Characterisation and Modelling of Voice Traffic in First Responder Networks

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***Abstract*—Analysing and modelling traffic is one important step in the performance evaluation of communication systems. In this paper we focus on first responder (FR) networks. The goal is to figure out models that can be used to generate realistic synthetic push to talk voice traffic for single talk groups to be used in network simulation. Our work is based on an empirical long-time measurement of one FR channel. The analysis of the trace shows significant short- and long-range correlations as well as variations of load over time. As the characteristics analysed are similar to ones observed in disaster area (DA) traces, we consider n-state and 3-state (Semi)-Markov models. After fitting the parameters of these models to the traces, synthetic traffic streams for the different models are generated and finally evaluated by both visual and statistical analysis.**

I. Introduction

In the last decade, there has been a lot research in the area of ad hoc and mesh networks. These networks can overcome failure of single components by their very definition. Thus, ad hoc and mesh networks are seen as reliable solutions for public safety wireless communication systems. Simulative performance evaluation is used during the development of algorithms and protocols for these networks. However, for these simulations realistic traffic modelling is required. In this paper we focus on traffic modelling for first responder (FR) communication systems, i.e. communication systems used by paramedics and fire fighters during their daily work.

Even though we find slowly upcoming data services, the main application today still is voice communication: different users communicate via push to talk voice calls. Each call is initiated by one sender that starts speaking and stops after a certain amount of time. There is only a half-duplex connection (unlike a telephone call): while one user speaks, the others have to listen. Different calls with semantic connection (e.g. question and answer) may be regarded as one conversation or session. In that sense a conversation consists of an arbitrary number of calls between two callers, and typically, the callers alternate in calling each other. The users that communicate with each other share one broadcast voice communication channel. Technically this broadcast voice communication channel may be realized e.g. as a separated physical channel or as a multicast group. The term *talk group* abstracts from the technical realization.

In this paper, we analyse and model the push to talk traffic typical for FR systems. The kind of traffic in FR communication systems is similar to the push to talk voice traffic in catastrophe or disaster area (DA) scenarios. Thus, one goal in this paper is to evaluate whether models we developed for DA scenarios can be adapted for FR scenarios. We base our analysis on real traces obtained on the main FR channel of Bonn (Germany) in 2006.

The remaining part of this paper is structured as follows: Section II describes related work. In section III we describe our previous work, in particular the models developed for DA scenarios. Section IV describes the specific area in which the trace was acquired, the measurement architecture, as well as the generation of time series. Next, the time series are analysed with respect to short and long term dependencies and heavy load periods (section V). In this context, we also point out the differences between FR and DA traffic. Section VI deals with the fitting of the parameters of the different traffic models to our traces. After that, we study the traffic generated by different models to analyse their impact (section VII). Finally, we conclude the paper and point out topics for future work (section VIII).

II. Related Work

Paul T. Brady analysed telephone voice conversations in the 1960s and discovered that on and off periods of voice are exponentially distributed ([1], [2]). Based on his work [2], the ITU-T standardised (ITU-T P.59 - 1993) a commonly accepted model for artificial conversational speech [3] where a voice channel is modelled by a two-state markov model (cf. figure 1) assuming one state as talk spurt (*ON-state*) and the other as silence (*OFF-state*). In analogy to Brady's analysis the holding times in ON- and OFF-state are exponentially distributed.

The analysis of group communication in land mobile radio systems began in the 1980s. The purpose was to derive models to be used in the design of the new trunked radio systems. The analyses of Hess ([4], [5]) characterise session length and

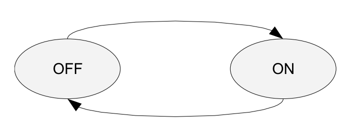

Fig. 1. 2-state (On-/Off-Model) (semi-)markov model

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interarrival times as exponentially distributed (similar to Brady cf. figure 1) and suggest models for peak load. He finally recommends to use the Erlang-C model. His results were confirmed by the Public Safety Advisory Committee [6]. Other studies (e.g. [7]) examine the behaviour of different talk groups to the system and suggest more complex models. However, the traffic is still modelled with exponentially distributed session length and interarrival times.

Later studies ([8], [9], [10], [11]) show that modelling the channel holding and idle times as exponentially distributed is inaccurate. For channel holding times lognormal and for inter arrival time weibull or gamma distributions are closer to reality. Furthermore, correlations between calls with respect to short- and long-range dependencies have been examined. The call holding times show no correlation whereas interarrival times showed dependencies (cf. [10]). Nevertheless, the studies still imply a two state model as presented in figure 1 with different (non-exponential) state holding time distributions.

Studies of the 1980s consider the traffic of a single channel (talk group) whereas newer studies consider the traffic of the complete trunked radio systems (multiple talk groups mixed). However, the lack of examining single channels results in less accuracy when modelling the traffic of one talk group. In [12] new traffic models are proposed that model single talk group push to talk traffic in disaster areas and consider conversational dependencies. These traffic models are described in detail in the following section.

III. Traffic Models

In this section we give a short description of our earlier work. In [12] voice traces from a large catastrophe manoeuvre were analysed. The time series were examined with respect to dependencies and heavy load periods. Examining dependencies of the call idle times due to conversational dependencies, a n-state (semi-)markov model was provided (see figure 2). A brief description is given in the following.

After a conversation idle time $Conv\_IDLE$ a new conversation starts with at least one call with channel holding time $Call\_CHT$. After this call there may be either a short idle time $Call\_IDLE$ (with probability p_1) or a longer one $Conv\_IDLE$ (with probability $q_1 = 1 - p_1$). In case of a long idle time we return to the first state ($Conv\_IDLE$). In case of a short idle time, the conversation contains another call with channel holding time $Call\_CHT$. After this again there may be either a short idle time $Call\_IDLE$ (with probability p_2) or a longer one $Conv\_IDLE$ (with probability q_2) and so on (with probabilities p_k and q_k, respectively).

The transition probabilities p_k and q_k were determined from the measured conversations calculating conditional probabilities as follows:

$$COL_k := \begin{cases} \emptyset & k \leq 0 \\ \{\text{Conversations} : \text{CallCount} \geq k\} & k \geq 1 \end{cases}$$

$$COE_k := \begin{cases} \emptyset & k \leq 0 \\ \{\text{Conversations} : \text{CallCount} = k\} & k \geq 1 \end{cases}$$

$$q_k := P\{\text{CallCount} = k \mid \text{CallCount} \geq k\} = \frac{\mid COE_k \mid}{\mid COL_k \mid}$$

$$p_k := 1 - q_k$$

The probability for a conversation containing at least k calls is the product of the probabilities $p_1, .., p_{k-1}$, whereas exactly k calls is the product of the probabilities $p_1, .., p_{k-1}, q_k$.

Different state holding time distributions were obtained for call holding times, call idle times, and conversation idle times by fitting the distributions to the traces. For the call holding times and conversation idle time the best fit was achieved by a lognormal distribution. For the call idle times the best fit was achieved by the gamma distribution.

Furthermore, the load of a channel was varying and heavy load periods were determined. The conversation idle times were found to be the characteristic parameter of the heavy load periods. Intuitively it is quite obvious: heavier load implies more conversations which implies smaller conversation idle times. Thus, heavy load periods should be considered when fitting the distribution for the conversation idle times.

As the channel holding and call idle times are modelled identically for all calls due to similar distributions, a simpler 3-state model (see figure 3) was provided. After a call with call holding time $Call\_CHT$ (state in the middle) there may be either a short idle time or a longer one. The difference to the n-state model is that the count of short calls in a row is not modelled explicitly due to a memoryless property of this model. The probabilities p_k and q_k do not change for different k. After k short idle times it is as probable that a long one follows as it is after the first short idle time. In theory there is no maximum number of calls per conversation in the 3-state model in contrast to the n-state one. However, the probability for a larger number of calls per conversation is arbitrary small.

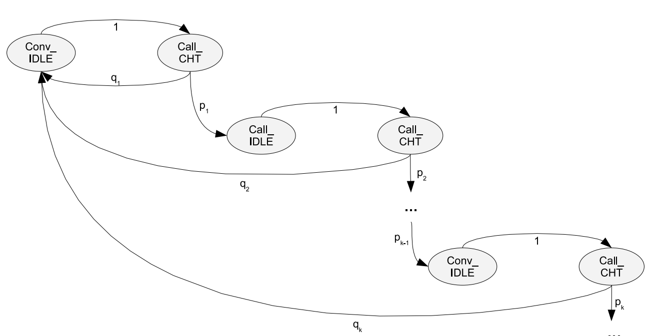


Fig. 2. n-state (On-/Off-Model) (semi-) markov model

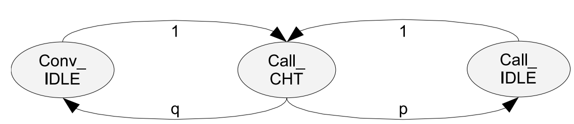


Fig. 3. 3-state (semi-)markov model

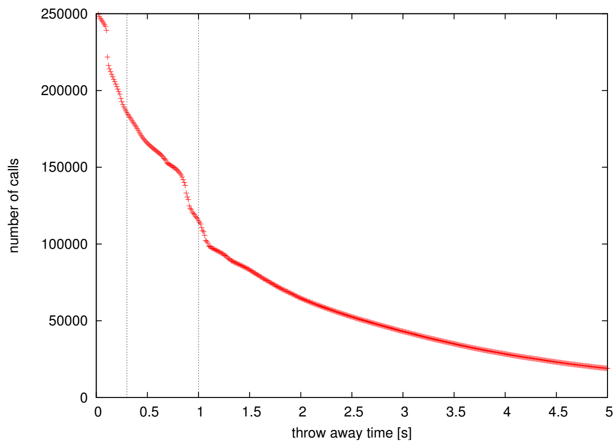


Fig. 4. Number of calls over throwaway times

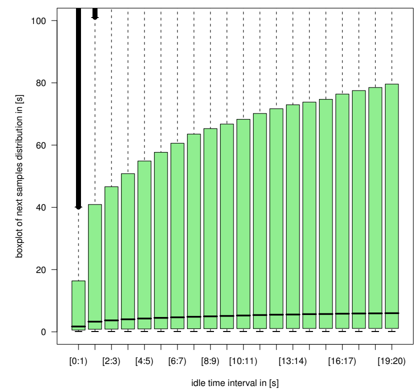


Fig. 5. Dependencies idle times - box plots for intervals over time

In visual, statistical and simulative evaluations both models resulted in realistic synthetic traffic for DA scenarios. In this paper, we address the question whether these models are also applicable for modelling (non-catastrophe) load on FR communication systems.

IV. Measurement Architecture

To obtain realistic time series of a public safety wireless communication system we performed traffic measurement on the analog German national radio system, called BOS-system (68-87.5 MHz and 146-174 MHz). We measured the main FR channel (85.915 MHz) of the FR district of Bonn. The district contains an area of more than 140 km^2 and more than 310,000 residents. The channel is dispatched by the fire department of Bonn. The channel is used by about twelve ambulances and three fire brigades in parallel on average. Of course, during larger planned events (e.g. concerts or sport events) or catastrophes the number of users rises. In the BOS-system different talk groups are separated by different physical channels. Thus, all users of the district build one talk-group. We measured for more than six months (02.06.2006 to 06.12.2006).

Our goal was to determine On- and Off-times for the channel. Based on short term fourier transformation (stft) we filtered out the relevant frequencies for human speech (100Hz - 7kHz) and summed up the intensities. When the sum was above a threshold, the channel was considered as being used (On-Time). We chose parameters such that a granularity of the resulting On- and Off-times of 10ms was achieved. A smaller value does not provide any benefit, because voice coders like G.729 [13] or the enhanced Mixed Excitation Linear Prediction (MELPe) [14] (for tactical environments) split the audio signal into frames of 10ms or 22.5ms, respectively. Thus, assuming such a vocoder to be used in a future digital system, more accurate On- and Off-Times have no impact on the traffic modelled.

After this analysis there are still a lot of small false calls, that only comprise spurious noise. These false calls need to be discarded. As threshold value a throwaway time had to be found to discard calls smaller than it (cf. [1]). In our previous work [12] we performed a two stage method which yielded a value of 300ms. However, figure 4 shows the number of calls over throwaway times up to 5s. There is a significant decrease around 1s. The reason for this are digital messages that are sent to reduce usage times for standard messages. Up to four short messages each 48bits long are send using frequency shift keying. Sending one block of four messages takes up to 1s to be transmitted (for further information see [15]). As these messages are no voice messages they need to be filtered out. After an empirical verification of the content of calls smaller 1s, we decided to set the throwaway time to 1s.

Finally, we base our analysis in the following section on 115,100 calls. We calculate idle and channel holding times and obtain the time series.

V. Analysis of Time Series

In this section we analyse the time series of the FR traffic obtained with respect to short-range dependencies, variation of load and long-range dependencies. Furthermore, we look for similarities of the FR time series to DA ones and also point out the differences.

A. Short Range Dependencies

For FR traffic we expect short range dependencies similar to the DA ones due to the conversational manner of the communication. If the communication follows a conversational manner there are many short idle times that are followed by a short one (calls in one conversation), short idle times that are followed by a long one (last call of the conversation), and long idle times that are followed by a short one (first call of the conversation). But long idle times followed by long ones are rare (single call conversations).

Figure 5 shows a box plot for the idle time series obtained in the previous section. The samples $x_1, x_2, .., x_n$ are regarded as points (x_i, x_{i+1}) for $i = 1, 2, .., n-1$. The data of the x-axis x_i's are pooled in intervals (of 1s in figure 5). The y-axis

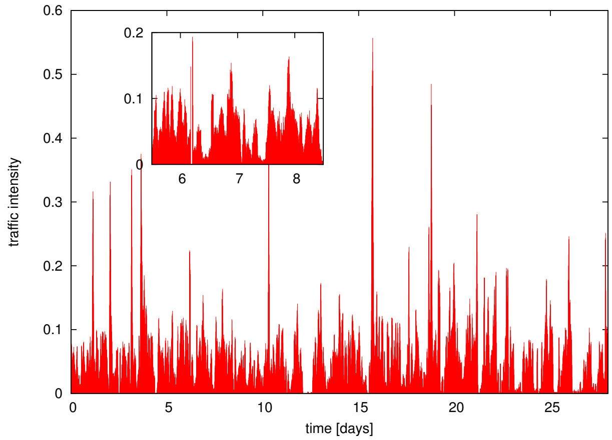


Fig. 6. Traffic intensity over time

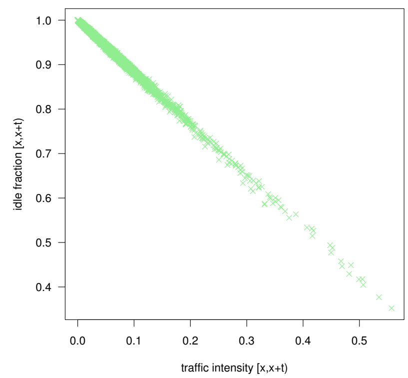


Fig. 7. Correlation of traffic intensity and idle fraction

shows box plots for the intervals. The box plot shows median, quartiles, octiles, and extremes (for further details see [16]). The figure shows that both the boxes and the medians for the first intervals are much smaller when compared to later ones. Thus, many short idle times are followed by short ones which confirms our expectation of short range dependencies due to conversational manner of the communication.

To allow for an analysis of conversations, these conversation have to be identified in the trace files. In principle there are three possible approaches: speaker recognition, manual analysis, and time threshold based approach (cf. [12]). As speaker recognition is too complex and error-prone for noisy channels like ours and manual analysis is not possible for such a long trace, we decided to use the time threshold based approach. A new conversation is assumed to have started when the idle time is larger than a certain threshold.

Inaccuracies may occur if the idle time in between two conversations is smaller than the threshold. In this case two conversation are regarded as one. However, this may especially be the case under heavy load. Even in this situations a kind of human backoff can be experienced before a new conversation is started in case the users are not to stressed up. The load on an FR channels (as we will see in section V-D) is lower than in catastrophe scenarios. Furthermore, the users of the FR channels are more professional and are less stressed than the ones in catastrophe situations. Thus, there are not too many inaccuracies to be expected.

As threshold value we decided to use 3s, as it turned out to be a good choice during the analysis of DA traces in [12]. By grouping calls to conversations the following four time series result:

call channel holding time:	time one call lasts
call idle time:	time between two calls of a conversation
conversation idle time:	time between two conversations
calls per conversation:	number of calls per conversation

B. Variation of load

Emergencies do not happen one after another with constant pause time in between. They also differ from one to another. Thus, the number of conversation is variable. Furthermore, as mentioned above, during larger events (e.g. concerts or sport events) or catastrophes the number of users and within this the number and frequency of conversation arises. Thus, there is a variation of load on the channel observed.

As metric to examine the load, the *traffic intensity* may be used:

$$TI_{[i;i+t)} = \frac{\text{time medium allocated}_{[i;i+t)}}{\text{time}_{[i;i+t]}}$$

It can be calculated for different interval sizes t. Figure 6 shows the traffic intensity over the time of four weeks (2,419,200s) for an interval size of $t = 1h$. It can be seen that there is some variation. It is interesting that differences between day and night can be seen. As during night many people sleep the number of emergencies is smaller (cf. the extension in fig. 6). Thus, the number of missions and with it the traffic intensity on the communication channel is lower during the night. Nevertheless, the overall traffic intensity is quite small compared to the DA channels (cf. [12]).

The time series that has the main influence on the traffic intensity is supposed to be the conversation idle time. To confirm this, we calculated the idle-fraction over time for the same month:

$$IF_{[i;i+t)} = \frac{\sum \text{Conversation idle times}_{[i;i+t)}}{\text{time}_{[i;i+t]}}$$

As visualising the idle fraction is more or less an inverse of figure 6, we prefer to show a correlation plot of traffic intensity to idle fraction. Figure 7 shows a strong negative correlation. Calculating a correlation coefficient results in -0.9992194. This implies that the conversation idle times are the ones that excite the variation of load. Furthermore, it shows that the conversation idle time (distribution) is the one to modify when wanting to change the load of the generated traffic.

C. Long-range dependencies

In [10] signs for long-range dependence of interarrival times are observed in traces of trunked radio systems containing multiple talk groups aggregated. Long-range dependence intuitively means correlation between distant events in time. Self-similarity usually implies long-range dependence.

A stochastic process $X = \{X(t)\}_{t\in\mathbb{R}}$ is called *self-similar*, if:

$$\forall a > 0 : \{X(at)\}_{t\in\mathbb{R}} \equiv \{a^H Z(t)\}_{t\in\mathbb{R}}$$

where $\equiv$ denotes the equality of the finite-dimensional distributions (cf. [17]). The Hurst parameter H $(0.5 \leq H \leq 1)$ is a measure for the degree of self-similarity. The larger H the larger the indication for self-similarity. Intuitively, self-similarity means that certain properties do not depend on the scaling in space or time (cf. e.g. [18]). Aggregating multiple on-off streams asymptotically can result in self-similar traffic (cf. [19]). However, the question remains whether there is also long-range dependence between the conversations of one talk group.

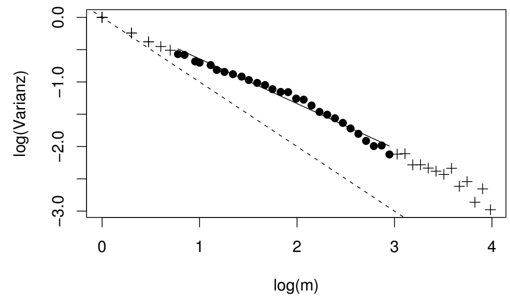
To study self-similarity, we estimate the Hurst parameter H. There are different analytical methods to estimate H. We use three different methods to estimate H:

1) The Variance-Time plot method relies on the slowly decaying variance of self-similar time series with rising aggregation level.
2) The rescaled range (R/S) plot method is based on the fact that self-similar datasets show a rescaled range or R/S statistics growing according to the power-law with exponent H.
3) The periodogram method estimates H by the slope of the frequency spectrum as frequency approaches zero.

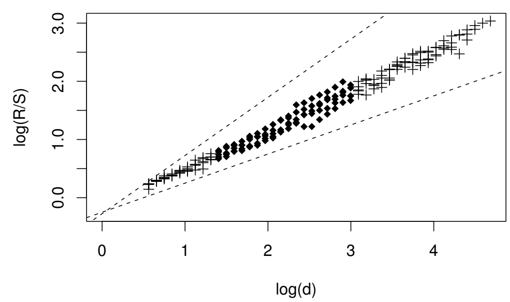
Further details can be found e.g. in [19]. Figure 8 visualises these estimations. All estimated values for H are significantly larger than $\frac{1}{2}$ and thus indicate self-similarity. A reason for this may be high variability caused by bursts of conversations. The amount and size of emergencies is varying over the time. Within this, the amount of active users and the amount of conversations varies as well. Thus, the long range dependencies of the conversation idle times are probably caused by the high variability of the emergencies.

Note, that estimating long range dependencies as well as self-similarity is complicated and non-stationary and periodic time series may produce falsified results (cf. e.g. [20], [21]). We examined periodicity by calculating a spectrum using fourier transformation; but there were no significant signs of periodicity. Concerning stationarity the conversation idle times seem to contain non-stationary effects at different time-scales. Unfortunately, the sample size is not large enough to let us calculate Hurst parameters for disjoint intervals as e.g. done in [18] for Internet traffic.

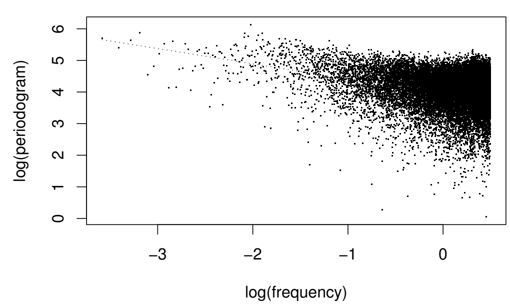
However, concerning simulations it makes only sense to consider long-range dependence, if a simulation run lasts long



(a) Time-Variance plot (H=0.6535674)



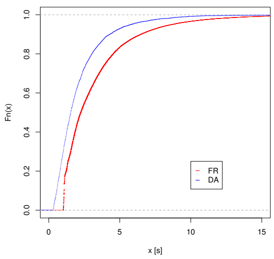
(b) R/S plot (H=0.6783222)



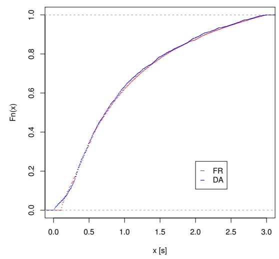
(c) Periodogram (H=0.7414332)

Fig. 8. Estimations of Hurst parameter for FR time series

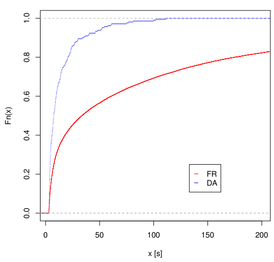
enough. Otherwise, the long range dependent effects would not have a significant impact. Typical simulation times for network simulation are significantly smaller than 60 minutes (3600s). Thus, complex models would not have an impact on the simulation. Therefore, we do not consider long-range dependence in the following section. Nevertheless, we consider long-range dependence as one important aspect and want to examine it in detail in the future.



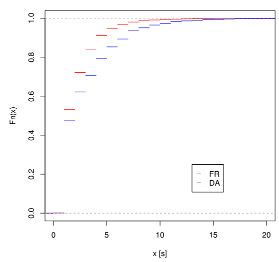
(a) Call Channel Holding Times



(b) Call Idle Times



(c) Conversation Idle Times



(d) Conversation Call Count

Fig. 9. Comparison of distributions of FR and DA time series via cumulative distribution functions

i	p_i	q_i
1	0.467798321212914	0.532201678787086
2	0.596171522199576	0.403828477800424
3	0.568910041560531	0.431089958439469
4	0.564039118652056	0.435960881347944
5	0.580948401921872	0.419051598078128
6	0.611650485436893	0.388349514563107
7	0.617871840094062	0.382128159905938
8	0.673644148430067	0.326355851569933
9	0.672316384180791	0.327683615819209
10	0.728991596638656	0.271008403361345
11	0.723342939481268	0.276657060518732
12	0.705179282868526	0.294820717131474
13	0.706214689265537	0.293785310734463
14	0.832	0.168
15	0.836538461538462	0.163461538461538
mean	0.888192502517706	0.111807497482294
mean(1:10)	0.608234186032742	0.391765813967258

TABLE II
PROBABILITIES FOR N-STATE MODEL

D. First Responder vs. Disaster Area traffic

In section V-A we showed that the FR time series show dependencies similar to DA time series. Thus, the approach using (semi-)markov models described in section III may be sufficient to model the traffic in FR networks. As a further step, it is interesting to compare the distribution of FR and DA time series. In the following, we study whether the distributions of FR and DA times series may be configured with the same or with different parameters.

Figure 9 shows cumulative distribution functions for the different time series for FR as well as DA. For DA the time series of [12] are used for reference purposes. The channel holding time of the calls (figure 9(a)) for the FR is a little larger when compared to the DA ones. The reason for this is that the users in catastrophe situations are more stressed up. Furthermore, in FR networks detailed information (e.g. addresses) is given more often. Moreover, in DA networks it is impossible to send standard messages using frequency shift keying. Thus, even for short standard information voice calls have to be used. The call idle times (figure 9(b)) show a perfect similar distribution. Thus, similar parameters can be used for FR and DA distributions.

Figure 9(c) shows significant differences of conversation idle times between FR and DA distributions. The load in catastrophe situation is higher than in FR networks. This fits to the results observed in section V-B compared to the ones in [12]. The average traffic intensity of the FR channel is smaller than that of the DA channels.

The average count of calls per conversation (figure 9(d)) differs slightly with two compared to one call per conversation. The conversations on the FR channel are shorter. A reason for this may be that the users are more professional and used to work together. Thus, they need less calls to exchange the same information.

In general, there are significant differences for all distributions other than for the call idle times. However, the impact of the conversation idle time is by far the largest. The differences of the other distributions may only have little impact on the modelled traffic. Nevertheless, we will search for optimal distributions and parameter sets for all time series.

VI. Fitting to Models

As argued above, the 3-state and n-state-model may be used as they realise conversational dependencies. In this section we estimate optimal parameters for the 3-state and n-state-model. Furthermore, we also fit the standard 2-state model even if it does not realise conversational dependencies, as we will use it in the following section for reference purposes. For estimating optimal parameters we use the Maximum-Likelihood-Method. Having found the optimal parameters, the quality of the fitting to the empirical data was evaluated using the Kolmogorov-Smirnov (K-S) test. We performed tests with four different distributions. The exponential distribution is the standard distribution used in the past (cf. section II). Recent studies show better fittings for lognormal, weibull and gamma distributions.

Table I shows the results for the different time series obtained in the previous section. The first column shows the fittings for the call channel holding time that is used for all models. The second and third column show idle time fittings separated for calls and conversations for the n-state and 3-state model. The right column shows the (mixed) idle times as needed for the two state model. The best fittings for all time series except the conversation idle time were achieved by the lognormal distribution. For the conversation idle times the weibull distribution achieves a slightly better fit than the lognormal distribution. However, both fittings achieve a very

Distribution	Call CHT		Conv. idle time		Call idle time		Call and Conv. idle time	
	Parameters	K-S dist.	Parameters	K-S dist.	Parameters	K-S dist.	Parameters	K-S dist.
exponential	rate = 0.3122918	0.27	rate = 0.007625337	0.2985	rate = 1.030362	0.1069	rate = 0.01191654	0.5729
lognormal	meanlog = 0.8997390 sdlog = 0.6872737	0.0971	meanlog = 3.139367 sdlog = 2.225036	0.0603	meanlog = -0.3481742 sdlog = 0.8482944	0.0444	meanlog = 1.434116 sdlog = 2.272971	0.1043
weibull	shape = 1.329617 scale = 3.524368	0.1724	shape = 0.5215525 scale = 66.7706266	0.0386	shape = 1.363882 scale = 1.064338	0.0539	shape = 0.4146688 scale = 13.8497172	0.1339
gamma	shape = 2.0443904 rate = 0.6384465	0.1279	shape = 0.386194137 rate = 0.002948838	0.0685	shape = 1.718836 rate = 1.771023	0.0461	shape = 0.241572882 rate = 0.002905988	0.2221

TABLE I
FITTING OF DIFFERENT DISTRIBUTIONS TO TIME SERIES

small K-S distance. As the lognormal distribution showed better fittings for the conversation idle time in our previous work and the weibull distribution (with the parameters obtained) tends to produce slightly lower load due to larger idle times, we decided to prefer the lognormal distribution.

Please note, that due to the threshold based approach used for grouping calls to conversation, values smaller than three seconds do not exist. Therefore, we shifted the values by three seconds and fitted the distributions. Random variates produced by these distributions have to be reshifted (plus 3 seconds).

Finally, we decided to use the lognormal distributions with parameters as shown in table I for all models and time series in the following section.

Furthermore, we calculated the transition probabilities for the n-state model as described in section III (see results in table II). For the 3-state model we use the mean value over the first ten probabilities as means over more values are falsified by single outliers.

VII. EVALUATION

In this section we provide visual and statistical evidence of the appropriateness of the models. The goal is to show differences between the models and compare the models to the original trace. For the evaluation we used the state holding time distributions and transition probabilities as described in the previous section. We generated one large trace of four weeks (2,419,200s = 28days) for each model and compare it to four weeks of the original trace.

Figure 10 shows 100 samples of idle times of each time series. The y-axis is limited to 6s to show details inside the conversations. Values larger than 3s are regarded as a new conversation. Figure 10(a) for the 2-state model looks denser than the trace in figure 10(d). Longer conversation with larger numbers of calls are seldom. The 3-state model (figure 10(b)) shows slightly better visual results. The size of the conversation visually fits to the trace. The n-state model (figure 10(c)) shows the largest conversations. Compared to the trace the conversations seem to contain too many calls.

After a first visual impression, we examined the count of calls per conversation. Table III shows the average count of calls and 95% confidence intervals over all conversation of the whole time series (28days). The number of calls per conversation produced by the 2-state model is significantly smaller; the mode does not consider conversational dependencies observed in section V-A. In contrast to this, the 3-state as well as the n-state model gain to model the dependencies. The amount of call per conversation is quite similar to the trace. However, the 3-state model tends to produce slightly longer conversations compared to the trace.

Model	average	0.95 conf. int.
2 state model	1.793815	0.014903
3 state model	2.525616	0.036259
n state model	2.127673	0.034291
trace	2.151705	0.016614

TABLE III
COUNT OF CALLS PER CONVERSATION

Finally, we wanted to perform further statistical evaluation based on traffic intensities. Therefore, we calculated traffic intensities for intervals of $t = \{60s; 900s = 15min; 3,600s = 1h; 21,600 = 6h\}$ for the different traces. Table IV shows mean and coefficient of variation of the traffic intensities for the different models and time intervals. The table shows that even if the mean of the 2-state model is the closest to the trace, the variations over time are not modelled sufficiently. The 3-state model achieves better results. The n-state model tends to model larger average traffic intensity and larger variation. However, the 3-state and n-state model can be regarded as lower and upper bounds for the trace.

The 3-state and n-state show benefit modelling FR traffic as they reflect the conversational dependencies. These have significant impact on the performance evaluation concerning delay and packet loss (cf. [12]). In network simulation of ad-hoc and mesh networks normally simulation times smaller than one hour (3600s) are used. Thus, more complex models would not have a significant impact on the results of these simulations.

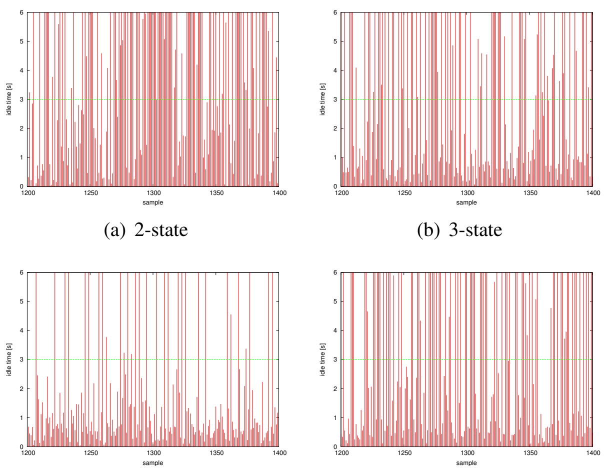
VIII. CONCLUSION AND FUTURE WORK

In this paper, we have analysed traffic that was measured over six months in a FR network. Based on this traffic, we calculated time series for single talk group push to talk traffic. The time series were analysed with respect to short-range and long-range dependencies as well as variation of load over the time. Furthermore, we have pointed out differences to traffic measured in a disaster area scenario. As the characteristics are similar, we adapted two models developed for disaster area traffic. We fitted standard distributions to the different models using the samples of our measurements. Lognormal distributions provided the best fit for all distributions.

Model	$t = 60s = 1min$		$t = 900s = 15min = 1/4h$		$t = 3600s = 1h$		$t = 21600s = 6h$	
	mean	coeffi. of var.	mean	coeffi. of var.	mean	coeffi. of var.	mean	coeffi. of var.
2 state model	0.05260401	0.2130546	0.05258575	0.05238997	0.05252715	0.02381036	0.05213978	0.009148676
3 state model	0.03169022	0.2725159	0.03168634	0.05990502	0.03168634	0.02563872	0.03150104	0.007801865
n state model	0.07487302	0.4595133	0.07487117	0.1722872	0.07487117	0.08771904	0.07431902	0.03500988
trace	0.05532976	0.2874941	0.05535319	0.08588609	0.05535319	0.05147096	0.05535319	0.01798584

TABLE IV

STATISTICS FOR TRAFFIC INTENSITY OVER DIFFERENT INTERVALS



(a) 2-state (b) 3-state

(c) n-state (d) trace

Fig. 10. Idle Times (100 samples of each time series)

Finally, we generated traffic streams for the different models. These streams were evaluated visually and statistically. The 2-state models shows larger differences to the measured data than 3-state and n-state models because the conversational correlations observed are not considered. Neither the 3-state nor the n-state model consider long-range dependence or differences between days and nights. Nevertheless, the models should be used for simulative network performance analysis of voice communications in FR networks as they consider conversational correlations sufficiently.

In the future, we want to investigate the aspects of long range dependencies in detail. Besides this, we plan to perform further measurements to analyse push to talk voice traffic in other scenarios (e.g. taxis, busses). Furthermore, we plan to examine functional relations between the parameters for the conversation idle time distribution and traffic intensity. Our goal is to adjust the traffic intensity of a scenario by adjusting the conversation idle time distribution. Additionally, we want to carry out a simulative performance analysis in ad-hoc and mesh networks e.g. of routing protocols.

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