Data and Traffic Models in 5G Network

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Abstract This chapter presents data and traffic analyses in 5G networks. We setup experiments with Zigbee sensors and measure different traffic patterns by changing the environmental conditions and number of channels. Due to the differences in read, write operations, message fragmentations and backoff of the Carrier Sense Multiple Access/Collision Avoidance algorithm we demonstrated that the traffic flows are changing dynamically. This leads to different behaviour of the network domain and requires special attention to network design. Statistical analyses are performed using Easyfit tool. It allows to find best fitting probability density function of traffic flows, approximation toward selected distributions as Pareto and Gamma and random number generation with selected distribution. Our chapter

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concludes with future plan for distribution parameters mapping to different traffic patterns, network topologies, different protocols and experimental environment.

Keywords Sensor measurements · Best-fitting pdf · 5G traffic

1 Introduction

The aim of this chapter is to present generic approach to modelling of traffic flow patterns in 5G sensor networks. The transparency of data in place and time combined with node mobility, distributed data processing and network virtualization cause traffic patterns to change dynamically and often unexpectedly. Depending on the type of communication (peer-to-peer, client/server, machine-to-machine, sensor and personal area networks, delay tolerant applications) and the layer of observation (application, virtual platform, Internet Protocol (IP) or physical machine) traffic sources produce distinct traffic patterns, which are further complicated by traffic shaping and engineering applied by overlay networks [16], network services [9] and software defined network functionality [8].

The diversity in flow behaviour needs appropriate and customized modelling to support the development of network management schemes able to cope with modern traffic patterns. Topology adaptations, mapping of sources to network paths (scheduling), traffic engineering and policing, reliability and failover algorithms fall under management. Main part of the challenge ahead of traffic models is the variety and dynamic nature of modern application and services [7]. While some may generate rather static, predictable patterns, e.g., replicated storage backups or software updates, others generate high variable and difficult to predict patterns, e.g., opportunistic content dissemination [5], distributed media services [9], sensor data, machine-to-machine data flows. For example, a large network of Zigbee sensor, although generating only few bytes of payload, can produce high intensity traffic in real-time. Worse is the case of surveillance and security or social analytics, which make a perfect example of big data applications, causing distinctly different traffic patterns in and across data centers. Newly emerging device-to-device

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communications (in mobile networks) and peer-port application lead to more fuzzy data models [8]. Additional aspects which influence the construction of traffic models and on which we will reflect are engineering approaches such as redundancy, power-efficient operation and distributed processing. Redundancy benefits service availability but also causes traffic to be load balanced over several available paths and when applied at the packet level breaks the flow traffic pattern at the source. Power consumption dictates certain transmission policies, especially in energy-constraint devices and with green technology requirements [4]. Distributed processing often results in big amounts of data transferred across the network. Understanding and simulation of the complexity of the traffic sources, including the statistical parameters and probability density functions (pdf) of the inter-arrival and servicing processes in 5G, is essential for further network planning and design [16].

This chapter consists of state of the art part that explains details on traffic measurements, Zigbee sensor networks and their traffic specific features. After detailed description of the experiments in the next section, main results are shown and commented. Finally, we expose views of open-research issues for offering analytical traffic models that fit to the traffic flows and will allows optimization in the 5G traffic.

2 State of the Art

Zigbee technology and especially applications in body/personal area networks and smart environments became popular recent years. Connection to the cloud and cloud-based data gathering and analyses allows high level of data processing and better data interpretation [8]. Usually the traffic generated by these networks is considered small or even negligible. When the number of sources is significant, the networks are dynamically created and destroyed, traffic sources are moving and change their behaviour it is difficult to predict the load to the processing equipment and plan the resources properly. Details on similar software defined networks and the interfaces and attributes could be found in [15]. In our papers [10, 11] we demonstrate Zigbee technology and its applicability to the body/personal environments. We setup experiments there to measure round trip delays and loss in the network. In this chapter, we enrich the analyses toward delay distributions and statistical parameters.

An interesting approach using priorities at application/session layer is presented in [1, 2]. The authors demonstrated the complexity of the traffic models when the traffic is prioritized and is transmitted via congested network elements. Possible solution for network node configuration taking into account the nature of the traffic could be found in [3]. Specific applications [6] and the influence on the network configuration could be diverse and irregular by nature. More abstract and complete approach to network design is presented in [13]. Machine-to-machine vehicle network is shown in [19]. In [20] authors demonstrated an approach for assisted living networks. A very specific almost complete underwater network is presented in [14]. A decision for energy harvesting and big data analyses in sensor network could be seen in [18].

Delay and priority analyses could be found in [21]. Reliable solution through different access scenarios is presented in [22].

3 Experiment Setup

In order to analyze the behaviour of the sensors as traffic sources we setup an experiment in the laboratory shown on Fig. 1. The channel is duplex. Under the same serial radio channel, at least three pairs of sensors are transmitting simultaneously interfering all the time. In different measurements (Table 1) the conditions are changing. The operations are reads and writes with different length of the information sent. During part of the experiments, there are additional radio transmissions that emulate a radio noise and/or an 802.11 radio signal with two levels of intensity.

The protocol is Modbus RTU. Sensors are connected to the controller for data gathering and acquisition. For more complexity, the number of transmitting sensors could be increased. Such case is not presented in this chapter. Session 1 between sensors 1 and 4 is used for delay and loss measurements. Session 2 between sensors 2 and 5 as well as session 3 between sensors 3 and 6 are used for changing the conditions in the radio channel. In Table 1 there are 21 experiments presented. In Sect. 4, we show only part of the results concerning the best fitting probability density function of packet round trip delays. The collected data for delay is exported and evaluated by Easyfit statistical tool. The fitting is also performed

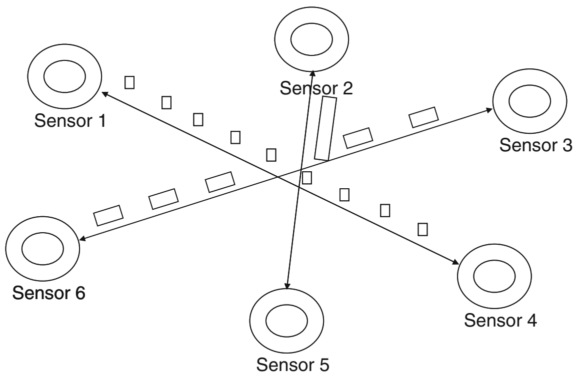

Fig. 1 Many sensors transmitting simultaneously over the same radio channels

Table 1 List of measurements in Zigbee network

No	Description
1	No interference, sessions 1 and 2 active, read operation with 2 and 40 bytes at 200 and 500 ms intervals, Burr distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov and Anderson-Darling approximations
2	No interference, sessions 1 and 2 active, read operation with 120 and 40 bytes at 200 and 500 ms intervals, Burr (4P) distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov and Anderson-Darling approximations
3	No interference, sessions 1 and 2 active, read operation with 240 and 40 bytes at 200 and 500 ms intervals, Cauchy distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared approximations
4	No interference, sessions 1, 2 and 3 active, read operation with 240, 40 and 240 bytes at 200, 500 and 1,000 ms intervals, Cauchy distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared approximations
5	No interference, sessions 1, 2 and 3 active, read operation with 240, 40 and 2 bytes at 200, 500 and 10 ms intervals, Cauchy distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov and Anderson-Darling approximations
6	No interference, sessions 1, 2 and 3 active, read operation with 240, 40 and 240 bytes at 200, 500 and 10 ms intervals, Cauchy distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared approximations
7	RF radio interference, sessions 1 and 2 active, read operation with 240 and 40 bytes at 200 and 500 ms intervals, Cauchy distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared approximations
8	Doubled RF radio interference, sessions 1 and 2 active, read operation with 240 and 40 bytes at 200 and 500 ms intervals, Cauchy distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared approximations
9	802.11 radio interference, sessions 1 and 2 active, read operation with 240 and 40 bytes at 200 and 500 ms intervals, Cauchy distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared approximations
10	Doubled 802.11 radio interference, sessions 1 and 2 active, read operation with 240 and 40 bytes at 200 and 500 ms intervals, Cauchy distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared approximations
11	Doubled RF and 802.11 radio interference, sessions 1, 2 and 3 active, read operation with 240, 40 and 240 bytes at 200, 500 and 10 ms intervals, Cauchy distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared approximations
12	Doubled RF and 802.11 radio interference, sessions 1, 2 and 3 active, read operation with 240, 40 and 240 bytes at 10, 500 and 10 ms intervals, Cauchy distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared approximations
13	Doubled RF and 802.11 radio interference, sessions 1, 2 and 3 active, read operation with 240, 40 and 240 bytes at 1000, 500 and 10 ms intervals, Cauchy distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared approximations

(continued)

Table 1 (continued)

No	Description
14	No radio interference, sessions 1 and 2 active, write operation with 2 and 40 bytes at 200 and 500 ms intervals, Gen. Pareto distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov and Burr distribution in accordance to the Anderson-Darling approximation
15	No radio interference, sessions 1 and 2 active, write operation with 120 and 40 bytes at 200 and 500 ms intervals, Burr distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov and Log-Logistic (3P) distribution in accordance to the Anderson-Darling approximation
16	No radio interference, sessions 1 and 2 active, write operation with 240 and 40 bytes at 200 and 500 ms intervals, Log-Logistic (3P) distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov and Frechet (3P) distribution in accordance to the Anderson-Darling approximation
17	Doubled RF and 802.11 radio interference, sessions 1, 2 and 3 active, write operation with 240, 40 and 240 bytes at 200, 500 and 10 ms intervals, Beta distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov and Anderson-Darling approximations
18	Doubled RF and 802.11 radio interference, sessions 1, 2 and 3 active, write operation with 240, 40 and 240 bytes at 10, 500 and 10 ms intervals, Phased Bi-Weibull distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov and Anderson-Darling approximations
19	Doubled RF and 802.11 radio interference, sessions 1, 2 and 3 active, write operation with 240, 40 and 240 bytes at 1000, 500 and 10 ms intervals, Pearson 5 (3P) distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov and Anderson-Darling approximations
20	Doubled RF and 802.11 radio interference, sessions 1, 2 and 3 active, read operation with 240, 240 and 240 bytes at 1000, 10 and 10 ms intervals, Cauchy distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared approximations
21	Doubled RF and 802.11 radio interference, sessions 1, 2 and 3 active, write operation with 240, 240 and 240 bytes at 1000, 10 and 10 ms intervals, Beta distribution as the best fitting pdf in accordance to Kolmogorov-Smirnov and Anderson-Darling approximations

towards well known from our previous experiments Pareto and Gamma distributions for better comparison. Sensors collide when tried to transmit at once. The protocol for collusion avoidance applies backoff timer. Depending on the number of collisions, the losses and delays also change rapidly.

4 Results

Part of the results concerning best fitting probability density functions are already shown on Table 1. In order to save space we demonstrated only part of the data graphically and numerically in Tables 2 and 3 as well as next graphs. Table 2 demonstrates the best fitting pdf parameters and fitting parameters to the Gamma

Table 2 Fitting distribution parameters

Experiment	Fitting pdf	Approximation	Parameters
1: Low traffic	Best fitting: Burr	Kolmogorov-Smirnov and Anderson-Darling	k = 0.1229; α = 141.6777; β = 143.55
	Gen. Pareto	Kolmogorov-Smirnov	k = −0.01455; σ = 9.74865; μ = 142.564
	Gen. Gamma (4P)	Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared	k = 0.4714; α = 13.7316; β = 0.052; γ = 137.216
2: Medium traffic	Best fitting: Burr (4P)	Kolmogorov-Smirnov, Anderson-Darling	k = 0.422; α = 17.661; β = 52.644; γ = 300.24
	Gen. Gamma (4P)	Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared	k = 1.61; α = 13.96; β = 10.8313; γ = 303.51
	Gen. Pareto	Kolmogorov-Smirnov, Anderson-Darling	k = 0.5558; α = 7.002; μ = 349.1967
3: High traffic	Best fitting: Cauchy	Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared	σ = 5.133; μ = 484.046
	Gen. Pareto	Kolmogorov-Smirnov, Anderson-Darling	k = 0.658; σ = 10.221; μ = 470.6347
	Gamma (3P)	Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared	α = 5.915; β = 32.458; γ = 308.528
4: High interference and high traffic	Best fitting: Cauchy	Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared	σ = 21.95; μ = 535.91
	Gen. Gamma (4P)	Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared	k = 0.381; α = 26.393; β = 0.09564; γ = 50.675
	Gen. Pareto	Kolmogorov-Smirnov, Anderson-Darling	k = 0.59675; σ = 88.86; μ = 425.808
14: Writes, low traffic	Best fitting: Gen. Pareto	Kolmogorov-Smirnov, Anderson-Darling	k = −0.10785; σ = 10.696; μ = 162.399
	Gen. Gamma (4P)	Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared	k = 0.6; α = 9.424; β = 0.345; γ = 156.75
16: Writes, high traffic	Best fitting: Log-Logistic (3P)	Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared	α = 1.592; β = 8.7069; γ = 510.936
	Gen. Pareto	Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared	k = 0.915; σ = 13.72; μ = 509.53
	Gen. Gamma (4P)	Kolmogorov-Smirnov, Anderson-Darling	k = 1.62; α = 0.108; β = 1562.184; γ = 511.0

(continued)

Table 2 (continued)

Experiment	Fitting pdf	Approximation	Parameters
18: Writes, high traffic, high interference	Best fitting: Phased Bi-Weibull	Kolmogorov-Smirnov, Anderson-Darling	$\alpha_1 = 0.87184$; $\beta_1 = 367.225$; $\gamma_1 = 474$; $\alpha_2 = 0.4053$; $\beta_2 = 1{,}660.4535$; $\gamma_2 = 99$
	Gen. Gamma (4P)	Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared	$k = 0.524$; $\alpha = 1.106$; $\beta = 1{,}045.74$; $\gamma = 474.0$
	Pareto	Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared	$\alpha = 0.8856$; $\beta = 474$

and Pareto distributions. The data allows random number generation and comparison to the well known distributions [12]. Tables 3 and 4 present general data of the measured traffic flows. The values for variance on Table 3 are very high due to the irregularity of the sources. Table 4 contains data percentiles.

The main conclusion from the experiments is that the traffic in sensor networks is varying rapidly depending on the protocol, topology, interference, amount, mobility, etc. Keeping this in mind and knowing that in the Internet of Things environment billions of traffic sources will transmit simultaneously and will need processing the design of the platforms could be done in the way to meet these challenging requirements. On Fig. 2 best fitting pdf is shown from the 1,000 independent measurements during experiment 1. On the figure bars represent the measured data as well as continuous line represents the approximated density function. When the traffic increases, the pdf is not always changing (Fig. 3). The main differences in comparison to the Fig. 2 are due to the collisions and backoff.

Modbus RTU limits the maximal interval between bytes from any single message. Zigbee protocol limits the number of bytes in a single message in the radio interface. Due to this Modbus RTU messages are often fragmented over the radio interface adding additional delay for fragmentation and end-to-end transmission.

Further increase of the traffic, collisions and interference results in best fitting distribution change to Cauchy (Fig. 4). The main differences between reads and writes (Figs. 4, 5, 6, 7 and 8) are due to the difference in sensor sensitivity and the power needed to perform the operations.

On Figs. 6, 7 and 8 experiments with writes demonstrate different best fitting distributions depending on the traffic from Generalized Pareto, Log.-Logistics and Phased Bi-Weibull. Special attention should be paid to the last one. Due to the big messages, fragmentation and collisions the delays for part of the messages are increasing rapidly and they form the second right peak on the graph (Fig. 8).

Table 3 Descriptive statistics, sample size 1,000 experiments, RTT range, mean, variance in ms

Experiment	Sample size	Range	Mean	Variance	Std. deviation	Coef. of variation	Std. error	Skewness	Excess Kurtosis
1, read	1,000	238	152.17	134.8	11.61	0.08	0.37	8.3	141.01
2, read	1,000	4,964	364.96	25,592.96	159.98	0.44	5.06	29.415	895.37
3, read	1,000	5,590	500.52	66,836.8	258.53	0.52	8.175	17.92	340.08
4, read	1,000	5,857	646.2	507,598.4	712.46	1.1	22.53	6.034	37.30
14, write	1,000	82	172.05	84.285	9.18	0.0534	0.29	2.2	8.547
16, write	1,000	5,480	670.955	638,642	799.15	1.191	25.27	5.385	28.026
18, write	1,000	5,528	2,515.88	5,247,481	2,290.7	0.91	72.44	0.4	−1.7

Table 4 Percentile

Experiment	Min	5 %	10 %	25 % (Q1)	50 % (Median)	75 % (Q3)	90 %	95 %	Max
1	138	143	144	146	149	156	164	168	376
2	314	347	349	353	357	364	369	375	5,278
3	312	475	476	478	485	489	497	503.95	5,902
4	72	356	386	518	536	560	605.9	666.95	5,929
14	157	163	164	166	169	176	184	187	239
16	511	513	514	516	519	526	536	548.95	5,991
18	474	547	554	566	626	5,364	5,678.5	5,777.95	6,002

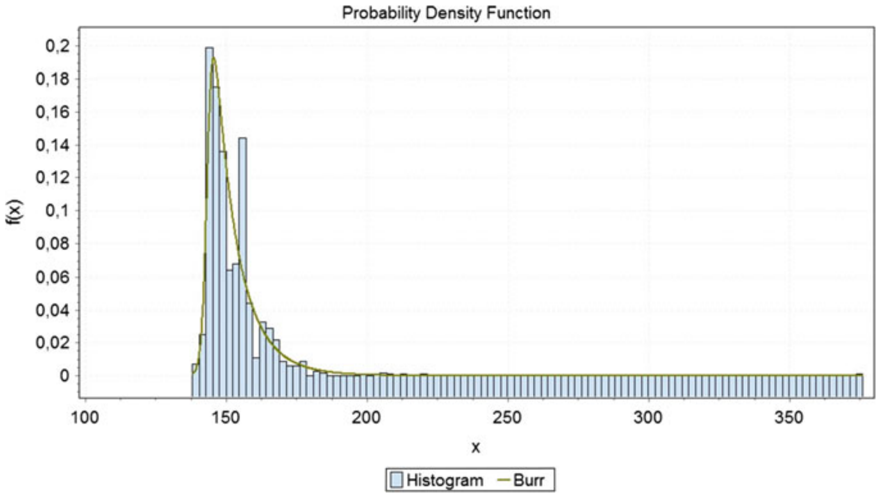

Fig. 2 Experiment 1, standard traffic, no backoff because the channel is idle

Such multimodal functions had been investigated previously also in [17]. As a general rule in case of the lack of fragmentation, a high interference in the channel does not change round trip time variations due to the CSMA/CA during read operations. The only visible effect is reduced peak that means that the round trip times are spread around the mean value due to the backoff.

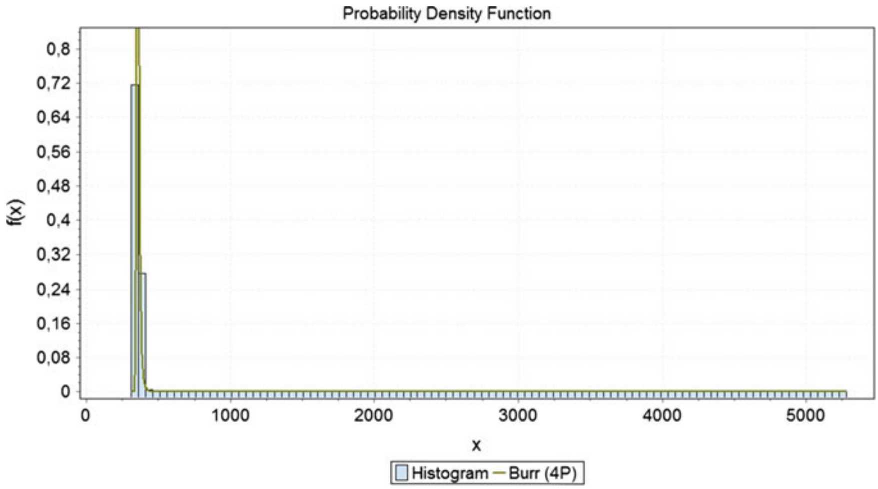

Fig. 3 Experiment 2, increased traffic, backoff because the channel is not always idle

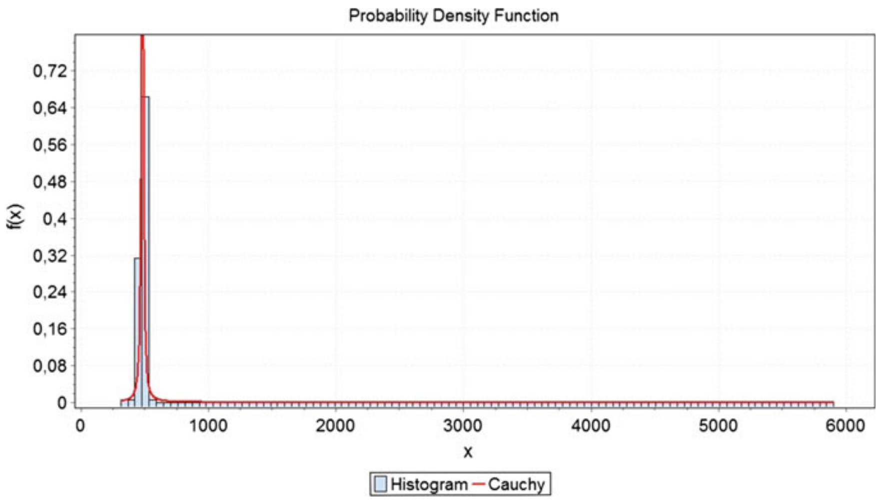

Fig. 4 Bigger traffic in experiment 3 and bigger probability for backoff

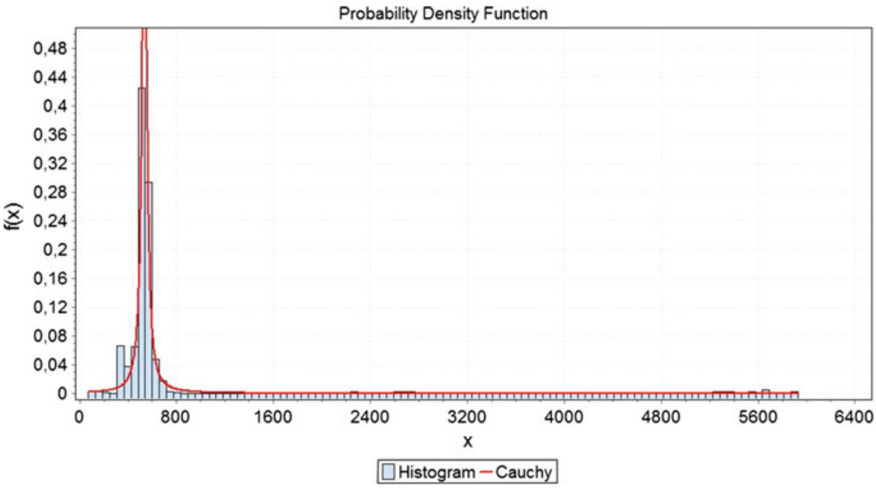

Fig. 5 Experiment 12, very high interference, very high traffic

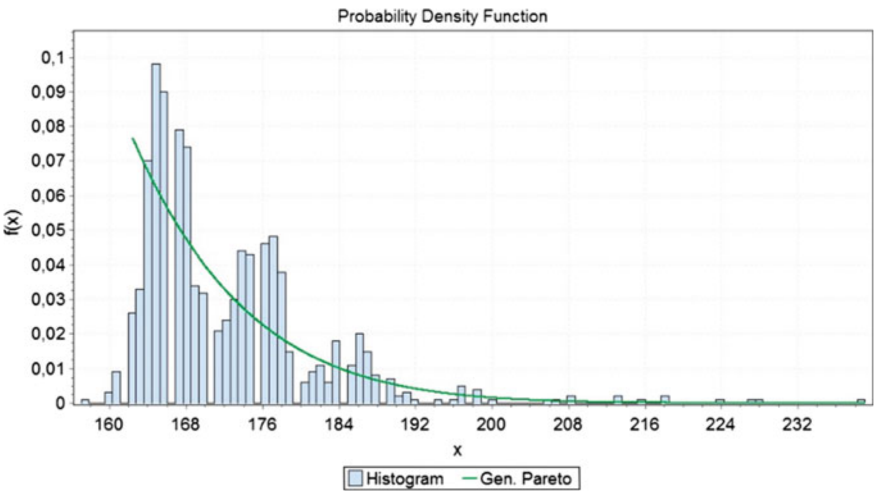

Fig. 6 Experiment 14, write operation with 2 bytes payload

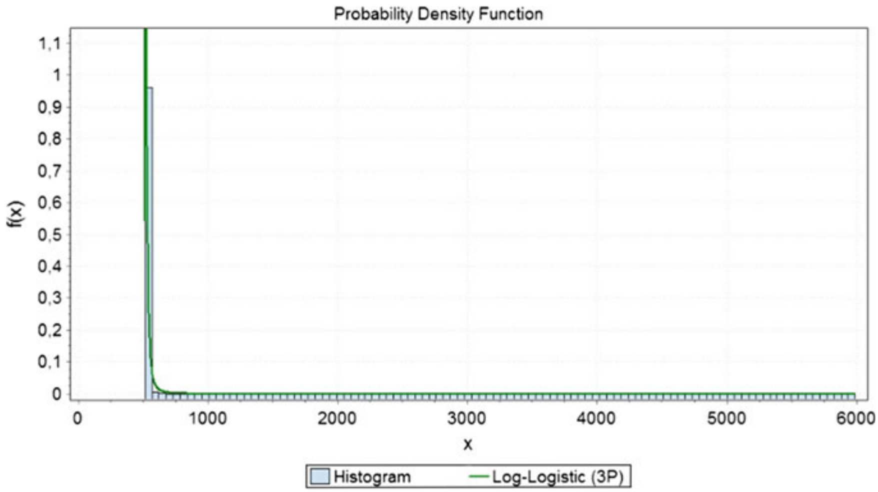

Fig. 7 Experiment 16, write operation with 240 bytes payload

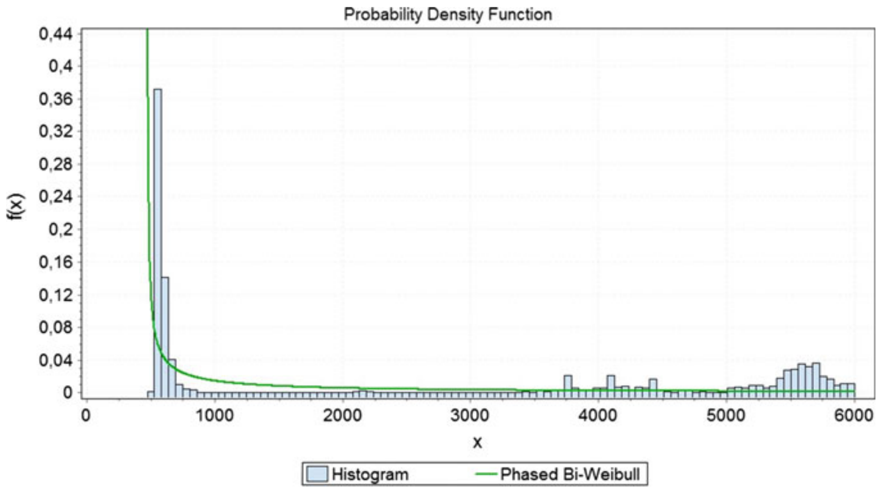

Fig. 8 Experiment 18, write operation with high traffic and high interference

5 Conclusion and Future Work Plan

In this chapter, we show traffic measurements and analyses in sensor networks aiming to obtain necessary information for network design. We investigated round trip delay of read, write operations, and found them different from traffic point of view. Round trip delay depends mostly on transmission channel characteristics and end-devices. Backoff timer influences the data significantly as well as message fragmentations. With high traffic, write operation round trip time variance tends to become similar to read operation round trip time variance with higher mean value. Due to the high traffic and interference, the distribution could become multimodal.

Our future research continues with mesh network measurements and analyses as well as traffic relaying phenomenon investigation. We continue our experiments with different types of sensors. We aim also to map inter-arrival times to Gamma distribution and find mapping between gamma parameters and transmission nature.

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