Statistical Analysis of Traffic Measurements in a Disaster Area Scenario Considering Heavy Load Periods

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***Abstract*— Catastrophes cause an area of destruction including destroyed infrastructure. These disaster area scenarios are typical usage scenarios for mobile wireless ad-hoc networks (MANETs). The results of simulations used for performance analysis in MANETs strongly depend on the traffic model. In this paper, we perform statistical analysis of data, measured in a civil protection maneuver. Based on the analysis we generate traffic and compare it to the measured one by doing simulations of two broadcast routing protocols. Finally, we extend our model to concerning heavy load periods and examine the impact on the simulation results.**

I. Introduction

Catastrophes, be it natural ones (like hurricanes or tornados), human caused ones (like explosions or fires), or technical ones (like material-fatigue) cause an area of destruction. Buildings, bridges as well as the infrastructure of the private and public systems for mobile communication may be destroyed. Civil protection units have to go into the disaster area trying to minimize the destruction, help injured people and set up an auxiliary infrastructure. For doing so, the public safety units need reliable communication independent of any infrastructure because this may also have been destroyed. Thus, one of the most interesting scenarios for mobile ad hoc networks (MANETs) is the disaster area scenario. “Wireless peer networks that involve ad hoc wireless routing networks [..] offer a promising solution to the many challenges of information sharing in OOH [Out-of-Hospital] disaster response.”([1])

Performance evaluation in MANETs is mainly done by using simulation. Of course, the results strongly depend on the mobility and traffic models used. In this paper we focus on one scenario in which civil protection units set up a pontoon-raft and analyze the data traffic based on measurements. We perform a proof of concept by simulating and comparing generated and real-world traffic. Finally, we improve our model by an extension considering heavy load periods.

The remaining part of the paper is structured as follows. First, we describe the scenario and the movement characteristics in this scenario (section II). Next, we show and explain the measurements and the statistical analysis of the traffic (section III). In section IV, we study whether generated and measured traffic yield similar simulation results. After this, in section V, we describe some extensions and perform simulations with these extensions (section VI). Finally we conclude our paper and describe future work (section VII).

II. The Scenario

The scenario is a disaster area where a bridge over a river as well as the communication infrastructure is destroyed. To enable the crossing of the river, a pontoon-raft is built by the civil protection units, to ferry cars, trucks etc. with the raft. We were able to observe such a scenario in a maneuver of German civil protection units. The units (107 people) set up a pontoon-raft to cross the river Rhine.

Beside the traffic measurements and analysis described in section III, we used our observations to generate a movement file based on our disaster area mobility model presented in [2]. The mobility model is based on a concept in the German civil protection called *separation of the room*: The units do not move randomly. Instead, there is a central instance (e.g. technical operational command) which tells everybody where and how to move or in which area to work. Thus, the simulation site is divided into different areas. Each unit belongs to one of these areas and moves in this specific area. Depending on the kind of area the movement was modeled with the Random Waypoint mobility model [3] or Reference Point Group Mobility model (RPGM) [4]. The RPGM is used for nodes that either transport material in groups (4 persons) or shipping on a boat (3 persons). The Random Waypoint model is used for nodes within the other areas. The minimum speed was set to one meter per second, the maximum speed of the nodes depends on the area; a boat moves faster (up to 11m/s) than a man carrying heavy material (up to 2m/s). Obstacles were not modelled, because in the concrete scenario near the Rhine there were none. That is also the reason for using the Two-Ray-Ground propagation model in simulation (section IV).

We created the movement file and analyzed it statistically with *Bonnmotion* [5] concerning:

- the *average node degree*: to how many nodes is one node connected in average (for all nodes throughout the whole simulation time)

Transmission Range	50m	100m	250m
average node degree	15.3819	24.4329	50.1617
partitions	9.0332	3.9335	1.0
partitioning degree	0.8041	0.5644	0.0
average link duration (s)	181.2623	272.1985	338.5600

TABLE I

ANALYSIS OF THE MOVEMENT FILE USED IN SIMULATIONS

- the *average number of partitions*: one means the network is always connected
- the *partioning degree*: how likely is it that two randomly chosen nodes are in different partitions at a randomly chosen point of time
- the *average link duration*: how long is a link up before it breaks e.g. due to node movement.

The results for different transmission ranges may be seen in table I, and may help interpreting the simulations results in the following chapters. It can be seen that there is a relatively high average node degree and the partitioning degree for the smaller transmission ranges is also high, which matches with the results in [2].

III. DATA TRAFFIC ANALYSIS

In the scenario described above the analog German national radio system, called BOS-system, that is used by public services was used. The voice traffic on channel 51WU (168.56 MHz) was measured. We analyzed the measured audio-stream by using a C-program, which is based on libsndfile [6]. By doing so we analyzed the start time and the end time of each call.

Definition 1 *A call is done by one sender that starts speaking and stops after a certain time. Note, there is only a simplex connection - unlike a telephone call.*

Our measurements contain 1039 calls. We analyzed channel holding times and idle times for the calls. Having identified the empirical distributions, the next step is to find theoretical probability distributions that fit. At first, a set of theoretical distributions has to be chosen. We decided to test against exponential, lognormal, gamma, and weibull distribution (see Appendix for density functions).

For each distribution the optimal parameters were found by using the Maximum-Likelihood-Method. With the Kolmogorov-Smirnov (K-S) test the distance between the theoretical distribution and the empirical distribution is represented in a value, the so called K-S distance. The lower the distance, the better the theoretical distribution fits to the empirical distribution. Furthermore, the p-value is shown, which is the result of the significance test. Thus, a good fitting results in a large p-value, while large differences result in small p-values. The analysis has been performed with the statistical computing tool R [7] and its MASS (Modern Applied Statistics with S) package.

The results of the statistical analysis may be found in table II (channel holding time) and table III (idle time). The analysis

Distribution	Parameters	K-S dist.	p-value
lognormal	μ = 0.85455191 σ = 0.71647243	0.0606	0.6783
weibull	α = 1.38056927 β = 3.39215098	0.1071	0.07865
exponential	β = 0.32578125	0.1961	3.905e-05
gamma	α = 2.02831883 λ = 0.66113455	0.1076	0.07643

TABLE II

RESULTS OF MAXIMUM-LIKELIHOOD-METHOD AND KS-TEST FOR CHANNEL HOLDING TIMES

Distribution	Parameters	K-S dist.	p-value
lognormal	μ = 0.63455097 σ = 2.16227968	0.0448	0.03078
weibull	α = 0.46367602 β = 5.56921527	0.0918	5.116e-08
exponential	β = 0.058398437	0.4578	<2.2e-16

TABLE III

RESULTS OF MAXIMUM-LIKELIHOOD-METHOD AND KS-TEST FOR IDLE TIMES

shows that the lognormal distribution has the lowest distance for the channel holding times.

For the idle times it was not possible to fit the gamma distribution, so there are no values. The results of the K-S test concerning the lognormal distribution, which shows the best fit, is poor (small p-value). Figure 1 gives an impression of the fitting of the different distributions to the empirical data. The empirical data is shown by the empirical cumulative distribution function. There is a small difference between the data and the lognormal distribution (see arrow in the figure), which explains the low p-value. Next, we will evaluate whether lognormally distributed (generated) data produces similar simulation results compared to the empirical data.

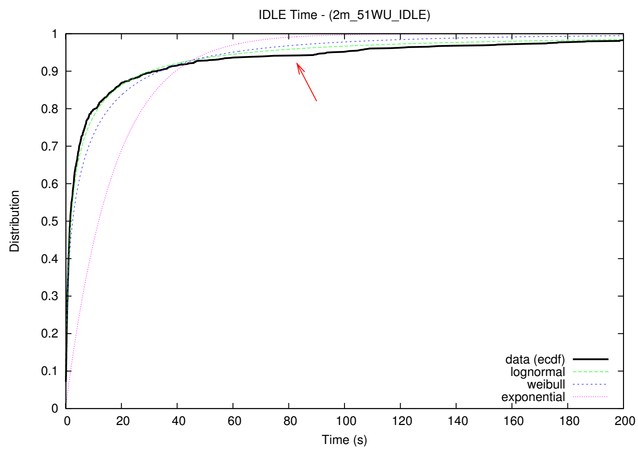

Fig. 1. Idle time distributions

IV. SIMULATIONS

For the simulation, each unit (one person) modeled as a node takes part in the mobile communication. This is not obvious, because nowadays several persons that belong to one tactical unit sometimes share one mobile terminal. Anyway, in the future each person will own a separate mobile terminal. Today, the traffic in disaster areas is mainly broadcast voice traffic. Thus, we decided to perform the simulation with two different broadcast routing protocols over an IEEE-802.11b Wireless LAN bearer. We used simple flooding [8] and a Multipoint Relay (MPR) based approach [9]. The optimization of the MPR-based flooding is similar to those used by the Optimized Link State Routing (OLSR) protocol [10] for propagating the topology information. Only the MPRs forward the information. Each node sends Hello-messages to explore its 2-Hop neighborhood. Based on the received answers, it chooses a set of its 1-Hop neighbors as MPRs so that it reaches all its 2-Hop neighbors. The MPR-based flooding minimizes the broadcast storm problem, described in [11]. The disadvantage is that there is a structure (MPR election) which has to be updated in intervals. This may lead to packet loss in case of small link duration, e.g. caused by mobility. For our simulation, we set the hello interval to the default value (2s) of the standard ([10]).

We used the following metrics:

- packet delivery fraction:

$$\frac{\text{data packets received}}{\text{data packets sent} * \text{count of nodes}}$$

  Note, it is broadcast traffic, so the count of nodes has to be considered.
- number of retransmitting nodes:

$$\text{the count of nodes that forward a packet}$$

- normalized routing load:

$$\frac{\text{number of routing packets sent}}{\text{number of data packets received}}$$

We performed simulations for transmission ranges of 50m, 100m, and 250m using the Two-Ray-Ground propagation model, as already motivated above. The goal of this simulation is to evaluate whether the generated (lognormally distributed) data produces similar simulation results compared to the empirical data. Thus, the actual performance values are only of minor interest. For the generated as well as for the empirical data ten simulations of 900s should be performed. The question was how to choose the ten simulation ranges of the empirical data, because the stream was significantly longer (about 19000s). One requirement we set was that the data ranges to be simulated should not overlap. Thus, we divided the measured stream in ten equal parts and chose the interval in each part randomly. The results of the simulations concerning the defined metrics can be seen in figures 2, 3, and 4. The normalized routing load for simple flooding was

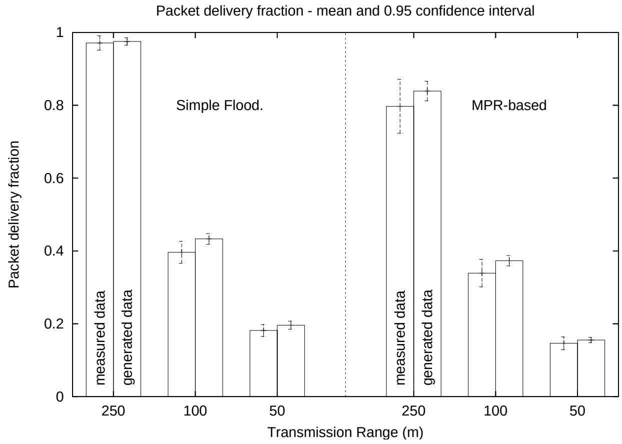

Fig. 2. Packet delivery fraction

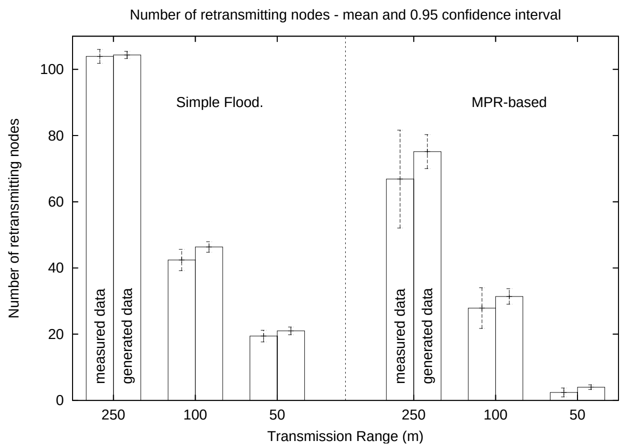

Fig. 3. Number of retransmitting nodes

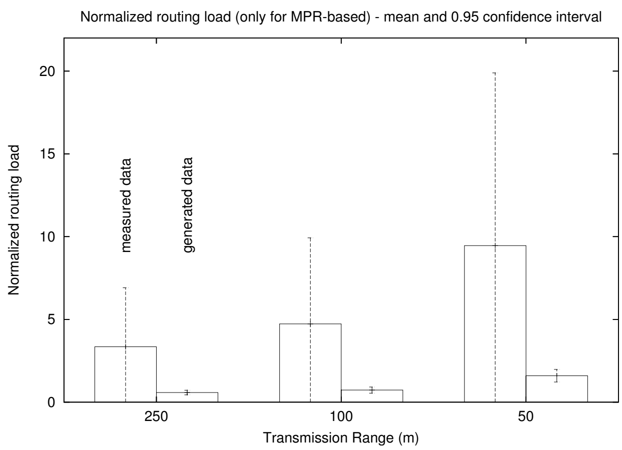

Fig. 4. Normalized routing load (only for MPR-based)

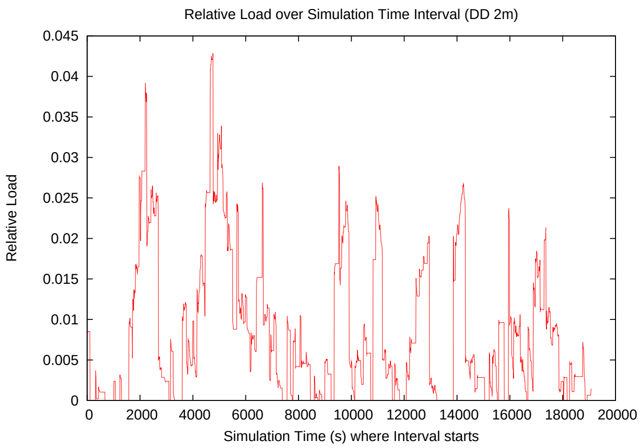

Fig. 5. Relative load over simulation time interval

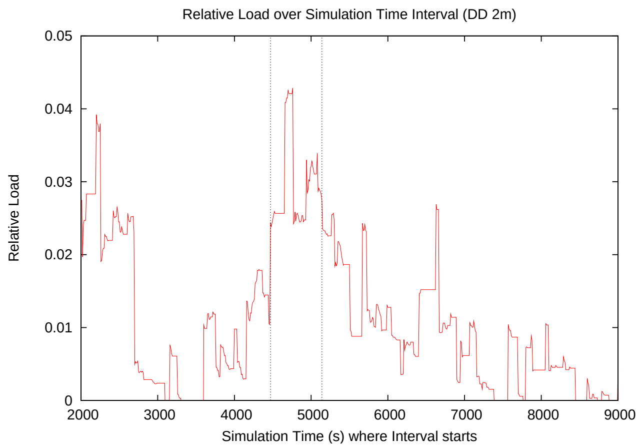

Fig. 6. Relative load over simulation time interval with range for statistical analysis

omitted, because there are no routing packets sent. Thus, the routing load is always zero.

Generally, the results are similar. The mean values are quite close together. However, it seems that the mean values of the generated data in all three plots are larger, even if the confidence intervals do overlap. Furthermore, it is striking that the confidence intervals concerning all metrics and all transmission ranges are larger for the measured data than for to the generated data. It seems that the generated traffic brings more load to the network, while the measured load is more varying.

Looking at the results of the performance evaluation, it can generally be said that the packet delivery fraction (figure 2) decreases with smaller transmission ranges. This is caused by the high movement and the higher partitioning degree within smaller transmission ranges (cf. table I). The packet delivery fraction of the MPR-based is lower than the one of simple flooding. It seems that the load in the scenario is rather low, because no broadcast storm or overload behavior can be seen at the simple flooding. However, the MPR-based approach successfully reduces the number of retransmitting nodes (see figure 3). This advantage results in a lower packet delivery fraction of MPR-based flooding compared to simple flooding. The losses are caused by problems reaching the MPR due to movement. The routing load (figure 4) increases with a smaller transmission range. With a smaller transmission range we experienced less packets arriving at the receivers, thus, the routing load is reduced. Obviously, for the routing load there are considerable differences between measured and generated data. Thus, we decided to perform an advanced analysis of the measured empirical data to find the reason for the variating confidence intervals.

V. Advanced Data Traffic Analysis

We defined a new metric to measure the load within an interval of the measured stream.

$$\mathcal{L}_{int} = \frac{U_{int}}{I_{int}} * \frac{C_{int}}{C}$$

- $\mathcal{L}_{int}$: relative load $\in [0;1]$
- U_{int} : used Time in interval
- I_{int} : interval time / length of the interval
- C_{int} : count of calls in interval
- C : count of calls of the stream

The relative load $\mathcal{L}_{int}$ is an indicator of the load in one interval relative to the load of the whole stream. As factors the used time U_{int} and the count of calls C_{int} are used. If all calls happen within one interval and the complete interval is used, $\mathcal{L}_{int}$ will be one. If there are no calls, the complete interval is idle and $\mathcal{L}_{int}$ will be zero. With this metric it is possible to calculate the relative load for all possible intervals of a stream. Figure 5 shows the relative load for 900s intervals, calculated in steps of 10s. The figure shows that there are enormous differences between the intervals. This explains the large confidence intervals observed in the last section. When doing performance analysis in networks, the heavy load periods are in the center of interest. If there is no overload in the heavy load periods, there will probably also be no overload in other periods. Thus, we decided to perform our analysis again for a heavy load periods. Figure 5 has the highest peak around the interval 4760-5660s simulation time. For the statistical analysis we choose a range around this peak (see figure 6). The range was chosen from 4470 to 5140 interval starting times, which is equal to $\mathcal{L}_{int} > 0.023$ around the peak.

We performed the statistical analysis (analogous to the one described in section III) for the IDLE times. The results can be seen in table IV. Note that this time the p-value for the lognormal distribution, which has again the best K-S distance, is much better with 0.42.

Distribution	Parameters	K-S dist.	p-value
lognormal	μ = 0.01880347 σ = 2.08856696	D = 0.0742	0.4200
weibull	α = 0.48692002 β = 2.88155249	D = 0.1079	0.0751
exponential	β = 0.1288574	D = 0.4496	$<$ 2.2e-16

TABLE IV

RESULTS OF MAXIMUM-LIKELIHOOD-METHOD AND KS-TEST FOR IDLE TIMES

Distribution	Parameters	K-S dist.	p-value
lognormal	μ = 0.85455191 σ = 0.71647243	D = 0.0606	0.07865
weibull	α = 1.38056927 β = 3.39215098	D = 3.0677	0.0003785
exponential	β = 0.32578125	D = 0.1961	3.905e-05
gamma	α = 2.02831883 λ = 0.66113455	D = 0.1076	0.07643

TABLE V

RESULTS OF MAXIMUM-LIKELIHOOD-METHOD AND KS-TEST FOR CHANNEL HOLDING TIMES

It is questionable whether a new statistical analysis for the channel holding times is necessary. Do heavy load or stress periods in a disaster area only influence the idle times, or are there also differences in the channel holding times? The answer can be seen in table V. Again, the lognormal distribution has the best K-S distance. The p-values in general are very low, in fact: too low for an appropriate model. One reason for this may be the small sample size generated by the restriction to the heavy load period. The parameters of the lognormal distribution are the same as for the first analysis described above. In that analysis an acceptable p-value was also achieved. Thus, we decided to use the lognormal distribution with the parameters of both analyses. Within our data, heavy load or stress periods in a disaster area scenario seem to influence the idle times but seem not to have an impact on the channel holding times: The statistical analysis yields identical parameters. In our opinion this is very interesting and should be checked in future work with other data sets.

VI. ADVANCED SIMULATIONS

Based on the results of the advanced data traffic analysis, we performed simulation again. We simulated with the same protocols and parameters as described above. This time we used the new parameters from the last section. When choosing intervals to be simulated of the data stream, we set the requirement that the simulation intervals should not overlap. The heavy load period analyzed in the last section is only 1570s long. It is not possible to choose ten non-overlapping intervals of 900s length. Thus, the requirement could not be kept. Due to the small heavy load period only five simulation runs were performed for each - the empirical and generated - distribution. The results of the simulation concerning simple and MPR-based flooding are depicted in figures 7, 8, and 9.

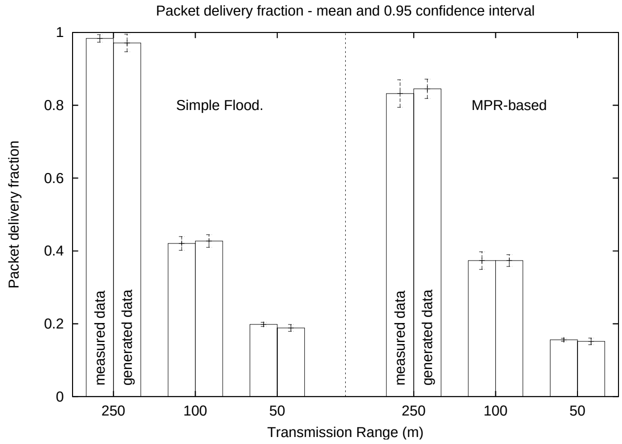

Fig. 7. Packet delivery fraction

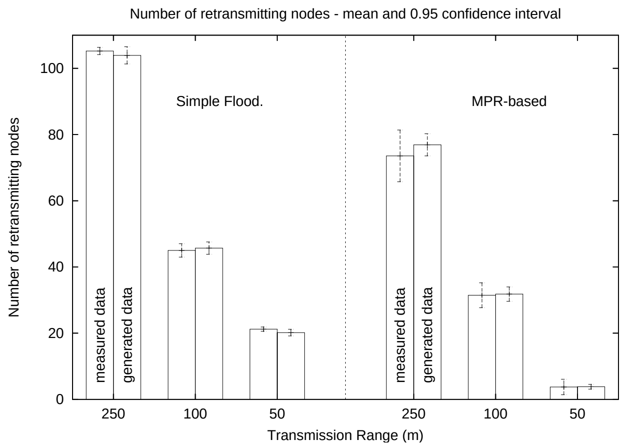

Fig. 8. Number of retransmitting nodes

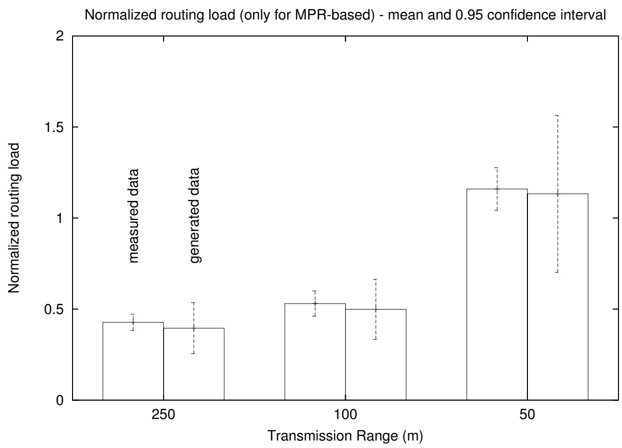

Fig. 9. Normalized routing load (only for MPR-based)

In general, the means of the different metrics are much closer to each other and there is no general trend of larger mean values for the generated data anymore. The confidence intervals of the measured data are smaller. Especially in figure 9 the difference to figure 4 concerning the means and confidence intervals is striking (Note, the different range of the y-axis). The confidence intervals of the generated data seem to have grown as it was expected due to the lower count of simulation runs.

Concerning the results of the performance evaluation, the result is similar to the one in section IV. There is no broadcast storm or overload problem recognizable, so the MPR-based approach can not benefit from its strength, i.e. the smaller number of retransmitting nodes (see figure 8). On the contrary, it achieves a lower packet delivery fraction caused by packet loss due to node movement and non-updated MPR relationships.

All in all, the results concerning the performance of the routing protocols are equal. The goal was to compare simulation results of measured and generated traffic. Thus, the results of the analysis in section IV are acceptable, even if the results achieved by considering heavy load periods are smoother. It can be summed up: if the count of samples is large enough, an analysis concerning heavy load periods should be preferred. If there are not enough samples for a heavy load period analysis, the "global" analysis can be performed instead. In general, the kind of modelling, measuring the real data and performing statistical analysis, produces realistic traffic that can be artificially generated.

VII. Conclusion and Future Work

In this paper we have shown that it is more accurate to model traffic in disaster area scenarios by considering heavy load periods. We introduced the metric relative load $\mathcal{L}_{int}$ and analyzed the heavy load periods of voice traffic in disaster area scenarios. Smoother results are achieved when considering heavy load periods. It was also shown that the general results of the performance evaluation are not influenced in this scenario. Thus, a "global" analysis may be an alternative, when the amount of samples is too small to perform an examination of heavy load periods. All in all, the approach to measuring real traffic and perform statistical analysis yields realistic traffic and similar simulation results.

During the analysis we observed that the heavy load or stress periods in a disaster area scenario mainly seem to influence the idle times and not the channel holding times. In our opinion, this is a task for future examination concerning other samples. In general, the results shown in this paper should be backed by further samples and analysis, which is another task for future work. Furthermore, different scenarios may show different characteristics. Thus, we plan to perform extended performance analysis of routing protocols also in different disaster area scenarios.

Appendix

- Lognormal Distribution

$$f(t) = \frac{1}{t\sigma\sqrt{2\pi}} e^{(-\frac{(log(t)-\mu)^2}{2\sigma^2})}, t > 0$$

- Weibull Distribution

$$f(t) = \frac{\alpha}{\beta}(\frac{t}{\beta})^{\alpha-1} e^{-(\frac{t}{\beta})^{\alpha}}, t \geq 0$$

- Exponential Distribution

$$f(t) = \frac{1}{\beta} e^{-\frac{t}{\beta}}, t \geq 0$$

- Gamma Distribution

$$\Gamma(\alpha) = \int_0^{\infty} e^{-x} x^{\alpha-1} dx, \alpha > 0$$

$$f(t) = \frac{\lambda^{\alpha} t^{\alpha-1} e^{-\lambda t}}{\Gamma(\alpha)}, t \geq 0$$

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