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EFFECIENCY ASSESSMENT OF IOT DEVICES CONTROL WITH TELETRAFFIC THEORY

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In connection with the global decarbonization program until 2050, the transition to clean green energy, the growth of the Internet of Things (IoT) number, and energy distribution and control across the load are being raised. The relevance of the work is confirmed that there has been significant growth of the industrial IoT for years, significantly changing the mechanism of industrial enterprise management programs. The object of the research is the IoT device control system for efficient energy distribution using a Queuing Theory, namely the Teletraffic Theory. The novelty of the work is that the Teletraffic Theory, which deals with the mathematical modeling and analysis of traffic patterns in communication networks, can be explicitly applied to IoT device control. The authors developed a mathematical model of IoT control using the Teletraffic Theory and, based on it, created a simulation model of a network router and a transition schedule in the "GPSS World" software. The obtained results of the work were 16 states and a balance equation in which all probabilities were found. Probabilities were used to calculate nodes and network characteristics. 100,000 requests from IoT devices coming to two routers were simulated. The study results showed that the first node's load is 63.2 % with an average processing time per transaction of M=1.436 sec., and the load of the second node is 32 % with M=0.914 sec. The created network router model worked with minimal losses during transactions. Accordingly, the IoT control system developed in this study has shown its effectiveness and is applicable for practical use in controlling IoT devices in Smart Grid. It is planned to research the possibility of using Teletraffic Theory in energy distribution control systems in Smart Grids

Keywords: teletraffic theory, queuing theory, IoT devices, network router simulation model, GPSS world

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1. Introduction

The Internet of Things (IoT) has grown exponentially in the past several years. IoT devices are increasingly pervasive in a variety of areas, including smart homes, healthcare, transportation, manufacturing and more. Smart meters, pressure, and temperature sensors etc., for industry, sensors for medical applications, monitoring of hard-to-reach areas and sensors for smart home and smart city systems [1] – all this is just a part of the possible applications of the Internet of Things [2].

In recent years, rapid advancements in IoT technology have made it possible to connect several smart devices/objects to communicate and exchange data via the internet without human intervention [3]. Sensors, actuators, and transducers will be critical in providing real-time energy monitoring services in the next generation of power grids. IoT (Internet of Things) has evolved into a technology that enables creative solutions to difficulties in power grid systems [4]. IoT-enabled sensors are widely employed in electrical grid schemes to communicate valuable data over the internet and web apps, allowing for better grid management [5]. The smart grid is the leading technology for the next generation of power networks with several advantages compared to traditional power networks [6]. It explicitly allows smart power distribution to neighborhoods based on dynamic pricing and demands. Moreover, it allows for a bi-directional flow of power in which consumers can also contribute to the power grid and get benefits. The sensors and smart meters installed at consumer premises [7] can provide feedback about increasing power demand, and the energy provider can reconfigure the distribution network and employ other techniques, such as price increases, to discourage electricity usage [8].

With the proliferation of IoT devices, effective control mechanisms are essential to ensure their proper operation, safety, and optimized performance. In other side efficient control mechanisms are essential for optimizing the performance and efficiency of IoT systems. Research in this area focuses on traffic management, resource allocation, load balancing, and QoS provisioning to enhance network responsiveness, reduce latency, minimize energy consumption, and ensure reliable communication among IoT devices. The scalability of IoT deployments is a critical concern. As the number of connected devices continues to grow, efficient control mechanisms are needed to manage large-scale IoT networks. It is necessary to conduct research in IoT device control explores techniques for scalable device management, fault detection, remote monitoring, and minimizing management overhead. Efficient control mechanisms are essential for optimizing the performance and efficiency of IoT systems especially in industrial Internet of Things systems. In this area it is necessary to focuses on traffic management, resource allocation, load balancing, and QoS provisioning to enhance network responsiveness, reduce latency, and ensure reliable communication among IoT devices.

Large numbers of IoT Devices (IoTDs) sending packets to IoT Gateways are handled by IoT networks. It might result in a buffer overflow, significant end-to-end delays, and missed deadlines due to the IoT Massive Access Issue. Congestion on IoT gateways can result in packet loss and loss of information or data. One of the main challenges in this regard is utilizing modern Information and Communication Technologies (ICT) to improve reliability, observability, and power efficiency while meeting diverse power grid requirements [8]. One upcoming concept is deploying conventional telegraphic tools to control electrical loads effectively. Since each load controller acts independently of the others, focusing on one load controller is possible. Systems in which, on the one hand, mass requests (requirements) arise for the performance of any services, and on the other hand, these requests are satisfied are called Queueing Theory (Teletraffic Theory). The queuing system includes the following elements: a source of requirements, an incoming flow of requirements, a queue, a service device, and an outgoing flow of requirements. Queueing theory receives service requests randomly, while the received requests are serviced using the service channels available to the system [9]. Based on this work, it is possible to conclude that it is possible to decrease losses and increase the efficiency of controlling Internet of Things devices by applying the Teletraffic Theory.

The scalability of IoT deployments is a critical concern. As the number of connected devices grows, efficient control mechanisms are needed to manage large-scale IoT networks. It is necessary to conduct research in IoT device control to explore techniques for scalable device management, fault detection, and remote monitoring.

The immediate relevance of the work. The study on controlling IoT devices using the Teletraffic Theory presented in this paper is of great importance in global decarbonization programs, the transition to clean energy, and the exponential growth of the Internet of Things (IoT). The demand for advanced control systems is growing with the increase in the scalability of IoT devices and the need for efficient power distribution and control. The novelty of the work is that the Teletraffic Theory, which deals with the mathematical modeling and analysis of traffic patterns in communication networks, can be explicitly applied to IoT device control. This study satisfies this requirement by proposing a new approach that combines the Queuing Theory, particularly the Teletraffic Theory, with the control of IoT devices. Having developed a mathematical model and simulation using the GPSS World software, the authors demonstrate the effectiveness of the proposed method. The results demonstrate the system's ability to handle many IoT device requests while maintaining minimal losses and optimal network performance. Applying the Teletraffic Theory in energy distribution management systems within Smart Grids opens up new opportunities for efficient control and optimization. The emphasis on Teletraffic Theory as a cost-effective alternative to sophisticated machine learning contributes to the novelty of this study, making it a valuable addition to the existing literature on IoT device control.

Based on the listed problems, research on the Internet of Things control is highly relevant and necessary.

2. Literature review and problem statement

The authors of paper [10] considered the Waiting Time in queuing systems with variable arrival frequency in the presence of long-term correlations and periodic trends. The authors focused on a simplified model in which the contribution of periodic and stochastic components can be analyzed separately. This resulted in a queue length demonstrating periodic and stochastic demand, respectively, with additive summation of their effects.

The authors of paper [11] created a model to reduce the time of walking around the Kaaba, control congestion and the high density of people, and reduce the possibility of transmission of viral diseases. In addition to changes in the crowd movement pattern, smart planning, and architectural changes, the study proposes using Internet of Things (IoT) and radio frequency identification (RFID) technologies to monitor crowds at exit/entry points, which will help in capacity assessment and planning. IoT management is carried out using the Queuing Theory. The queue length Lq represents the expected number of pilgrims in the queue. The length of the spiral loop and the number of pilgrims making Istilam are defined as Ls. The expected Waiting Time in the system is Ws. The expected Waiting Time in the queue is defined as Wq. The expected number of servers is denoted as c. The queue is modeled using (M/M/1):(FCFS). The pilgrim's arrival rate, λ, and service rate μ are a Markovian (M) distribution. The model results showed high efficiency and a significant reduction in maintenance time, but the implementation of the results of the work requires significant architectural interventions and a preliminary business case.

In the study [12], the authors proposed a queueing model to characterize the task response time in a fog-enabled IoT with a total service time of M/G/1 at TD and M/G/c at the fog. The model culminates in three equations for task response time, revealing insights that can be used to improve offload performance. The model ended with three equations that characterize the response time: one for the expected local response time, one for the expected remote response time, and one for the expected overall response time. The developed theoretical queuing model for a scheme in which tasks are generated in TD as a Poisson process has a disadvantage. Each task requires exponential processing time. If this time exceeds the user-defined threshold, the task is unloaded; otherwise, it is saved.

To mitigate the effect of congestion on IoT gateways, the authors of paper [13] proposed predictive network planning based on complex algorithms [14] that analyze data flows using computationally expensive machine learning methods. The studies were based on real data from paper [15] from many thousand IoT devices. Methods have also been proposed that use such predictions to reduce traffic selectively. QTP does not drop any traffic; it just delays packets in a certain way, so packets entering IoTG result in much shorter packet queues. The authors analyze QDTP using conventional queuing techniques without any restrictive assumptions about the arrival process and service time. Poisson packet generation times were taken to obtain simple numerical expressions for the average effective QDTP delay generated by packets and an upper bound for IoTG with QDTP. For many systems, using computationally expensive machine learning methods can become an obstacle to implementing this solution.

The article [16] deals with vehicles connected as Internet things using Smart Connection. In this study, the authors propose a new algorithm for predicting the rotation of vehicles – IoT at intersections. The method is based on the Markov chain and can predict vehicle trajectories using GPS location sequences. The proposed model can dynamically adjust the weights of the influence of each intersection on the current trajectories based on data, unlike fixed weights in traditional models. The prediction accuracy of the traditional method was 49.61 %, while the proposed method achieved a prediction accuracy of 60.66 % for 100,000 sets of trajectory data, which is almost 11 % more; it is possible to improve the accuracy of the proposed method to 79.31 % as the GPS sampling frequency increases. The simulation results show that the algorithm based on the improved Markov model provides accurate prediction and that the prediction effect improves with the expansion of the trajectory data set and an increase in the GPS sampling rate. This work is of high scientific value, but the application of this algorithm for the industrial Internet of Things is complicated by the narrow focus of this solution in determining the location.

In the paper [17], the authors studied AoI-based optimal network resource management and the problem of computational offloading in a dynamic industrial IoT (IIoT) scenario with multiple IoT devices and edge servers. Based on an extensive analysis of a real IoT dataset, Markov queuing models were created to account for the dynamics of IoT devices and edge servers, and their corresponding analysis was provided. With the results of the quantitative analysis, the authors formulated a dynamic Markov decision problem to minimize long-term energy consumption while satisfying the limitations of the application area for real-time data processing. However, for real-time system operation, the authors propose using deep reinforcement learning (DRL) methods to adapt to large-scale dynamic IIoT environments. An intelligent energy management and calculation system has been developed as a loading algorithm (ECCO). Using deep learning methods requires a significant increase in computing power, which is not always possible.

In industry, the energy sector and Smart Grid, it makes sense to develop a cheap and efficient Internet of Things management system because many sensors with a massive amount of data are used in these industries. Expensive methods of solving forecasting problems, such as machine learning, are not always necessary, but it is important to implement high-quality IoT management, the ability to quickly scale, and reduce data packet loss.

The authors propose to exclude the introduction of deep learning methods, limiting ourselves only to the Queuing Theory, namely the Teletraffic Theory, which has already shown its effectiveness in the work of authors with queues [18], including in Smart Grid [19].

In summary, researchers have made significant efforts to develop models and methodologies for controlling IoT devices, particularly in industrial IoT applications. The studies discussed in the text highlight the use of Queuing Theory to address various challenges, such as congestion management, response time improvement, crowd monitoring, and energy consumption optimization. While some studies propose complex algorithms and machine learning methods, the value and effectiveness of Queuing Theory, specifically Teletraffic Theory, is recognized as a cost-effective alternative for IoT control systems. The focus on implementing efficient and scalable IoT control systems without relying heavily on expensive techniques like machine learning is crucial in industries that require reliable control of IoT devices and data packet loss reduction.

3. The aim and objectives of the study

The aim of the study is to propose and investigate the application of Teletraffic Theory in control systems of IoT devices to analyze the performance, losses, scalability, and efficiency of IoT device networks.

To achieve this aim, the following objectives are accomplished:

– to develop a mathematical model based on Teletraffic Theory tailored explicitly for IoT environments and calculate the output parameters;

– to create a simulation model of two network routers and a transition schedule in the "GPSS World" software based on the created mathematical model;

– to determine the indicators of "Router 0" for analyzing the effectiveness of the developed simulation model;

– to determine the indicators of "Router 1" for analyzing the effectiveness of the developed simulation model;

– to determine a network performance with a large transaction flow from IoT devices controlled by Teletraffic Theory.

4. Materials and Methods

4. 1. Including parameters

The research object is the Internet of Things (IoT) devices, explicitly focusing on controlling and managing these devices in various applications, such as industrial IoT. The research subject is developing and evaluating models and methodologies for effectively controlling and optimizing IoT devices using Teletraffic Theory.

The authors developed a mathematical model of an IoT control system using the Teletraffic Theory [20]. According to D. J. Kendall's classification, denoted as M/M/v [21], the classical Erlang model [22] was used to create the model for networks adapting to the Internet of Things networks with the setting of incoming parameters. Based on the incoming parameters and the created mathematical model, a network simulation model was developed for the Internet of Things control system in "GPSS World" software. The study results were tested, and probabilities and mean square deviations were revealed.

Input parameters include two routers connected to two smart meters through switches. Two smart meters were connected to 100,000 IoT devices, shown in Fig. 1.

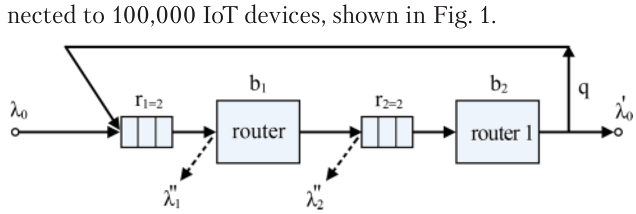

Fig. 1. Single-channel queuing network

For such many active IoT, two external channels connected to gigabit ports with a traffic volume of 2000 megabits are required – an average of 0.5 megabits per IoT. The "Router" processes two signals in one millisecond, and "Router 1" processes four in one millisecond. All nodes are single-channel network queueing theory. The number of nodes in the network: n=2. All nodes are single channels: $K1=K2=1$. Queues of network nodes are limited.

A marked-up transition graph of a random process is shown in Fig. 2.

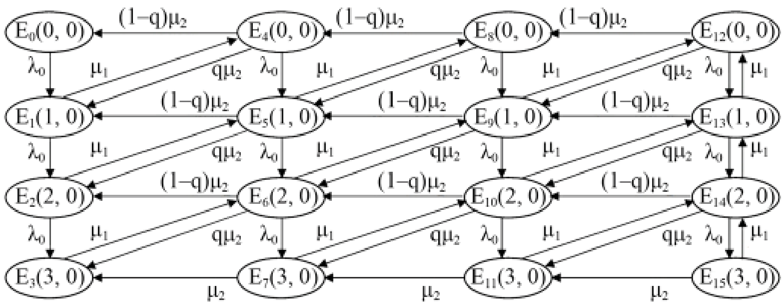

Fig. 2. Marked-up transition graph of a random process

Fig. 2 shows a marked-up transition graph of a random process in 16 states. According to this marked-up transition graph it is possible to create the mathematical model of the IoT control system.

4. 2. The Model Description

E0: (0,0) – there are no requests.

E1: (1,0) – node 1 contains one request (in the device).

E2: (2,0) – node 1 contains two requests.

E3: (3,0) – node 1 contains three requests.

E4: (0,1) – node 2 contains one request.

E5: (1,1) – node 1 contains one request, and node 2 contains one.

E6: (2,1) – node 1 contains two requests, and node 2 contains one.

E7: (3,1) – node 1 contains three requests; node 2 contains one.

E8: (0,2) – node 2 contains two requests.

E9: (1,2) – node 1 contains one request, and node 2 contains two.

E10: (2,2) – node 1 contains two requests, and node 2 contains two.

E11: (3,2) – node 1 contains three requests, and node 2 contains two.

E12: (0,3) – node 2 contains three requests.

E13: (1,3) – node 1 contains one request, and node 2 contains three.

E14: (2,3) – node 1 contains two requests, and node 2 contains three.

E15: (3,3) – node 1 contains three requests, and node 2 contains three.

To create a mathematical model, drawing up a balance equation is necessary.

The Probability of the i-th state of the model $p_i(t)$ is the Probability that at time t, the system will be in state S_i. For any moment, the sum of all state probabilities is (1):

$$\sum_{i=1}^{n} p_i(t) = 1. \quad (1)$$

The rule for compiling the Kolmogorov system of equations [23]: in each equation of the system, on its left side is the final Probability of a given state pi multiplied by the total intensity of all flows leading from this state, and on its right side is the sum of the intensities multiplication of all flows included in i-th state, on the probabilities of those states from which these flows come.

At $t\to\infty$, the probabilities $p_1(t)$, and $p_2(t)$, regardless of the system's initial state, tend to the limits in which they are called the final probabilities of the states:

$$\lim_{x\to\infty} p_i(t) = p_i, i = \overline{1,n}, \quad (2)$$

where n is the final number of system states.

The Probability of the system being in each state can be written as:

$$\frac{P_n(t)}{dt} = P_{n-1} + (1-(\lambda+\mu))\times P_n + \mu\times P_{n+1} - \\ -P_n\times(\mu+1-(\lambda+\mu)+\lambda). \quad (3)$$

Using this rule, the authors of this article wrote a system of equations for each state Fig. 2 (4)–(19):

Balance equation:

$$p_0\lambda_0 = (1-q)\mu_2 p_6. \quad (4)$$

$$(\lambda_0+\mu_1)p_1 = q\mu_2 p_4 + (1-q)\mu_2 p_5 + p_0\lambda_0. \quad (5)$$

$$p_2(\lambda_0+\mu_1) = q\mu_2 p_5 + p_1\lambda_0 + (1-q)\mu_2 p_6. \quad (6)$$

$$p_3(\mu_1) = q\mu_2 p_6 + p_2\lambda_0 + \mu_2 p_7. \quad (7)$$

$$((1-q)\mu_2 + \lambda_0 + q\mu_2)p_4 = \mu_1 p_1 + (1-q)\mu_2 p_8. \quad (8)$$

$$((1-q)\mu_2 + \lambda_0 + q\mu_2 + \mu_1)p_5 = \\ = p_4\lambda_0 + q\mu_2 p_8 + \mu_1 p_2 + (1-q)\mu_2 p_9. \quad (9)$$

$$((1-q)\mu_2 + \lambda_0 + q\mu_2 + \mu_1)p_6 = \\ = p_5\lambda_0 + q\mu_2 p_9 + \mu_1 p_3 + (1-q)\mu_2 p_{10}. \quad (10)$$

$$(\mu_2+\mu_1)p_7 = p_6\lambda_0 + q\mu_2 p_{10} + \mu_2 p_{11}. \quad (11)$$

$$((1-q)\mu_2 + \lambda_0 + q\mu_2)p_8 = (1-q)\mu_2 p_{12} + \mu_1 p_5. \quad (12)$$

$$((1-q)\mu_2 + \lambda_0 + q\mu_2 + \mu_1)p_9 = \\ = p_8\lambda_0 + q\mu_2 p_{12} + \mu_1 p_6 + (1-q)\mu_2 p_{13}. \quad (13)$$

$$((1-q)\mu_2 + \lambda_0 + q\mu_2 + \mu_1)p_{10} = \\ = p_9\lambda_0 + q\mu_2 p_{13} + \mu_1 p_7 + (1-q)\mu_2 p_{14}. \quad (14)$$

$$(\mu_2+\mu_1)p_{11} = p_{10}\lambda_0 + q\mu_2 p_{14} + \mu_2 p_{15}. \quad (15)$$

$$((1-q)\mu_2 + \lambda_0 + q\mu_2)p_{12} = \mu_1 p_{13} + \mu_1 p_9. \quad (16)$$

$$((1-q)\mu_2 + \lambda_0 + q\mu_2 + \mu_1)p_{13} = \mu_1 p_{14} + \mu_1 p_{10} + p_{12}\lambda_0. \quad (17)$$

$$((1-q)\mu_2 + \lambda_0 + q\mu_2 + \mu_1)p_{14} = \mu_1 p_{15} + \mu_1 p_{11} + p_{13}\lambda_0. \quad (18)$$

$$(\mu_2+\mu_1)p_{15} = p_{14}\lambda_0. \quad (19)$$

Knowing the balance equations, the authors include the initial data. Substituting values:

$$0.5p_0 = (1-0.5)\times 4p_6. \quad (20)$$

$$2.5p_0 = 2p_4 + (1-0.5)\times 4p_5 + 0.5p_0. \quad (21)$$

$$2.5p_0 = 4p_5 + (1-0.5)\times 4p_6 + 0.5p_1. \quad (22)$$

$$2p_3 = 0.5p_2 + 4p_6 + 4p_7. \quad (23)$$

$$6.5p_4 = 2p_1 + (1-0.5)\times 4p_8. \quad (24)$$

$$6.5p_5 = 0.5p_4 + 2p_8 + 2p_2 + (1-0.5)\times 4p_9. \quad (25)$$

$$6.5p_6 = 0.5p_5 + 2p_9 + 2p_3 + (1-0.5)\times 4p_{10}. \quad (26)$$

$$6p_7 = 0.5p_6 + 2p_{10} + 4p_{11}. \quad (27)$$

$$4.5p_8 = 2p_5 + (1-0.5)\times 4p_{12}. \quad (28)$$

$$6.5p_9 = 0.5p_8 + 2p_{12} + 2p_6 + (1-0.5)\times 4p_{13}. \quad (29)$$

$$6.5p_{10} = 0.5p_9 + 2.5p_{13} + 2p_7 + (1-0.5)\times 4p_{14}. \quad (30)$$

$$6p_{11} = 0.5p_{10} + 2p_{14} + 4p_{15}. \quad (31)$$

$$4.5p_{12} = 2p_{13} + 2p_9. \quad (32)$$

$$6.5p_{13} = 2p_{14} + 2p_{10} + 0.5p_{12}. \quad (33)$$

$$6.5p_{14} = 2p_{15} + 2p_{11} + 0.5p_{13}. \quad (34)$$

$$6p_{15} = 0.5p_{14}. \quad (35)$$

Find p_{15} from all equations is shown in Table 1.

Table 1

Equations to find p_{15}

p_i	Data
p_0	$52049.68p_{15}$
p_1	$59074.072p_{15}$
p_2	$17119.0776p_{15}$
p_3	$32479.5994p_{15}$
p_4	$21769.7852p_{15}$
p_5	$24589.8925p_{15}$
p_6	$13012.42p_{15}$
p_7	$1087.495p_{15}$
p_8	$11677.73p_{15}$
p_9	$3663.3p_{15}$
p_{10}	$0.04p_{15}$
p_{11}	$4.67p_{15}$
p_{12}	$1685p_{15}$
p_{13}	$127.9p_{15}$
p_{14}	$12p_{15}$

The authors know that all probabilities are (1):

$$\begin{aligned}&21769.7852p_{15} + 59074.072p_{15} + 17119.0776p_{15} +\\&+52049.68p_{15} + 32479.5994p_{15} +\\&+24589.8925p_{15} + 11677.73p_{15} + 13012.42p_{15} +\\&+1087.495p_{15} + 3663.3p_{15} + 127.9p_{15} +\\&+4.67p_{15} + 0.04p_{15} + 1685p_{15} + 12p_{15} = 1.\end{aligned} \quad (36)$$

Formula (36) is the balance equation for this system of 16 states calculated according to formula (1). Based on the resulting balance equation (36), it was calculated the probability p_{15}=0.0000042.

4. 3. Calculation of the characteristics

Utilization of nodes:

$$\begin{aligned}\rho_1 &= p_1 + p_2 + p_3 + p_5 + p_6 +\\&+p_7 + p_9 + p_{10} + p_{11} + p_{13} + p_{14} + p_{15}.\end{aligned} \quad (37)$$

$$\begin{aligned}\rho_2 &= p_4 + p_5 + p_6 + p_7 + p_8 +\\&+p_9 + p_{10} + p_{11} + p_{12} + p_{13} + p_{14} + p_{15}.\end{aligned} \quad (38)$$

Downtime ratio of nodes:

$$\eta_1 = 1-\rho_1. \quad (39)$$

$$\eta_2 = 1-\rho_2. \quad (40)$$

The average number of requests in the queue:

$$l_1 = p_2 + p_6 + p_{10} + p_{14} + 2(p_3 + p_7 + p_{11} + p_{15}). \quad (41)$$

$$l_2 = p_8 + p_9 + p_{10} + p_{11} + 2(p_{12} + p_{13} + p_{14} + p_{15}). \quad (42)$$

An average number of requests in nodes:

$$m_1 = l_1 + \rho_1. \quad (43)$$

$$m_2 = l_2 + \rho_2. \quad (44)$$

The efficiency of nodes:

$$\lambda_1^{'} = \rho_1\mu_1. \quad (45)$$

$$\lambda_2^{''} = \rho_2\mu_2. \quad (46)$$

Probability of losing requests in nodes:

$$\pi_1 = 1-\frac{\lambda_1^{'}}{\lambda_0 + q\lambda_2^{''}}. \quad (47)$$

$$\pi_2 = 1-\frac{\lambda_2^{''}}{\lambda_1^{'}}. \quad (48)$$

The average Waiting Time in nodes:

$$\omega_1 = \frac{l_1}{\lambda_1^{'}}. \quad (49)$$

$$\omega_2 = \frac{l_2}{\lambda_2^{''}}. \quad (50)$$

The average time spent by requests in nodes:

$$u_1 = \frac{m_1}{\lambda_1^{'}}. \quad (51)$$

$$u_2 = \frac{m_2}{\lambda_2^{''}}. \quad (52)$$

Network characteristics:

– total utilization of nodes:

$$\rho = \rho_1 + \rho_2; \quad (53)$$

– the total number of requests in queues:

$$L = l_1 + l_2; \quad (54)$$

– the total number of requests in nodes:

$$M = m_1 + m_2; \quad (55)$$

– the efficiency of network queuing:

$$\lambda_0^{'} = (1-q) \times \lambda_2^{''}; \quad (56)$$

– probability of losing requests in the network:

$$\pi = 1 - \frac{\lambda_0^{'}}{\lambda_0}. \quad (57)$$

Based on (1)–(57) it is possible to calculate all Probabilities and create the simulation model on "GPSS World" software.

4. 4. The input parameters to the simulation model of the IoT control system

This study developed a system model in the GPSS World program. Adding additional conditions – the second-level provider – was necessary to create the model. Traffic comes to the router every 3.5 to 9.1 milliseconds – the duration of servicing requests in node 1, which is a single-channel network, equal to 4±3 [24]. The duration of servicing requests in node 2, a single-channel network, is 2±2. There are two routers: "Router" and "Router 1".

GENERATE 6.30, 2.80; the time interval between transactions is a random value evenly distributed in the interval (6.30±2.80), i. e., from 3.5 to 9.1.

TERMINATE 1; the transaction received in this block is removed.

From the model and the completion counter of the simulation process, the initial value set by the START command is reduced by 1.

ADVANCE 4,3; transaction delay time – a random value evenly distributed from 1 to 7 (4±3).

5. Results of research. Characteristics of the developed mathematical and simulation models of the IoT control system based on Teletraffic Theory

5. 1. Calculated probabilities and characteristics of nodes of the IoT control system in the mathematical model based on Teletraffic Theory

All Probabilities were calculated by the mathematical model of the IoT control system based on Teletraffic Theory with formulas (1)–(57) are shown in Table 2.

The Calculated Characteristics of nodes are shown in Table 3.

Table 3 shows calculated characteristics of sixteen states with data of Utilization of node1 and 2, Downtime ratio of node1 and 2, The average number of requests in the Queue No. 1 and No. 2, The efficiency of node No. 1 and No. 2, Probability of losing requests in node No. 1 and No. 2, The average Waiting Time in node No. 1, The average time spent by requests in node No. 1, Total utilization of nodes, Total number of requests in queues, The efficiency of network queuing and The Relative error.

Table 2

Calculated Probabilities p_i from 0 to 15

p_i	Data
p_0	0.21860866
p_1	0.24811111
p_2	0.07190013
p_3	0.13641432
p_4	0.0914331
p_5	0.10327755
p_6	0.05465216
p_7	0.00456748
p_8	0.04904647
p_9	0.01538607
p_{10}	0.00000017
p_{11}	0.00001961
p_{12}	0.007077
p_{13}	0.00053718
p_{14}	0.00005035
p_{15}	0.0000042

Table 3

Calculated Characteristics of nodes

Characteristic	Designations	Value
Utilization of node 1	ρ_1	0.663492033
Utilization of node 2	ρ_2	0.32605134
Downtime ratio of node 1	η_1	0.3650967
Downtime ratio of node 2	η_2	0.67394866
The average number of requests in the Queue No. 1	l_1	0.40861556
The average number of requests in the Queue No. 2	l_2	0.07978978
The average number of requests in node No. 1	m_1	1.04353589
The average number of requests in node No. 2	m_2	0.40584112
The efficiency of node No. 1	$\lambda_1^{'}$	1.26984066
The efficiency of node No. 2	$\lambda_2^{'}$	0.65210268
Probability of losing requests in node No. 1	π_1	0.46643214
Probability of losing requests in node No. 2	π_2	0.48646889
The average Waiting Time in node No. 1	ω_1	0.32178491
The average Waiting Time in node No. 2	ω_2	0.12235769
The average time spent by requests in node No. 1	u_1	0.82178491
The average time spent by requests in node No. 2	u_2	0.62235769
Network characteristics		
Total Utilization of nodes	ρ	0.96097167
Total number of requests in queues	L	0.48840534
Total number of requests in nodes	M	1.44937701
The efficiency of network queuing	$\lambda_0^{'}$	0.32605134
Probability of losing requests in the network	π	0.46031868
The relative error	δ	0,11 %

5. 2. The simulation model of IoT control system of two network routers and a transition schedule in the "GPSS World" software based on the created mathematical model

The simulation model was created based on mathematical model of IoT control system. The service of 100,000 transactions took 629500.263 minutes, and the model consists of 16 blocks and two service channels.

The number of generated transactions is precisely 100,000. In the first node, the average processing time of one transect is 3.990. The Probability of Utilization is equal to 0.634 or 63.4 %. In the second node, the average processing time per transaction is 2.003. The Probability of Utilization is 0.318 or 32 %.

The number of transactions passed through the simulation queue with zero Waiting Time-77458 and 93052.

The Network router model viewport is shown in Fig. 3.

Fig. 3 Shows the Network router model of the IoT control system with queue #1 for "Router 0" and queue #2 for "Router 1".

5. 3. Determination of the "Router 0" indicators for analyzing the effectiveness of the developed simulation model

The Plots Window – a view of up to plotted PLUS Expressions. The result is a graph of the traffic queue to the "Router"; as seen from the graph (Fig. 4), the queue is more than one traffic for an extended time, which is denied in a single channel.

The "Router" histogram with Queue #1 from Fig. 4 shows that most IoT devices are processed in the range 0–2, with an average Mean=0.408 (sec) and *S.D.*=0.970 (sec).

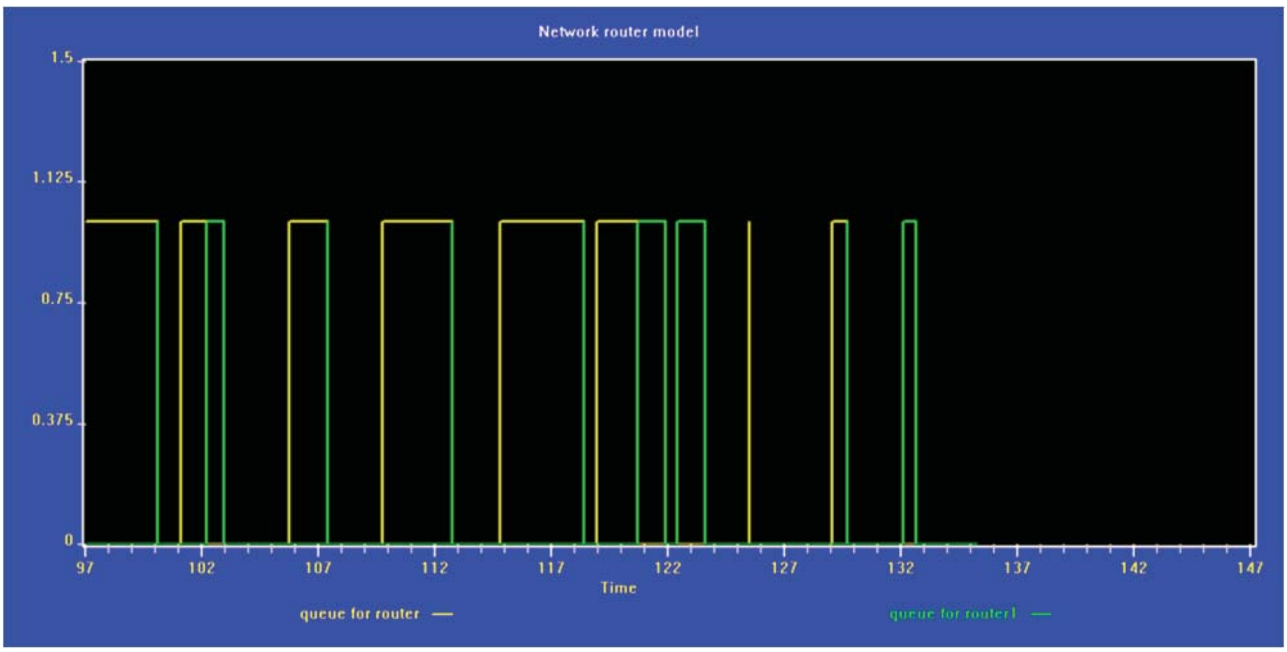

Fig. 3. Network router model of the system

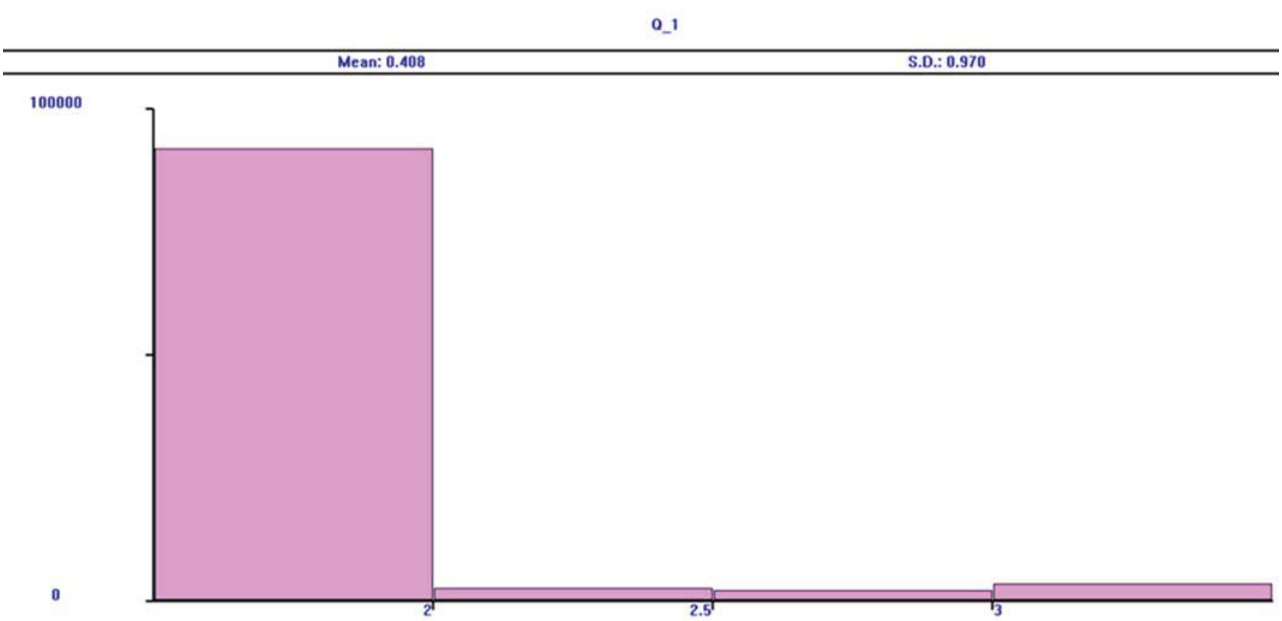

Fig. 4. Histogram of the "Router", Queue 1

5. 4. Determination of the "Router 1" indicators for analyzing the effectiveness of the developed simulation model

The histogram shows in Fig. 5 that the router copes with the signal flow, and no queues are formed.

The "Router 1" histogram with Queue #2 from Fig. 5 also shows that most IoT devices are processed in the first 0–0.5 bin, with Mean=0.069 (sec) and standard deviation *S.D.*=0.310 (sec).

5. 5. Determination of the network performance with a large transaction flow from IoT devices controlled by Teletraffic Theory

Fig. 6 shows a histogram of the Waiting Time. The histogram has a normal distribution with Mean=6.473 (sec) and standard deviation *S.D.*=2.275 (sec).

The number of transactions passed through the queue during the simulation with zero Waiting Time-77458, 93052.

In the first node, the Average Processing Time of one transect is 3.990. The Probability of Utilization is equal to 0.634 or 63.4 %. In the second node, the Average Processing Time per transaction is 2.003. The Probability of Utilization is 0.318 or 32 %.

6. Discussion of mathematical and simulation models of efficiency assessment of IoT devices control system with Teletraffic Theory

The results of this work can be explained by the successful application of Teletraffic Theory principles to IoT device control systems. Using the Teletraffic Theory, the authors analyzed and simulated the structure of traffic in the Internet of Things networks, optimizing the resources allocation.

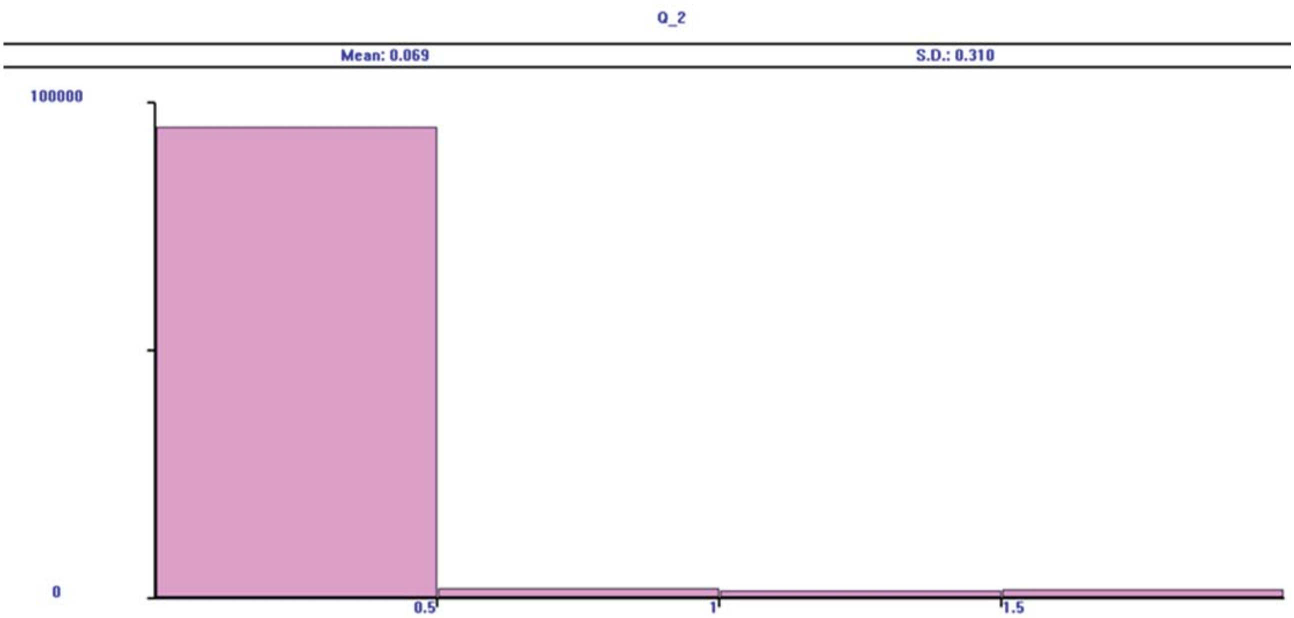

Fig. 5. Histogram of the "Router1 ", Queue 2

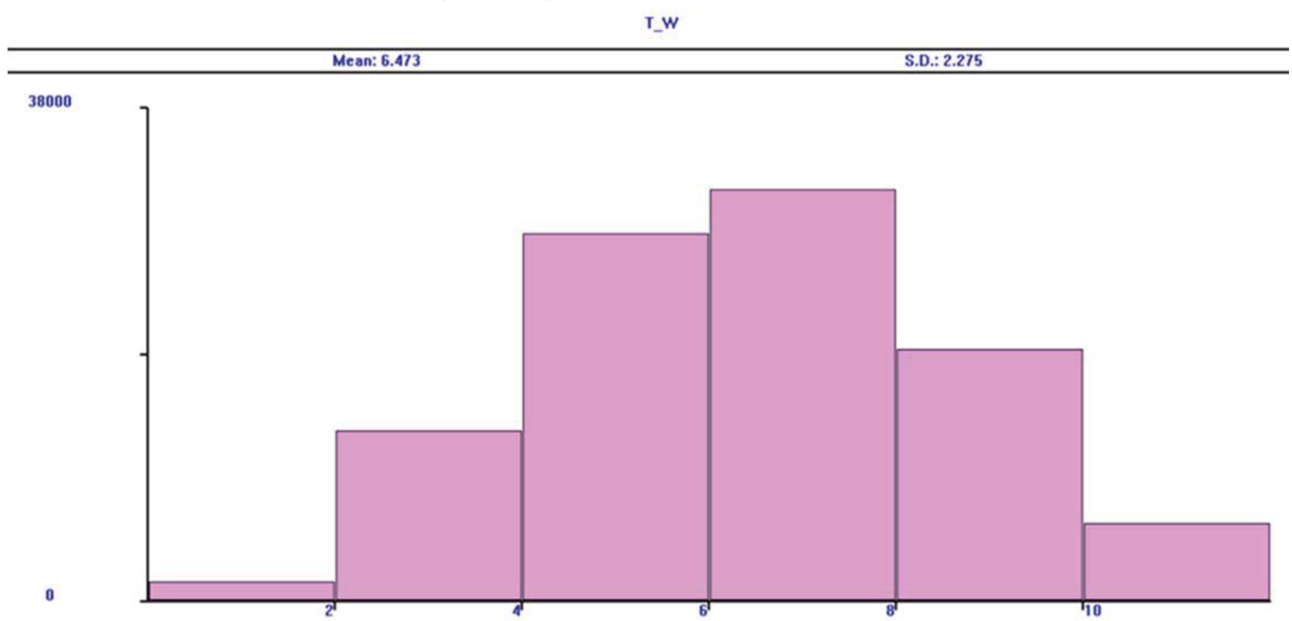

Fig. 6. Histogram of the Waiting Time

According to the test findings in Table 2 based on the Marked-up transition graph of a random process Fig. 2, all calculated probability characteristics were obtained from 0 to 15. From Table 2, it can be concluded that the probabilities of transfers p_i. It specifies the routes of applications in Fig. 2 decrease from 0 to 15. It suggests that the intensity of the λ_i application flows also decreases from node 0 to 15. According to the test findings in Table 3, the Utilization of node 1 ρ_1=0.663492033 exceeds the Utilization of node 2 ρ_2=0.32605134 almost twice. The downtime ratio of node 1 (η_1) is almost twice more minor than the downtime ratio of node 2 (η_2). The efficiency of node No. 1 $\left(\lambda_1^{'}\right)$ is almost two times bigger than the efficiency of node No. 2 $\left(\lambda_2^{'}\right)$, and the average Waiting Time in node No. 1 (ω_1) exceeds the average Waiting Time in node No. 2 (ω_2). According to Fig. 3, the Probability of Utilization in the first node is equal to 0.634 or 63.4 %. In the second node, the average processing time per transaction is 2.003. the Probability of Utilization is 0.318 or 32 %. This means that most of the load falls on "Router 0", and "Router 1" offloads the network, making the network smoother. The GPSS World model confirms the characteristics of the mathematical model in Table 2 – Fig. 4, 5, where there is also a tendency to decrease the probability of pi transmissions from 0 to 15.

According to Fig. 6, it is shown the histogram of The Waiting Time of the system. The histogram has a normal distribution with Mean=6.473 (sec) and standard deviation *S.D.*=2.275 (sec). It indicates that the applied model corresponds to the original data.

The obtained results of mitigating the impact of overload on the gateways of the Internet of Things in this work confirm the data of works [13]. Compared to [13], this work has no computationally expensive machine learning methods. However, the advantage of this work compared to [13] is that there are no computationally expensive machine learning methods because, for many systems, the use of computationally expensive machine learning methods can become an obstacle to implementing this solution.

The obtained results indicate that the proposed control mechanisms based on the Teletraffic Theory significantly impacted key performance indicators, as reduced network latency, increased bandwidth and improved scalability. These results demonstrate the effectiveness of Teletraffic Theory in solving problems related to the control of IoT devices.

The proposed method stands out for its unique features and advantages over existing methods. Unlike traditional rule-based systems or centralized control architectures, our approach considers dynamic traffic patterns, diverse device capabilities, and various data formats. The results obtained using the proposed method showed significant improvements compared to existing methods. Previously, the authors of this article considered the possibility of using blockchain technology in the management of IoT and the Internet of Energy in smart grids [25]. The authors have seen improved network responsiveness, optimized resource allocation between "Router 0" and "Router 1", and improved load balancing. This indicates that our method is superior to existing approaches in terms of performance, efficiency, and adaptability.

While this study provided valuable information, it is important to recognize its limitations. First, the study was focused on a specific set of IoT devices and network configurations, which may limit the ability to generalize the results to other scenarios, as well as the scope and depth of the study. In addition, the study made certain assumptions about traffic patterns and device behavior that may not fully reflect the complexities of the real world. These limitations should be considered when interpreting the results and applying the proposed method in different contexts.

Among the shortcomings of this study, which can be eliminated in the future, it should be noted the need to conduct an experiment on a real object. Implementation issues such as device heterogeneity and interoperability should be further explored and addressed to ensure smooth integration and deployment of the proposed method in the real world. Addressing these challenges will require collaboration with industry partners, the development of complex simulation systems, or the use of existing IoT platforms for experimentation.

This research has significant implications for future IoT system design. As IoT devices expand and become more common, it will be critical to build systems that can handle the rising amount and diversity of communication. Teletraffic Theory can provide a useful foundation for creating such systems by allowing to model and evaluate traffic patterns as well as design control mechanisms to better manage network resources.

This paper shows the potential benefits of using Teletraffic Theory to regulate IoT devices in networked contexts. It is possible to develop more efficient and effective control mechanisms that increase network performance, minimize congestion, and optimize the placement of IoT devices in a particular network architecture by using the insights provided by this Theory.

The research results are necessary for practice in various development fields. The mathematical model serves as a framework for analyzing and optimizing the performance of IoT networks in terms of energy distribution and control. The simulation model allows the authors to assess the performance of the proposed IoT control system and evaluate its efficiency. The practical results of the study demonstrate the effectiveness of the proposed IoT control system based on the Teletraffic Theory. The system showed promising performance in handling IoT device requests, optimizing network performance, and providing efficient energy distribution control. It suggested that the practical results could be effectively utilized for controlling IoT devices in the context of energy distribution and management within Smart Grids.

7. Conclusions

1. It was calculated all probabilities of 16 states of the model: p_0=0.21860866, p_1=0.24811111, p_2=0.07190013, p_3==0.13641432, p_4=0.0914331, p_5=0.10327755, p_6=0.05465216, p_7=0.00456748, p_8=0.04904647, p_9=0.01538607, p_{10}==0.00000017, p_{11}=0.00001961, p_{12}=0.007077, p_{13}==0.00053718, p_{14}=0.00005035, p_{15}=0.0000042. Calculated characteristics of sixteen states shows that the Total Utilization of nodes ρ=0.96097167, and The Relative error δ=0.11 This suggests that a Model with such a low relative error can be considered highly accurate and reliable.

2. Created simulation model of two network routers and a transition schedule in the "GPSS World" software based on the mathematical model shows that the service of 100,000 transactions took 629500.263 minutes, and the model consists of 16 blocks and two service channels. In the first node, the average processing time of one transect is 3.990. The

Probability of Utilization is equal to 0.634 or 63.4 %. In the second node, the average processing time per transaction is 2.003. The Probability of Utilization is 0.318 or 32 %. It is mean that The Probability of Utilization of the first node higher than the second node, and accordingly the average processing time of the second node is less.

3. Determined indicators of "Router 0" that show the effectiveness of the developed simulation model. The "Router" histogram with Queue #1 shows that most IoT devices are processed in the range 0–2, with an average *Mean*=0.408 (sec) and *S.D.*=0.970 (sec).

4. Determined indicators of "Router 1" that show the effectiveness of the developed simulation model. The "Router 1" histogram with Queue #2 also shows that most IoT devices are processed in the first 0–0.5 bin, with *Mean*=0.069 (sec) and standard deviation *S.D.*=0.310(sec).

5. The histogram of the Waiting Time has a normal distribution with Mean=6.380 (sec) and standard deviation *S.D.*=2.275 (sec). The number of transactions passed through the queue during the simulation with zero Waiting Time-77458, 93052. In the first node, the Average Processing Time of one transect is 3.990. The Probability of Utilization is equal to 0.634 or 63.4 %. In the second node, the Average Processing Time per transaction is 2.003. The Probability of Utilization is 0.318 or 32 %. Transaction losses are minimal. The use of histograms shows that the network handles the transaction flow well.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Manuscript has no associated data.

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