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## METHODOLOGY FOR ASSESSING THE SENSITIVITY OF QUEUING SYSTEM PARAMETERS WITH SELF-SIMILARITY PROPERTIES TO SUBSCRIBER ACCESS CHARACTERISTICS

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**Background.** The last decades were marked by a significant achievement in the field of teletraffic theory – the discovery of self-similar properties of processes occurring in modern networks. Modern telecommunication networks and information systems are complex, dynamic structures in which data flows are formed by a large number of independent sources. Studies show that traffic in such systems exhibits the property of correlation on different time scales. This means that changes in network load can affect its operation not only in the short term, but also over significant time intervals.

**Objective.** The purpose of the paper is to investigate how the queuing systems' (QS) characteristics sensitivity changes in the Hurst parameter (H) under conditions of self-similar traffic. Additionally, it aims to assess the impact of the traffic correlation properties on the quality indicators of the telecommunication networks' functioning.

**Methods.** The mathematical basis of the study is the use of the Weibull distribution for the incoming self-similar flow to describe the characteristics of the SMO, as well as the dynamics description of the self-similar traffic property for different values of the Hurst parameters.

**Results.** The influence of the traffic self-similarity property on the sensitivity of changes in service quality indicators in queuing systems, depending on the intensity of incoming traffic, the intensity of service requests, and different values of the Hurst parameters, was investigated.

**Conclusions.** The influence of the traffic self-similarity property on the sensitivity of changes in QS quality of service indicators is most significant with an increase in the intensity of incoming traffic, the intensity of application service, and with values of the Hurst parameter close to 1. This emphasises the importance of taking into account the self-similarity factor when determining the characteristics of similar information and communication systems.

**Keywords:** queuing system QS; self-similarity; quality of service QoS; the sensitivity of QS parameters.

### Introduction

The article aims to investigate how the queuing systems' (QS) characteristics sensitivity changes in the Hurst parameter (H) under conditions of self-similar traffic, as well as to assess the impact of the traffic correlation properties on the qualitative indicators of the functioning of telecommunication networks within the Weibull model to describe the characteristics of the incoming application flow.

**The object** of the study is a queuing system with incoming flows that exhibit self-similarity, characterised by a generalised structure of the class G/M/1.

Modern telecommunication networks and information systems are complex, dynamic structures in which data flows are formed by a large number of independent sources [1-4]. Studies show that traffic in such systems demonstrates the property of correlation on different time scales [5-6]. This means that changes in network load can affect its operation not only in the short term, but also at significant time intervals.

**The task of the work** is to determine the sensitivity of the QS characteristics to changes in the parameter H, the intensity of incoming traffic  $\lambda$  and the intensity of service  $\mu$ .

**A new result of the study** is the determination of the sensitivity characteristics of the parameters of self-similar traffic to changes in the intensity of incoming service flows within the Weibull model, in contrast to the known results, where the object of the study was the absolute values of the QoS indicators without taking into account the degree of sensitivity of such indicators to factors of the organization of the telecommunication network.

### Problem statement

Traditional models of queuing systems (QS), based on the assumption of a Poisson distribution of the incoming flow of requests [7], do not account for this feature, which can lead to inaccurate estimates of network performance.

An alternative approach is to use self-similar models that take into account long-term correlation in traffic and allow for more accurate prediction of

network behaviour for different loads, in particular, using the Weibull distribution to describe the intervals between neighbouring incoming service requests [8-11].

The density of the Weibull distribution is determined by the formula:

$$P(x) = \alpha \cdot \beta \cdot x^{\alpha-1} \cdot e^{-\beta \cdot x^{\alpha}} \quad (1)$$

where  $\alpha = 2(1-H)$  is the argument of the Weibull function, which depends on the Hurst coefficient  $H$  and characterises the degree of self-similarity of the described process;

$\beta$  is the argument of the Weibull function, which is related to the coefficient  $\alpha$  and the intensity of incoming requests  $\lambda$ :

$$\beta = \left[ \lambda \cdot \Gamma \left( 1 + \frac{1}{\alpha} \right) \right]^{\alpha} \quad (2)$$

An additional parameter of the Weibull distribution is the variable  $\sigma$ , which depends on both coefficients  $\alpha$  and  $\beta$  and is used for the analytical description of service parameters in queuing systems [12-14]:

$$\sigma = \alpha \cdot \beta \cdot \int_0^{+\infty} e^{-(\mu - \mu \cdot \sigma) \cdot t} \cdot t^{\alpha-1} \cdot e^{-\beta \cdot t^{\alpha}} \cdot dt$$

$$\sigma = F(\mu - \mu \cdot \sigma), \quad (4)$$

where  $\sigma$  – the root of the equation  $0 \leq \sigma < 1$ ;

$F$  – Laplace-Stiltjes transformation of the density distribution of intervals between applications  $f(t)$  in queuing system.

Formulas (1) – (4) indicate the connection between traditional traffic parameters (incoming requests  $\lambda$ , service intensity  $\mu$ ), which are the parameters of classical, “Poissonian” QS, with the characteristics of the QS based on the properties of self-similarity.

The key parameter of self-similar traffic is the Hurst parameter ( $H$ ), which reflects the level of density between active users of the network [15].

The object of the study is a queuing system with incoming flows that have the property of self-similarity, with a generalised structure of the class  $G/M/1$  [11, 16, 17].

### Sensitivity assessment methodology

Given the importance of Hurst parameters ( $H$ ), intensities of incoming flow ( $\lambda$ ) and service ( $\mu$ ) for determining the performance of a queuing system (QS), it is important to investigate how changes in these quantities affect the quality of service (QoS) indicators. In particular, the sensitivity of quality-of-service (QoS) indicators to these parameters can have a significant impact on network efficiency.

To assess the sensitivity of each indicator to changes in the value of the SMO parameter, the following method is used. All parameters are fixed, except for one selected one, then all indicators are determined depending on the variable parameter [18,19].

From the totality of the obtained results, a matrix of dependencies of indicators  $P$  on the parameter  $r$  is formed, which can be used to conduct additional analysis of the prospects for movement (improvement of indicators) in one direction or another. The slope of the curves shows the sensitivity, the effect of movement for a certain indicator. In mathematics, this matrix is called the Jacobian  $J$ , in which the role of the slope of the curves is played by the values of the derivatives  $P_i/R_j$ :

$$\|J\| = \begin{vmatrix} J_{11} & J_{12} & J_{13} & \dots & J_{1,12} \\ J_{21} & J_{22} & J_{23} & \dots & J_{2,12} \\ \dots & \dots & \dots & \dots & \dots \\ J_{51} & J_{52} & J_{53} & \dots & J_{5,12} \end{vmatrix} = \begin{vmatrix} \frac{\Delta P_1}{\Delta R_1} & \frac{\Delta P_1}{\Delta R_2} & \frac{\Delta P_1}{\Delta R_3} & \dots & \frac{\Delta P_1}{\Delta R_{12}} \\ \dots & \dots & \dots & \dots & \dots \\ \frac{\Delta P_5}{\Delta R_1} & \frac{\Delta P_5}{\Delta R_2} & \frac{\Delta P_5}{\Delta R_3} & \dots & \frac{\Delta P_5}{\Delta R_{12}} \end{vmatrix}$$

In accordance with this methodology, analytical calculations were carried out, and graphical dependencies were constructed, which demonstrate different sensitivity zones of each indicator (low, medium and high sensitivity zones).

The low sensitivity zone is characterised by the fact that changes in the parameters ( $H, \lambda, \mu$ ) do not have a significant impact on the QoS indicators. It is usually observed at stable or close to optimal values of the incoming flow and service intensities. In this zone, the system can efficiently process requests, and changes in the parameters do not cause significant fluctuations in performance.

The zone of medium sensitivity indicates that changes in parameters have a noticeable, but not critical, impact on the efficiency of the system. In this zone, there is a certain fluctuation in the QoS indicators, but the system can adapt to these changes without significant disruptions in its operation.

The zone of high sensitivity reflects situations where even small changes in parameters can lead to significant changes in the performance of the queuing system. In this zone, the system exhibits a significant dependence on the values of  $H, \lambda$  and  $\mu$ , and each change can cause significant deviations in waiting time, throughput or other critical indicators of quality of service. This indicates the need for fine-tuning of these parameters to achieve optimal results.

### Analysis of the resulting dependencies

Matlab and Excel software were used to obtain the data.

Using Excel software, the values of service quality indicators were calculated and their changes were determined for sensitivity analysis.

For quantitative analysis of the influence of the parameter  $H$  on the system characteristics, the following metrics were used, which are based on the Little formula methodology [20, 14]:

– the absolute values of the average values of the parameters of the functioning of the QS:

✓ Average time the request is in the system ( $W_{\text{syst}}$ )

$$W_{\text{syst}} = \frac{1}{\mu \cdot (1-\sigma)} \quad (5)$$

✓ Average waiting time for a service request ( $W_{\text{wait}}$ )

$$W_{\text{wait}} = \frac{\sigma}{\mu \cdot (1-\sigma)} \quad (6)$$

✓ Average number of requests in the queue ( $L$ )

$$L = \frac{\rho \cdot \sigma}{1-\sigma} \quad (7)$$

✓ Average number of requests in the system ( $Q$ )

$$Q = \frac{\rho}{1-\sigma} \quad (8)$$

– indicators of the sensitivity of the average values of the parameters of the SMO functioning to changes in the intensity of application flows

✓  $\Delta W_{\text{syst}}$  – change in the average time the application stays in the system;

✓  $\Delta W_{\text{wait}}$  – change in the average waiting time of an application in the queue;

✓  $\Delta L$  – change in the average queue length;

✓  $\Delta Q$  – change in the average number of applications in the system.

The values of these indicators were calculated for the parameters  $H = 0.5 \dots 0.8$  with a step of 0.1, the values of the input flow intensity  $\lambda = 0.7 \dots 1.5 \text{ s}^{-1}$  with a step of  $0.1 \text{ s}^{-1}$  and the service intensity  $\mu = 1.75 \dots 2.75 \text{ s}^{-1}$  with a step of  $0.25 \text{ s}^{-1}$ .

To study the sensitivity of indicators depending on the intensity of service  $\mu$ , calculations of absolute values of indicators were performed [21].

**At the first stage**, for a visual comparison of the **sensitivity of the studied indicators**, namely: the average time of the application in the system  $\Delta W_{\text{syst}}$ , the average waiting time in the queue  $\Delta W_{\text{wait}}$ , the average queue length  $\Delta L$  and the average number of applications in the system  $\Delta Q$  – graphs of the dependence of the sensitivity indicators on the intensity of the incoming flow  $\lambda$  for certain values of the Hurst parameter in the service intensity designations  $\mu = 1.75 \text{ s}^{-1}$  (moderate length of applications) and  $\mu = 2.75 \text{ s}^{-1}$  (short length of applications) are presented (Fig. 1 – Fig. 4).

It should be noted that at  $H = 0.5$  the system is described by an exponential distribution, which corresponds to the classical model of random receipts of applications without the self-similarity property. Under such conditions, the system demonstrates more stable behaviour, and the

impact of changes in  $\lambda$  is less pronounced. As  $\lambda$  increases, the behaviour of the system also changes depending on the value of  $H$ . As  $H$  approaches 1, the self-similarity property becomes increasingly evident, which increases the sensitivity of the system to changes in the flow, in particular, in the indicator of the average residence time of the application in the system  $W_{\text{syst}}$ .

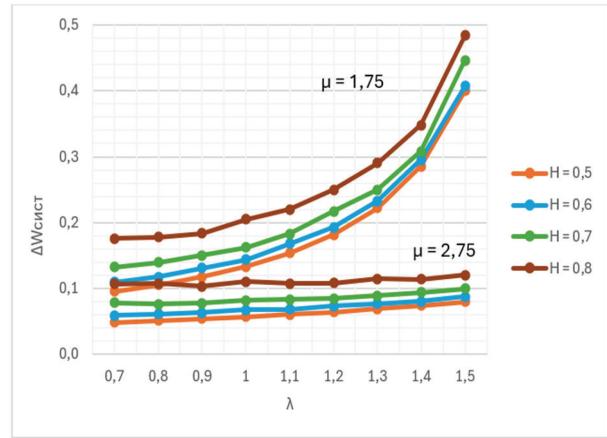


Fig. 1 Sensitivity of the average request dwell time in the system  $\Delta W_{\text{syst}}$  to the intensity of the incoming flow at  $\mu = 1.75 \text{ s}^{-1}$  and  $\mu = 2.75 \text{ s}^{-1}$

The graphs (Fig. 1) show that at lower service intensity, when  $\mu = 1.75 \text{ s}^{-1}$  (longer service time), the relative increase in the average request dwell time in the system  $\Delta W_{\text{syst}}$  changes significantly with increasing flow intensity ( $\lambda$ ) for all values of  $H$  (increasing the sensitivity index by 2.5...4 times). When  $\mu$  increases to  $2.75 \text{ s}^{-1}$  (service of short requests), the relative increase in  $\Delta W_{\text{syst}}$  for all values of  $H$  becomes smaller, which confirms the effectiveness of increasing service intensity to optimise system operation. For  $H = 0.5$ , the increase is limited to the range of 4.9% - 8.0%, and for  $H = 0.8$  - 10.7% - 12.0%.

Therefore, the relative increase in the average application dwell time in the system  $\Delta W_{\text{syst}}$  depends on the intensity of the incoming flow  $\lambda$  and the parameter  $H$ , and its decrease is possible due to an increase in the intensity of service. To minimise changes in  $\Delta W_{\text{syst}}$  at high values of  $\lambda$ , it is necessary to increase  $\mu$ , which allows compensating for the increasing load and improving the efficiency of application processing.

The analysis of relative changes in indicators depending on  $\lambda$  showed that for all values of  $H$ , the increase in the average application dwell time in the system ( $\Delta W_{\text{syst}}$ ) increases with increasing  $\lambda$ . However, this increase significantly depends on the parameter  $H$ : the sensitivity to flow changes

increases at high values of  $H$  (0.8), which is expressed in more significant relative increases in  $\Delta W_{\text{syst}}$ .

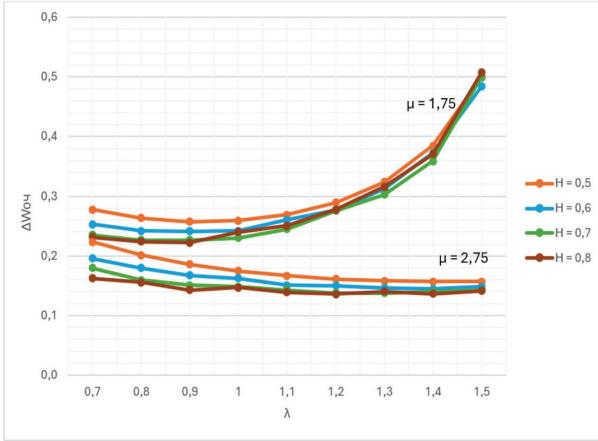


Fig. 2 Sensitivity of the average waiting time indicator  $\Delta W_{\text{wait}}$  to the intensity of the incoming flow at  $\mu=1.75 \text{ s}^{-1}$  and  $\mu=2.75 \text{ s}^{-1}$

The graphs in Fig. 2 indicate that the average waiting time in the queue  $\Delta W_{\text{wait}}$  also demonstrates high sensitivity to the service intensity  $\mu$ : at low values of the service intensity (long messages), the dependence of the waiting time in the queue  $W_{\text{wait}}$  on the parameter  $\lambda$  increases, creating significant delays in the passage of applications through the system. Increasing the service intensity  $\mu$  allows reducing the dependence of the indicator on the parameter  $\lambda$ . At the same time, the dependence of  $\Delta W_{\text{wait}}$  on the self-similarity factor  $H$  is more pronounced (50%...100%) at lower values of  $\lambda < 1 \text{ s}^{-1}$ .

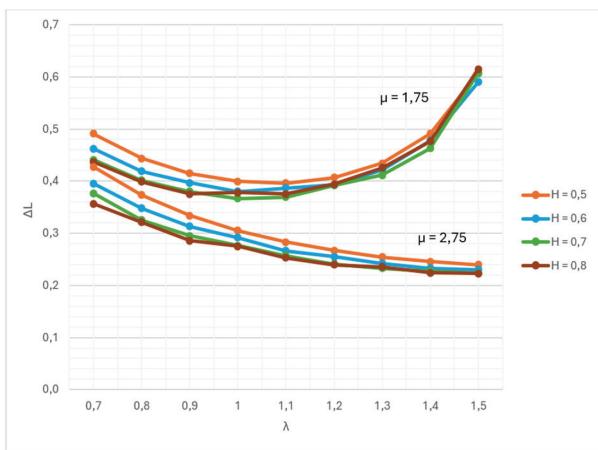


Fig. 3 Sensitivity of the average queue length indicator  $\Delta L$  to the intensity of the incoming flow at  $\mu=1.75 \text{ s}^{-1}$  and  $\mu=2.75 \text{ s}^{-1}$

Fig. 3 shows that the average queue length  $\Delta L$  directly depends on the service intensity  $\mu$ . At lower application processing intensity, the queues become longer, since the system does not have time to process them on time. With increasing service intensity, the queue length decreases.

Similar to the estimate of the average application dwell time  $W_{\text{syst}}$ , the relative level of the average queue length changes with increasing flow intensity, but the nature of these changes depends on the parameter  $H$  (20%...30%) only at low input flow intensity  $\lambda < 1 \text{ s}^{-1}$ .

At low service intensity values  $\mu=1.75 \text{ s}^{-1}$  (long messages), the dependence of  $\Delta L$  on  $\lambda$  has significant dynamics ( $\Delta L = 0.3 \dots 0.5$ ).

As  $\mu$  increases to  $2.75 \text{ s}^{-1}$ , the relative values of the average queue length ( $\Delta L$ ) decrease. For  $H = 0.5$ , this indicator changes from 42.8% to 24%, and for  $H = 0.8$ , from 35.6% to 22.3%.

This confirms that an increase in  $\mu$  contributes to a decrease in the relative indicators of the queue length, which improves load distribution and reduces the overall delay in processing requests.

Therefore, an increase in  $\mu$  allows you to reduce the dependence of the average queue length ( $\Delta L$ ), which indicates a more efficient use of system resources with increased service intensity.

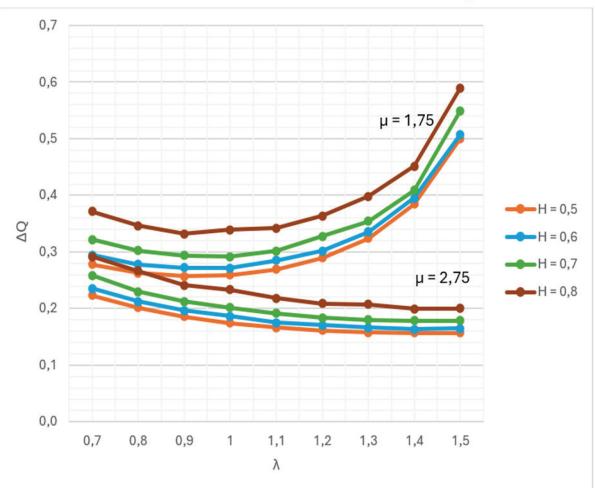


Fig. 4 Sensitivity of the indicator of the average number of requests in the system  $\Delta Q$  to the intensity of the incoming flow at  $\mu=1.75 \text{ s}^{-1}$  and  $\mu=2.75 \text{ s}^{-1}$

The graph in Fig. 4 shows that the average number of applications  $Q$  in the system also demonstrates sensitivity to changes in the service intensity  $\mu$ . At low values of the processing intensity ( $\mu=1.75 \text{ s}^{-1}$ ), this indicator  $\Delta Q$  increases significantly ( $\Delta Q = 0.4 \dots 0.6$ ), which indicates system overload simultaneously with an increase in both the input flow intensity  $\lambda$  and the self-

similarity factor  $H$ . With an increase in the service intensity ( $\mu=2.75$  s-1), the sensitivity of the indicator of the average number of applications in the system  $\Delta Q$  decreases ( $\Delta Q = 0.3\dots0.2$ ).

Thus, the analysis of the results shown in Fig. 1-4 shows that the average application stay time in the system  $\Delta W_{syst}$ , the average waiting time in the queue  $\Delta W_{wait}$ , the average queue length  $\Delta L$  and the average number of applications in the system  $\Delta Q$  change depending on the input flow intensity  $\lambda$ , the Hurst parameter and the service intensity  $\mu$ . But this dependence is more pronounced in a system with a significant load on the input stream  $\lambda$  and with long messages (small values of  $\mu$ ). The sensitivity of QoS parameters increases with increasing values of the parameter  $H$ .

**The next stage** is the study of the above indicators, namely: the average time an application spends in the system  $\Delta W_{syst}$ , the average waiting time in the queue  $\Delta W_{wait}$ , the average queue length  $\Delta L$  and the average number of applications in the system  $\Delta Q$  – graphs of the dependence of sensitivity indicators on the intensity of the incoming flow  $\lambda$   $\mu$  for certain values of the Hurst parameter for service intensity assignments  $\lambda = 0.7$  s-1 (moderate activity) and  $\lambda = 1.5$  s-1 (high activity) are presented (Fig. 5 – Fig. 8).

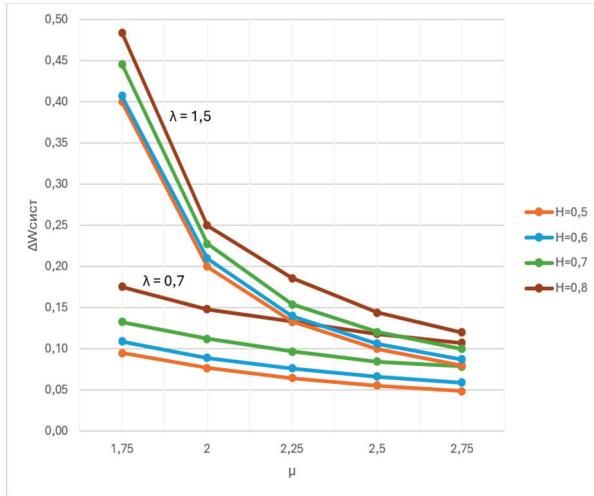


Fig. 5. Sensitivity of the average request dwell time in the system  $\Delta W_{syst}$  to the service intensity  $\mu$  at  $\lambda=0.7$  s-1 and  $\lambda=1.5$  s-1

As can be seen from Fig. 5, the sensitivity of the average request dwell time in the system ( $\Delta W_{syst}$ ) to changes in the intensities of the input flow  $\lambda$  and service  $\mu$  indicates its significant dependence on the load. At  $\lambda = 1.5$  s-1, the dependence of the average request dwell time in the system  $\Delta W_{syst}$  on the parameter  $\mu$  is

significantly determined by the range of values 0.5…0.1, especially at low values  $\mu < 2$  s-1.

At the same time, increasing  $\mu$  effectively reduces the dynamics of this indicator, and this effect is more pronounced at lower values  $\lambda = 0.7$  s-1.

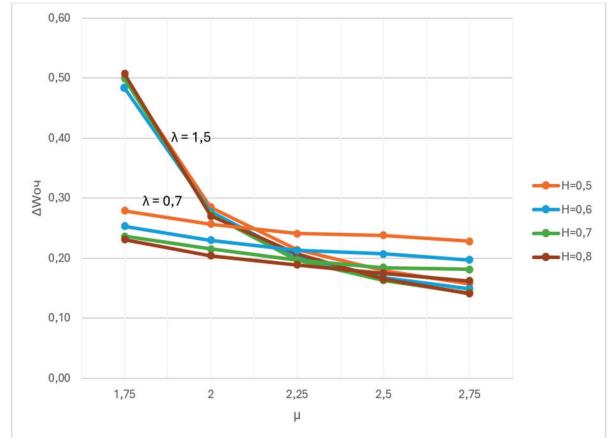


Fig. 6. Sensitivity of the average waiting time indicator  $\Delta W_{wait}$  to the service intensity at  $\lambda=0.7$  s-1 and  $\lambda=1.5$  s-1

Fig. 6 shows that the sensitivity of the average waiting time ( $\Delta W_{wait}$ ) is similar to  $\Delta W_{syst}$ : at  $\lambda = 1.5$  s-1, the dependence of the average waiting time  $W_{wait}$  on the parameter  $\mu$  is significantly determined by the range of values 0.5…0.2, especially at low values  $\mu < 2$  s-1. In this range of values, the service indicator practically does not depend on the values of the parameter  $H$ . At  $\lambda = 0.7$  s-1, the dependence of the load indicators depends to a significant extent on the dynamics of the parameter  $H$ .

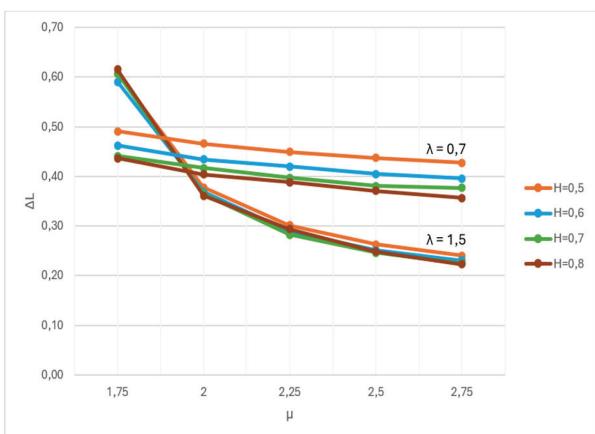


Fig. 7. Sensitivity of the average queue length indicator  $\Delta L$  to the service intensity at  $\lambda=0.7$  s-1 and  $\lambda=1.5$  s-1

From the graphs in Fig. 7 it is seen that the sensitivity of the average queue length ( $\Delta L$ ) is manifested in its growth with increasing  $\lambda$ , especially at low values of  $\mu < 2.25 \text{ s}^{-1}$ . However, increasing  $\mu$  allows effectively reducing the queue length, and this effect is most pronounced at lower values of  $\lambda = 0.7 \text{ s}^{-1}$ . At  $\lambda = 0.7 \text{ s}^{-1}$ , the  $\Delta L$  indicator loses sensitivity to the parameter  $H$ .

Therefore, the queue length ( $\Delta L$ ) also shows a dependence on  $H$ . The relative indicator – the change in the average queue length  $\Delta L$  – with a change in  $\lambda$  is higher for smaller values of  $H$ , which indicates better adaptation of the system at low values of the Hurst parameter. At high values of  $H$ , the system distributes the load less efficiently, which is manifested in a smaller decrease in the relative indicator of the queue length.

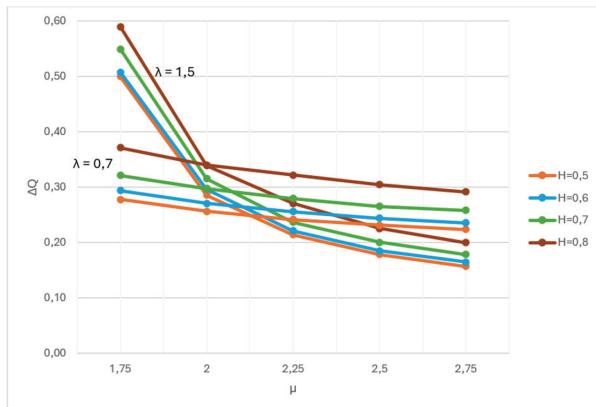


Fig. 8 Sensitivity of the average number of requests in the system  $\Delta Q$  to the service intensity  $\mu$  at  $\lambda=0.7 \text{ s}^{-1}$  and  $\lambda=1.5 \text{ s}^{-1}$

The graphs in Fig. 8 indicate that the sensitivity of the average number of requests in the system ( $\Delta Q$ ) shows a similar trend: at  $\lambda = 0.7 \text{ s}^{-1}$  the indicator is smooth (0.38...0.28), and at  $\lambda = 1.5 \text{ s}^{-1}$  it has significant dynamics (0.60...0.18), the dynamics of changes is highest at  $\mu < 2.25 \text{ s}^{-1}$ . The sensitivity of  $\Delta Q$  to  $\mu$  is higher at high  $\lambda$ , which indicates the need to increase the intensity of service to prevent the accumulation of requests in the system.

## Conclusions

1. Traditional models of queuing systems (QS), based on the assumption of a Poisson distribution of the incoming flow of independent requests, do not take into account the peculiarity of modern information and communication systems associated with the manifestation of self-similarity (correlation) of information flows, which can lead to inaccurate estimates of network performance and other characteristics.

2. A new result of the study is the determination of the sensitivity characteristics of the parameters of self-similar traffic to changes in the intensity of incoming service flows within the Weibull model, in contrast to the known results, where the object of the study was the absolute values of the QoS indicators without taking into account the degree of sensitivity of such indicators to factors of the organization of the telecommunication network.

3. Serving short messages (increasing  $\mu$ ) allows significantly reducing the relative residence time of requests in the system  $\Delta W_{\text{syst}}$ , making it less sensitive to changes in the input flow  $\lambda$  and changes in the parameter  $H$ . Therefore, increasing the parameter  $\mu$  is an effective way to improve performance, since it allows compensating for the influence of traffic self-similarity and stabilise the system performance.

4. The Hurst parameter  $H$  plays a key role in shaping the behaviour of the system. At the same time, increasing  $\mu$  allows compensating for the effect of self-similarity and improving the quality of service. At  $H = 0.5$ , the system operates more stably, while at  $H \rightarrow 1$ , the self-similarity of traffic causes significant sensitivity to changes in the flow.

5. The results obtained will be useful for optimising queuing systems, in particular, in telecommunication networks with self-similar traffic.

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**Методика оцінки чутливості параметрів системи масового обслуговування із властивостями самоподібності до характеристик абонентського доступу**

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**Проблематика.** Останні десятиліття ознаменувалися істотним досягненням у сфері теорії телетрафіку – відкриттям самоподібних властивостей процесів, що протікають у сучасних мережах. Сучасні телекомунікаційні мережі та інформаційні системи є складними динамічними структурами, в яких потоки даних формуються великою кількістю незалежних джерел. Дослідження показують, що трафік у таких системах демонструє властивість кореляції на різних часових масштабах. Це означає, що зміни в навантаженні мережі можуть впливати на її роботу не лише в короткостроковій перспективі, а й на значних інтервалах часу.

**Мета дослідження.** Метою роботи є дослідження чутливості характеристик систем масового обслуговування (СМО) до змін параметра Херста (Н) у випадку самоподібного трафіку, а також визначити, як кореляційні властивості трафіку впливають на якісні показники функціонування телекомунікаційних мереж.

**Методика реалізації.** Математичною основою дослідження є використання для опису характеристик СМО розподілу Вейбулла для вхідного самоподібного потоку, а також опис динаміки властивості самоподібного трафіку при різних значеннях параметрах Херста.

**Результати дослідження.** Досліджено вплив властивості самоподібності трафіку на чутливість зміни показників якості обслуговування в системах масового обслуговування в залежності від інтенсивності вхідного трафіку, інтенсивності обслуговування заявок та від різних значень параметрах Херста.

**Висновки.** Вплив властивості самоподібності трафіку на чутливість зміни показників якості обслуговування в QS найсуттєвіше має прояв при збільшенні інтенсивності вхідного трафіку, інтенсивності обслуговування заявок та при значень параметра Херста, наближеного до 1. Це підкреслює важливість врахування фактору самоподібності привизначені характеристик сучасних інформаційно-комунікаційних систем.

**Ключові слова:** система масового обслуговування (СМО); самоподібність; якість обслуговування; чутливість до параметрів СМО.

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