movement and clustering of humans. This model is comprised of several components that are fully exchangeable and adaptable. Therefore, the model can be customized to reflect many use cases by providing different behaviors for groups or single persons, movement of small groups or large masses, social interaction of groups, and more. The modularity and complexity of *CDM* is especially necessary since every disaster scenario provides different features and constraints that may not be addressed by simple mobility models. This also allows the flexible adaptation of *CDM* to portray various types of disasters. Comparing the communication properties of real-world traces with *CDM* and other state-of-the-art mobility models, we see that random movement models are especially unqualified for expressive simulation results. Additionally, non-group-based models like *SLAW* overestimate the DTN performance in the same scenario by around 20%. The proposed Civilian Disaster Mobility model closes this gap with only a 4% underestimation of the DTN performance. Simultaneously, *CDM* provides an extensive set of parameters to simulate a wide variety of different scenarios and group-based behaviors, that differ from the specific field test scenario given by Álvarez et al. 2018.

Future work may address open issues like a higher degree of clustering within villages by regarding the human movement in greater detail or also incorporate erratic behavior of humans that could not be defined by the used mobility models. Furthermore, the complexity could be increased by supporting a combination of mobility models for pedestrians, bikes, or cars concurrently. Most notably, the application of *CDM* must be tested in other scenarios than that of the field test, such as inner-city environments with higher node densities to provide a more thorough insight into DTN performance under varying influences.

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