Traffic simulation in the LoRaWAN network

Almira D. Mukhamejanova[1], Elans A. Grabs[2], Kumyssay K. Tumanbayeva[1], Eleonora M. Lechshinskaya[1]
[1]Department of Telecommunications and Innovative Technologies, Almaty University of Power Engineering and Telecommunications named after Gumarbek Daukeyev, Kazakhstan
[2]Department of Transport Telematics and Electronic Systems, Riga Technical University, Latvia

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ABSTRACT

LoRaWAN is one of the most commonly used technologies serving the internet of things (IoT) and machine-to-machine (M2M) devices. The traffic growth in the LoRaWAN network gives rise to many problems, which are solved using mathematical modelling. The actual task, in this case, is the development of a traffic simulation model in the LoRaWAN network. This article discusses the issues of traffic simulation in the LoRaWAN network and its research using the MATLAB system. The authors have developed a LoRaWAN network server model as a queuing system with incoming self-similar traffic in the MATLAB system using a separate subsystem for the input traffic modelling allowing to change the number of sources in the LoRaWAN network. The simulation results made it possible to establish the dependences of the network server's buffer memory, the probability of packet loss from the incoming self-similar traffic parameters, and reveal the possibilities of traffic modelling in the MATLAB system.

Corresponding Author:

Almira D. Mukhamejanova
Department of Telecommunications and Innovative Technologies, Almaty University of Power Engineering and Telecommunications named after Gumarbek Daukeyev, Kazakhstan
Email: Almira_md@mail.ru

1. INTRODUCTION

The scope of internet of things (IoT) technology is expanding to include such economic sectors as energy, transport, industry, housing and communal services, agriculture, and healthcare [1]. The overall infrastructure of 'smart' homes and 'smart' cities, emerging globally, is also managed using this technology [2]. The number of applications deploying IoT technology is rapidly growing, resulting in a significant increase in traffic from connected IoT/M2M devices [3].

LoRaWAN, presented in 2015 by Semtech and IBM Research [4], is one of the promising technologies designed to service IoT/M2M. LoRaWAN technology is part of a group of low-power wide-area network (LPWAN) technologies that connect IoT/M2M applications to a narrowband communication network with low radiation power and a range of up to several kilometres [5]. The LoRaWAN network allows for remote data collection from various connected metering devices, such as water meters, electricity meters [6]. 'Smart' homes, 'smart' transportation, and 'smart' city projects are all made possible by this technology. Much attention is paid to projects related to the automation of technological processes.

The diversity of applications generates a variety of traffic on the LoRaWAN network [7]. To carry out studies of traffic service processes at network nodes, which are necessary for solving network design problems and assessing service quality indicators, a mathematical model of traffic in a LoRa network is required. In this context, developing an adequate traffic model that reflects the traffic's real-word features and analyses its characteristics is a critical task.

The purpose of this article was to identify the possibilities of the network traffic simulation in the LoRaWAN network and analyse its results using the MATLAB software package. The scientific novelty of the work lies in the development of a simulation model of self-similar traffic arriving at the LoRaWAN network server in the form of the queuing system's subsystem, in determining the dependences of the digital storage buffer's size and the probability of packet loss on the parameters of self-similar traffic and simulation time.

In modelling, a network node (server, router, multiplexor) was viewed as a single-channel queuing system (QS). In this model, each IP packet was regarded as a request to be serviced, transmitted, received, and processed. The traffic generated by packets (packet traffic) had such parameters as the rate of packet arrival (packs/s), packet length (bits, bytes), the time interval between packets, and traffic intensity (bit/s). Before proceeding to the description of the development of the traffic simulation model in the LoRa network, let us consider its architecture, shown in Figure 1.

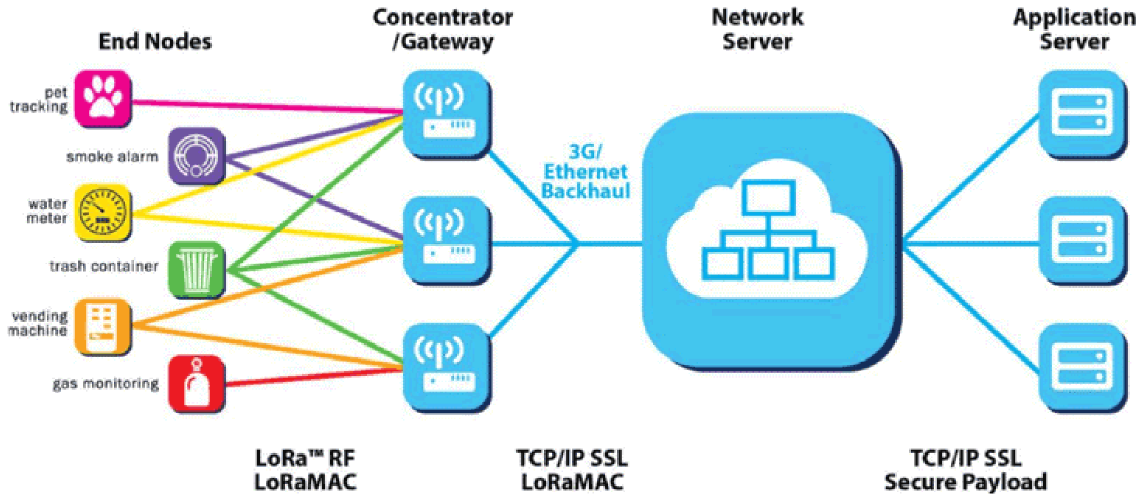

Figure 1. The LoRa network architecture

LoRa network architecture consists of four main parts; i) end nodes, ii) gateways, iii) network server, iv) application server [8]. The creation of a network traffic model has always been a critical part of fundamental network modelling [9]. Reliable models should adequately describe the actual characteristics of the network environment, that is why many works are devoted to the development of analytical and simulation models of traffic generated by IoT and M2M devices.

One of the first works devoted to developing M2M traffic models is work created by Laner *et al.* [10], considering three modelling strategies. In the first strategy, each device is modelled as a stand-alone entity, which provides greater accuracy and flexibility. However, the model becomes much more complex with the growth of M2M devices. In the second case, an aggregated traffic model is developed, the complexity of which is independent of the number of devices. The third strategy considers a hybrid approach. This paper compares all three models and shows the trade-off between accuracy and complexity.

It is widely known that today the traffic in modern networks is largely self-similar (fractal) [11], [12]. However, in some works, aggregated traffic from devices is modelled as Poisson traffic [13], [14]. In this paper, the superposition of traffic flows from n nodes was approximated by the Poisson process making it easy to calculate the characteristics of even such large-scale systems as the IoT.

There are several methods for modelling self-similar network traffic. In studies [15], [16], self-similar traffic is modelled as an 'ON/OFF' process, and an improved 'ON/OFF' methodology for modelling a 'smart' city's IoT traffic is presented.

Research by Gupta *et al.* [17] consider modelling of traffic from IoT devices connected via LPWAN technologies. Although it is impossible to create a single traffic model for many IoT applications, traffic can be classified as either periodic or event-triggered, or a combination of the two. This paper evaluates the performance of LoRaWAN, one of the LPWAN technologies, in which a hybrid of both types of traffic is present. In the practical deployment of sensor-based IoT devices, these devices are usually densely deployed to provide sufficient and reliable measurements. Thus, when an event occurs, they exhibit spatial and temporal correlation in their traffic rate due to the natural phenomena of the measured metric. The coupled markov modulated poisson processes (CMMPP) model is used to represent such event-triggered signature traffic from independent IoT devices. The CMMPP model, which combines the first two modelling strategies mentioned in [10], was previously proposed in the study of [18]. The accuracy and flexibility of such a model are substantiated in comparison with the aggregated traffic model.

Two network traffic models are proposed in the study of [19], both of which can characterize the self-similarity of traffic with the characteristic of packet loss. As a result of modelling, two self-similar traffic models were obtained, with the calculation of the Hurst parameter for each to estimate the degree of self-similarity. In conclusion, the authors showed that both models adequately describe network traffic. We should note that the models of self-similar traffic in the work were developed in the MATLAB environment. In the works reviewed earlier, the network traffic simulation models were developed in OPNet, OMNet, NS3, and the like. He *et al.* [19] showed the advantages of modelling in MATLAB, allowing to obtain more adequate network traffic models with a given self-similarity index. In this article, we considered the possibilities of modelling and researching a self-similar traffic model using the MATLAB software package and its Simulink environment.

2. RESEARCH METHOD

In recent years, traditional modelling technologies have been increasingly replaced by new technologies for creating and using models called intelligent technologies [20]. Using artificial intelligence assumes that most of the actions previously done by the developer are now performed by the computer [21], significantly changing the requirements to the developer, the nature of his actions, and the designed model properties [22].

This article describes a methodology for creating a simulation model of a LoRaWAN network server as a P/M/1/K type queuing system. To simulate the network server's operation, we suggested to use the MATLAB software package and its included Simulink environment. To model self-similar traffic, we considered the probability distribution of the size of the intervals between packet arrivals as the Pareto distribution (P). Simulink allows using the high-power SimEvents data set control block [23] to create models of queuing systems. Simulink also allows using any MATLAB library, as well as any custom blocks created by the user, for the estimation of traffic and control blocks.

All this sets MATLAB apart from other modelling environments. The Simevents block set includes models for; i) traffic sources, ii) queues (including priority ones), iii) servers and other blocks. SimEvents allows forming requirements with user-defined parameters and then connecting blocks in such a way so that the movement and processing of requests correspond to a real-life environment. It is known that network traffic is self-similar (fractal) [24], [25].

The authors examined network traffic coming from gateways to the network server. To study the properties and characteristics of this traffic, we carried out a statistical analysis of the data. Statistical data processing allowed us to obtain the following traffic characteristics results and calculate the Hurst parameter H=0.9, which confirms the property of traffic self-similarity. In the Simulink MATLAB system, we have developed a simulation model shown in Figure 2.

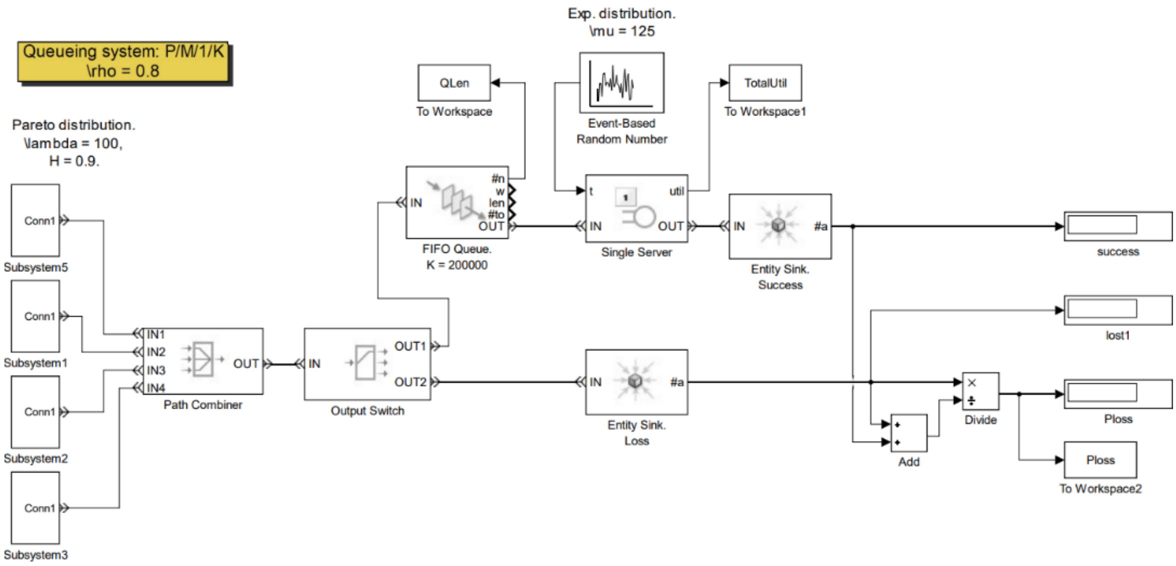

Figure 2. The P/M/1/K type queuing system simulation model

Figure 2 presents a complete model of the P/M/1/K system. The generator generates packet arrivals at time intervals specified by the Pareto distribution. To generate such traffic, the probability distribution function (PDF) of the inter-packet time must have a 'long tail'. The most commonly used distributions with this property are Pareto distributions. Unfortunately, the SimEvents block set does not include any of these distributions for the source content generators. However, we can use any external random number generator to specify the time interval between two events.

Figure 2 shows a basic model with 100 traffic sources. Figure 3 illustrates the subsystem itself: here, 25 sources were combined into one subsystem. Self-similar traffic came from each of the subsystems with the specified Hurst parameter. All subsystems had the same Hurst parameters and load factor. The performance of the serving node was taken equal to 1, thus the intensity of each source equalled to its load factor: $\rho=\lambda/\mu$, where $\mu=1$.

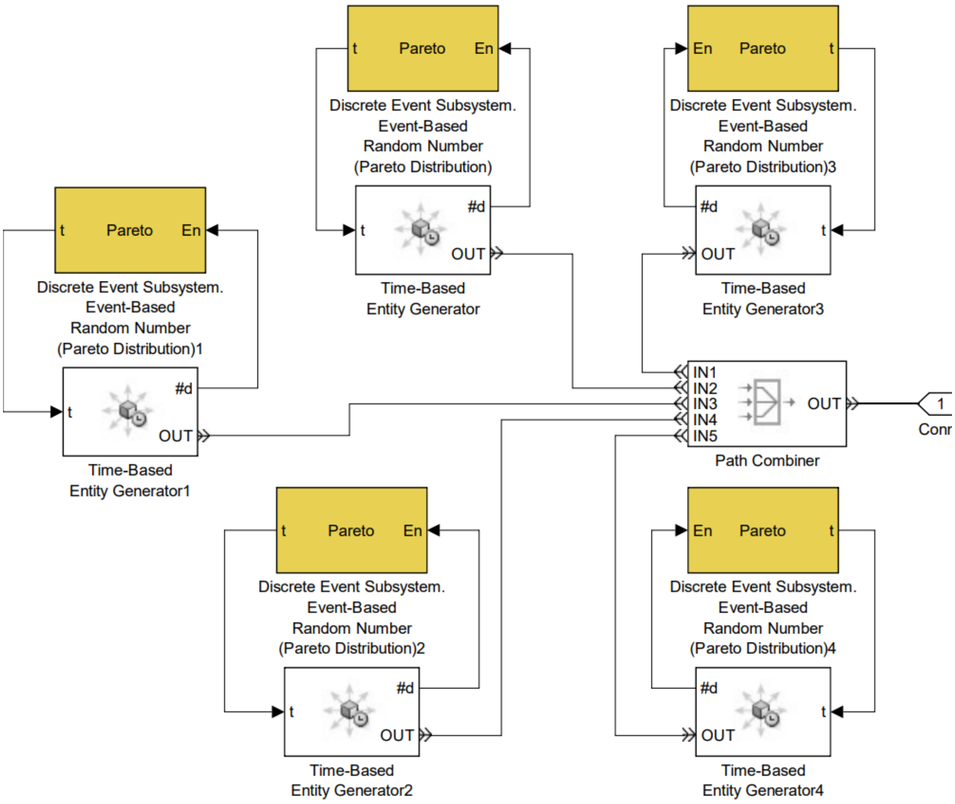

Figure 3. The self-similar traffic modelling subsystem

3. RESULTS AND DISCUSSION

The authors carried out experimental studies with a simulation model of the LoraWAN network server developed in a P/M/1/K type queuing system in the Simulink environment. The input data included such parameters of self-similar traffic as the H; hurst parameter, Lambda; the intensity of incoming packet traffic, BufSize; digital storage buffer size, and simTime; simulation time. As a result of modelling, the following arrays were filled in and saved: i) Qlen, the queue length at each moment of the experiment, ii) TotalUtil, the entire system load factor from 100 sources at each moment of the experiment; iii) Ploss, the value of the packet loss probability at each moment of the experiment.

To achieve acceptable values of the loss probability, it was necessary to set the size of the buffer memory. Therefore, first the model was run with infinite memory BufSize=Inf. In this way, the average and maximum queue lengths were estimated, which, respectively, were the average and maximum buffer sizes. However, for self-similar traffic, the degree of self-similarity H can also vary (in the range from 0.6 to 0.95). It is this parameter that has a huge impact on the irregularity of filling the buffer memory. For example, the set parameters are: i) hurst parameter H=0.9, ii) traffic intensity from one IoT/M2M device Lambda=0.009.

Thus, the intensity of aggregated traffic from 100 devices is expected to be about 0.9. For the service intensity $\mu=1$, we have $\rho=0.9$, which is a fairly large value and in practice means that the server is overloaded.

In such a case, regardless of the degree of self-similarity, a long queue is expected. However, self-similarity causes uneven traffic distribution there are 'bursts' of requests, followed by 'pauses' of calm. With the help of modelling, we could build a graph of changes in the queue length value Qlen (see Figure 4).

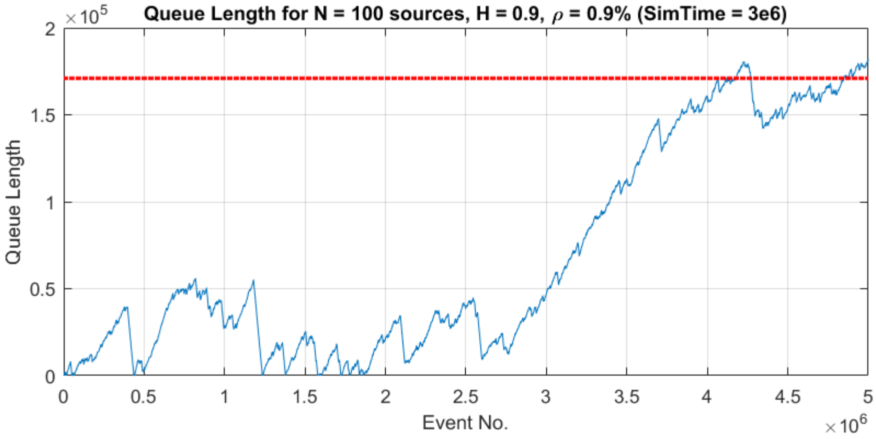

Figure 4. The queue length value change graph

We can see that the queue, in general, was growing. The red line marked 95% of the points constituting the value of 171,000 requests. We obtained these results for a relative simulation time of 3·106 (Simulink time units). However, there was no guarantee that the growth of the queue length would continue with a more long-time simulation. At the same time, we should note that the average queue length mean (QLen) was only 69,000 requests, which was almost three times less than the 95% value we had set. Therefore, when selecting the buffer memory size based only on the average queue length, the forecast would be too optimistic, and the loss probability would be increasing.

Then we used the specified 95% of the queue length as a buffer memory size limit, i.e. BufSize=171,000, and set a significantly longer simulation time simTime=1e8. After starting the simulation (which took a much more significant amount of time), we plotted the following values: i) instantaneous values of the buffer memory size, ii) instantaneous values of the loss probability. The graph clearly shows that further growth of the buffer memory size was impossible upon reaching the limit that we had set (see Figure 5).

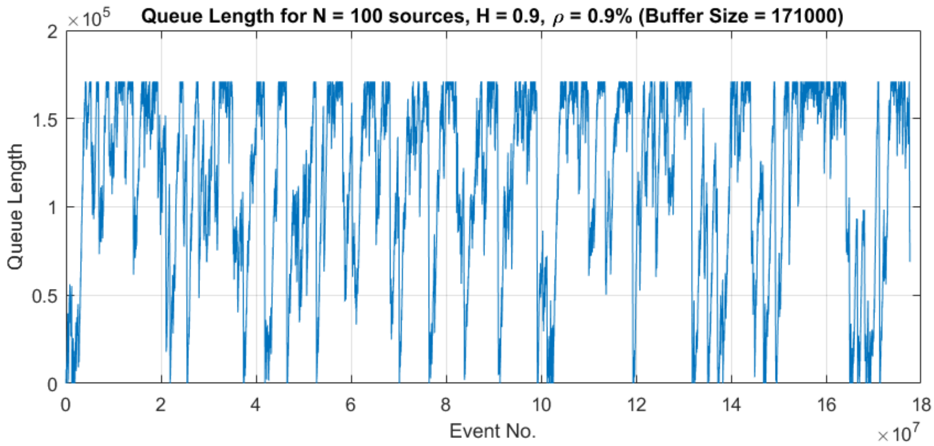

Figure 5. The graph of changes in the queue length instantaneous values

Accordingly, requests that did not fall into the buffer were discarded by the server and lost. The loss probability graph clearly shows that the maximum was slightly higher than the established value of about 5.5% (see Figure 6).

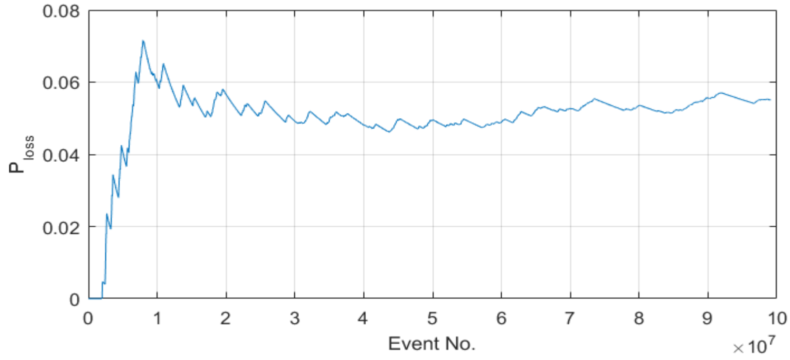

Figure 6. The probability loss change graph

Then we repeated the last experiment but did not limit the maximum size of buffer memory to see whether the growth would be constant and to what values it could continue with the given traffic and system parameters. To do this, we set BufSize=Inf (infinite memory size) and left the time unchanged (simTime=1e8). After modelling, we built an instantaneous queue length change graph (see Figure 7).

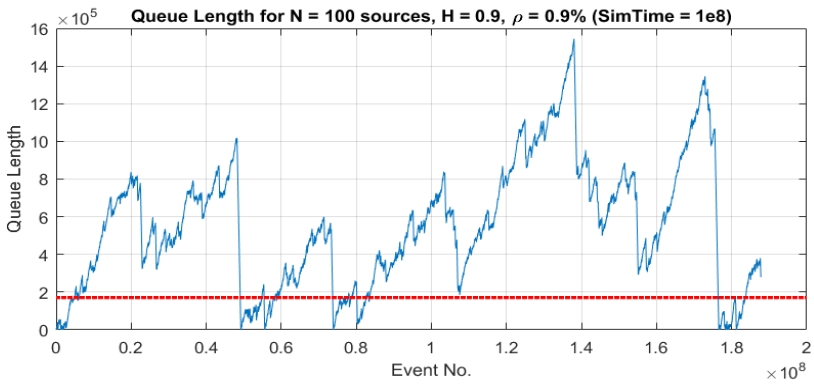

Figure 7. The instantaneous queue length change graph

The red line marks the same 95% level that was obtained for the previous simulation time 3e6. After that, we experimented without limiting the buffer memory size, while the Hurst parameter varied from 0.6 to 0.9, the load from one device varied from 0.005 to 0.009, and the simulation time was 1e6. The simulation result is shown in Figure 8 in the form of a three-dimensional graph. As we can see from the Figure 8, the largest values of the Hurst parameter and the load from one device correspond to the largest size of the buffer memory (we took the average queue length).

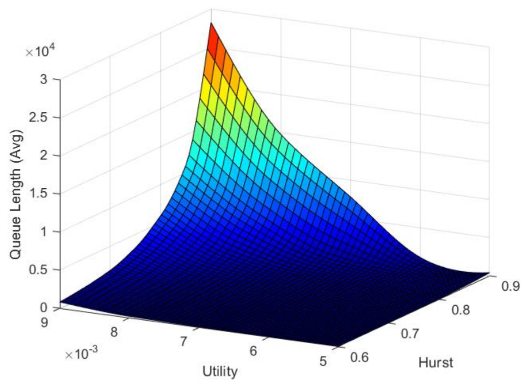

Figure 8. Dependence of the average queue length on the Hurst parameter and load

In the next experiment, we changed the load from one device within the limits of 0.005 to 0.009 and the buffer capacity of 100 to 50,000. The experiment results allowed us to determine the dependence of the loss probability on the load and buffer memory size presented in the form of a three-dimensional graph in Figure 9.

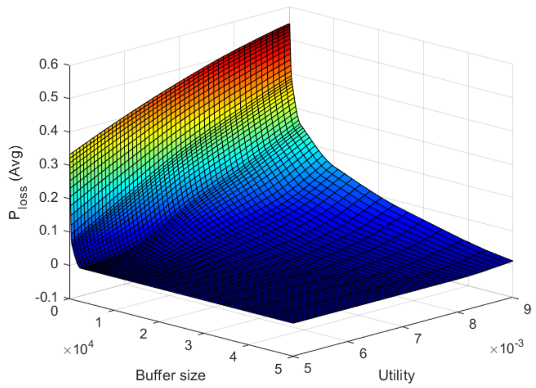

Figure 9. Dependence of the probability of loss on the load and buffer memory size

The Figure 9 shows that the packet loss probability grows with increasing load, starting with Utility=0.007, and decreasing buffer memory size (red). The maximum value of the packet loss probability Ploss=0.5 was achieved at the Utility load=0.009 and the smallest value of the buffer capacity (Buffer size=100). We should note that the Hurst parameter was taken constant, H=0.9, and the simulation time was SimTime=1e6.

4. CONCLUSION

This article demonstrates the possibility of using the Simulink environment with the SimEvents blockset from the MATLAB software package to simulate network traffic in a LoRaWAN network. The authors considered the network traffic arriving at the network server and being self-similar as a modelling object. We developed subsystems in the Simulink environment that generated self-similar traffic with a given Hurst parameter. The network server model was represented in the Simulink as a P/M/1/K type QS. Simulation modelling of the LoRaWAN network server operation made it possible to obtain the following results.

Modelling without limiting the buffer memory size, at which the Hurst parameter varied from 0.6 to 0.9, the load from one device varied from 0.005 to 0.009, and the simulation time was 1e6, showed that the highest values of the Hurst parameter (0.9) and the load from one device (0.009) corresponded to the largest size of the buffer memory (for the average queue length) equal to $3 \cdot 10^4$.

The results of modelling with a change in the load from one device in the range from 0.005 to 0.009 and the buffer capacity from 100 to 50,000, made it possible to define the dependence of the loss probability on the load and the volume of buffer memory. The maximum value of the probability of packet loss (Ploss=0.5) was achieved at the load Utility=0.009 and the smallest value of the buffer capacity (Buffer size=100). In the process, the Hurst parameter was taken constant (H=0.9) and the simulation time SimTime equalled 1e6.

In conclusion, we can note that it was critically important to conduct a sufficiently long simulation to estimate the size of the buffer memory. It can be seen from the presented graphs that the nature of filling the buffer memory is, in essence, a self-similar process since the buffer memory was empty at certain points in time the instantaneous value of the queue length dropped to 0.

REFERENCES

[1] K. K. Patel, and S. M. Patel, "Internet of Things-IOT: Definition, Characteristics, Architecture, Enabling Technologies, Application & Future Challenges," *International Journal of Engineering Science and Computing*, vol. 5, no. 5, pp. 6122-6131, 2016, doi: 10.4010/2016.1482.

[2] M. Al Mojamed, "On the Use of LoRaWAN for Mobile Internet of Things: The Impact of Mobility," *Applied System Innovation*, vol. 5, no. 1, p. 5, 2022, doi: 10.3390/asi5010005.

[3] M. A. M. Afifi, T. M. Ghazal, and D. Kalra, "The Impact of Deploying the Internet of Things and How Will It Change Our Lives," *Solid State Technology*, vol. 64, no. 2, pp. 2049-2055, 2021.

[4] M. A. M. Almuhaya, W. A. Jabbar, N. Sulaiman, and S. Abdulmalek, "A Survey on LoRaWAN Technology: Recent Trends,

Opportunities, Simulation Tools and Future Directions," *Electronics*, vol. 11, no. 1, 2022, doi: 10.3390/electronics11010164

[5] B. S. Chaudhari, M. Zennaro, and S. Borkar, "LPWAN Technologies: Emerging Application Characteristics, Requirements, and Design Considerations," *Future Internet*, vol. 12, no. 3, p. 46, 2020, doi: 10.3390/fi12030046.

[6] R. Marini, K. Mikhaylov, G. Pasolini, and C. Buratti, "LoRaWANSim: A Flexible Simulator for LoRaWAN Networks," *Sensors*, vol. 21, no. 3, p. 695, 2021, doi: 10.3390/s21030695.

[7] L. Casals, C. Gomez, and R. Vidal, "The SF12 Well in LoRaWAN: Problem and End-Device-Based Solutions," *Sensors*, vol. 21 no. 19, p. 6478, 2021, doi: 10.3390/s21196478.

[8] Q. Zhou, K. Zheng, L. Hou, J. Xing and R. Xu, "Design and Implementation of Open LoRa for IoT," *IEEE Access*, vol. 7, pp. 100649-100657, 2019, doi: 10.1109/ACCESS.2019.2930243.

[9] Zh. Tian, "Chaotic characteristic analysis of network traffic time series at different time scales," *Chaos, Solitons & Fractals*, vol. 130, 2020, doi: 10.1016/j.chaos.2019.109412.

[10] M. Laner, N. Nikaein, P. Svoboda, M. Popovic, D. Drajic, and S. Krco, "8-Traffic models for machine-to-machine (M2M) communications: types and applications," *Machine-to-machine (M2M) Communications*, pp. 133-154, 2015, doi: 10.1016/B978-1-78242-102-3.00008-3.

[11] S. Sharkovsky, and E. Grab, "Modelling self-similar traffic in networks," *Proceedings of the 52 International Scientific Conference*, pp. 19-23, 2011.

[12] R. Babiarz, and J. Bedo, "Issues and Applications of Internet Traffic Modelling," *Encyclopedia of Internet Technologies and Applications*, pp. 263-268, 2008, doi: 10.4018/978-1-59140-993-9.ch038.

[13] T. Hoßfeld, F. Metzger and P. E. Heegaard, "Traffic modeling for aggregated periodic IoT data," *2018 21st Conference on Innovation in Clouds, Internet and Networks and Workshops (ICIN)*, 2018, pp. 1-8, doi: 10.1109/ICIN.2018.8401624.

[14] M. López-Benítez, C. Majumdar, and S. N. Merchant, "Aggregated Traffic Models for Real-World Data in the Internet of Things," *IEEE Wireless Communications Letters*, vol. 9, no. 7, pp. 1046-1050, 2020, doi: 10.1109/LWC.2020.2980272.

[15] I. S. Amin, Y. Y. Khaled, K. Hesham, and A. Mohamed, "Traffic modelling of smart city internet of things architecture," *IET Communications*, vol. 14, no. 8, pp. 1275-1284, 2020, doi: 10.1049/iet-com.2019.1252.

[16] H. Nguyen-An, T. Silverston, T. Yamazaki, and T. Miyoshi, "IoT Traffic: Modeling and Measurement Experiments," *IoT*, vol. 2, no. 1, pp. 140-162, 2021, doi: 10.3390/iot20100087

[17] V. Gupta, S. K. Devar, N. H. Kumar, and K. P. Bagadi, "Modelling of IoT traffic and its impact on LoRaWAN," *GLOBECOM 2017 - 2017 IEEE Global Communications Conference*, 2018. doi: 10.1109/GLOCOM.2017.8254512

[18] M. Laner, P. Svoboda, N. Nikaein, and M. Rupp, "Traffic Models for Machine Type Communications," *ISWCS 2013; The Tenth International Symposium on Wireless Communication Systems*, pp. 1-5, 2013.

[19] Y. He, Y. Zhang, and Sh. Yuan, "The network traffic simulation models with packet loss characteristic," *2nd International Conference on Industrial and Information Systems*, pp. 328-331, 2010, doi: 10.1109/INDUSIS.2010.5565717.

[20] R. Marinov, "New Intelligent Technologies—Interactivity and Information Issues," *Advances in Journalism and Communication*, vol. 7, no. 3, pp. 94-108, 2019, doi: 10.4236/ajc.2019.73006.

[21] I. Tuomi, "The Impact of Artificial Intelligence on Learning, Teaching, and Education. Policies for the future," Publications Office of the European Union, Luxembourg, 2018, doi: 10.2760/12297.

[22] V. Ovodenko, "The model development for study of interrelation between the workload fluctuations and the management of network mechanism in MATLAB+SIMULINK SIMEVENTS environment," *Bulletin of the Institute of Civil Protection of Donbass*, vol. 2, no. 6, pp. 44-51, 2016.

[23] Y. Zhang, C. G. Cassandras, W. Li, and P. J. Mosterman, "A discrete-event and hybrid traffic simulation model based on SimEvents for intelligent transportation system analysis in Mcity," *Discrete Event Dynamic Systems*, vol. 29, pp. 265–295, 2019, doi: 10.1007/s10626-019-00286-w

[24] W. E. Leland, M. S. Taqqu, W. Willinger, and D. V. Wilson, "On the self-similar nature of Ethernet traffic," *IEEE/ACM Transactions on Networking*, vol. 2, no.1, pp. 1-15, 1994, doi: 10.1109/90.282603

[25] Y. I. Losev and K. M. Rukkas, "The analysis of probability models of packet loss in the router buffer with respect to the traffic fractality," *Bulletin of the Kharkov National University, The Mathematical Modelling. Information Technology. Automated control systems*, vol. 10, pp. 163-169, 2008.

BIOGRAPHIES OF AUTHORS

Almira D. Mukhamejanova is a Master of Engineering Science. She works as Associate Professor at the Department of Telecommunications and Innovative Technologies of Almaty University of Power Engineering and Telecommunications named after Gumarbek Daukeyev. Her main scientific interest is the analysis of traffic of telecommunication networks. Mrs. Mukhamejanova has scientific and pedagogical experience more than 17 years. She can be contacted at email: Almira_md@mail.ru.

Elans A. Grabs is an Assistant Professor. He works as a Senior Researcher at the Institute of Telecommunications, Department of Transport Telematics and Electronic Systems at Riga Technical University. His main research interests are: computer network traffic, machine learning, deep learning, digital signal processing. His teaching experience is more than 9 years (the last 4 years as an Assistant Professor). His research activities are related to the application of machine learning algorithms for network traffic. He can be contacted at email: elans.grabs@rtu.lv.

Kumyssay K. Tumanbayeva is a PhD. She works as a Professor at the Department of Telecommunications and Innovative Technologies at Almaty University of Power Engineering and Telecommunications named after Gumarbek Daukeyev. Her main scientific interests are teletraffic theory and mathematical modeling of telecommunication systems. Mrs. Tumanbayeva has scientific and pedagogical experience more than 50 years. She can be contacted at email: k.tumanbayeva@aues.kz.

Eleonora M. Lechshinskaya is a PhD. She works as a Professor of the Department of Telecommunications and Innovative Technologies at Almaty University of Power Engineering and Telecommunications named after Gumarbek Daukeyev. Her main scientific interest is analysis of the traffic of telecommunication networks. She can be contacted at email: e.leshinskaya@aues.kz.