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ОЦЕНКА ЭФФЕКТИВНОСТИ ЭТАЛОННЫХ МОДЕЛЕЙ МАШИННОГО ОБУЧЕНИЯ ДЛЯ ПРЕДСКАЗАНИЯ ОБЪЕМА БУФЕРНОЙ ПАМЯТИ ПРИ ПРЕОБРАЗОВАНИИ САМОПОДОБНОГО ВХОДНОГО ПОТОКА ПАКЕТОВ В ПОТОК, ИМЕЮЩИЙ ЭКСПОНЕНЦИАЛЬНОЕ РАСПРЕДЕЛЕНИЕ ПРИ УСЛОВИИ РАВЕНСТВА МАТЕМАТИЧЕСКИХ ОЖИДАНИЙ И МЕДИАН ПОТОКОВ

EVALUATION OF THE EFFICIENCY OF REFERENCE MACHINE LEARNING MODELS FOR BUFFER MEMORY PREDICTION WHEN TRANSFORMING A SELF-SIMILAR INPUT STREAM OF PACKETS INTO A STREAM HAVING EXPONENTIAL DISTRIBUTION UNDER THE CONDITION OF EQUALITY OF MATHEMATICAL EXPECTATIONS AND MEDIAN FLOWS

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Аннотация

С использованием методов машинного обучения разработаны модели для предсказания размера очереди в зависимости от показателя Херста на основании данных, полученных при выполнении преобразования входного самоподобного потока, распределенного по закону Парето в поток, имеющий экспоненциальное распределение при равенстве математического ожидания и при равенстве медиан. Выполнен сравнительный анализ полученных моделей. Каждая модель исследована с использованием следующих метрик качества: коэффициента детерминации, среднеквадратичной ошибки регрессии, средней абсолютной ошибки, величины штрафа, предполагаемая величина потерь. Лучшими по выбранным метрикам качества для способов преобразования входного и выходного потока пакетов при равенстве математического ожидания являются модели, которые используют методы изотонической регрессии и опорных векторов. Для способов преобразования входного и выходного потока пакетов при равенстве медиан лучшими являются линейные модели.

Ключевые слова: Телекоммуникационная сеть, самоподобный трафик, показатель Херста, производительность, распределение Парето, потери пакетов, регрессионноый анализ, метрики качества, функция штрафа, машинное обучение.

Abstract

Using machine learning methods, models have been developed to predict the size of the queue depending on the Hurst exponent based on the data obtained when performing the transformation of an input self-similar stream distributed according to the Pareto law into a stream having an exponential distribution with equal mathematical expectation and equal medians. A comparative analysis of the obtained models is carried out. Each model was examined using the following quality metrics: coefficient of determination, rms regression error, mean absolute error, penalty value, estimated loss. Models that use isotonic regression and support vector methods are the best in terms of the selected quality metrics for methods of transforming the input and output packet streams when the mathematical expectation is equal. For methods of transforming the input and output packet stream with equal medians, linear models are the best.

Keywords
Telecommunication network, self-similar traffic, Hurst exponent, Pareto distribution, packet loss, regression analysis, quality metrics, penalty score, machine learning

Introduction. In network traffic, packets at a high speed of their movement through the network arrive at the node not individually, but as a whole bundle. Traffic in such networks has a pronounced peak character, which increases the likelihood of congestion in network nodes, which lead to buffer overflows and cause losses and / or delays [1]. To eliminate the self-similarity of network traffic, various models and traffic conversion devices are used [2], one of which is the asynchronous simulation model described in [2], for which there is a software implementation [3]. In the proposed model, the input and output flows were compared with each other in terms of the value of the mathematical expectation. In other studies [4], the transformation of the input stream of packets with a self-similar law of distribution of time intervals between packets into the Poisson law is carried out when the median of the input and output streams is equal.

Formulation of the problem. Using machine learning methods, it is necessary to develop models for predicting the queue size depending on the Hurst exponent based on the data obtained by converting an input self-similar stream distributed according to the Pareto law into a stream having an exponential distribution with equal mathematical expectation and equal medians. Perform a comparative analysis of the obtained models and choose the best one.

Since machine learning includes many methods, at the initial stage, for further comparison with more complex models built, in particular, using deep learning methods, it is advisable to consider only the methods of paired regression analysis, isotonic regression and support vector machines.

As a quality metric (penalty), we will use a complex indicator [5], which takes into account both packet losses in the process of traffic conversion and inefficient use of buffer space.

Let's carry out a comparative analysis of the obtained models to predict the queue size, depending on the Hurst exponent of the input stream according to the following quality metrics:

determination coefficient;

rms regression error;

mean absolute error;

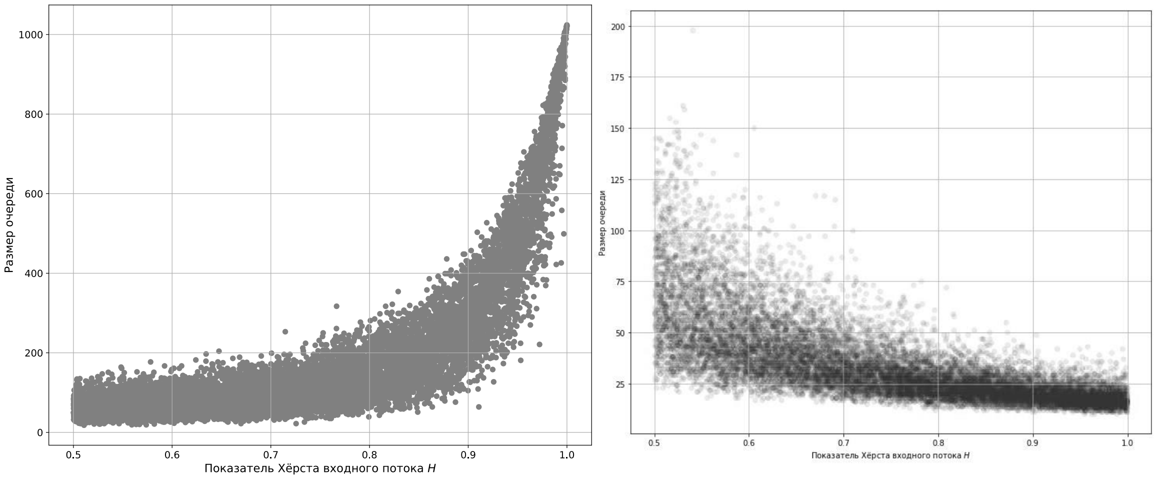
the amount of the fine;

estimated loss;

performance.

The solution of the problem. The computer program presented in [6] provides the transformation of the input stream of packets, which is obviously self-similar, into a given distribution law, in particular, into an exponential one. The object of the transformation is the one-dimensional density of the distribution of time intervals between packets of the input stream. Using the developed model, 11,000 tests were carried out and data were obtained for statistical analysis.

Initial data analysis. Figure 2 shows the scatterplots of the dependence of the queue size on the Hurst exponent for the cases of equal mathematical expectation and equal median input and output packet streams. The figure clearly shows that there is a certain correlation between the Hurst exponent and the amount of buffer memory. The level of significance in statistics is an important indicator that reflects the degree of confidence in the accuracy and truth of the received (predicted) data. A large volume of tests allows not to calculate p - the significance level, because, as practice shows, in this case p - the value is much less than 0.05 [7].



a) b)

Figure 2. Scatterplot of the dependence of the queue size on the Hurst exponent

Let us preliminarily group the tests according to the value of the Hurst exponent. Let's single out 30 groups to estimate the spread of the queue size.

Linear machine learning model. The relationship between the Hurst exponent *H* and the queue size is $\hat{y}$ determined according to the linear equation:

$$\hat{y} = b_0 + b_1 H.$$

Using the least squares method, we obtain the regression equations for the input and output flows compared by the median (1), for the flows compared by the mathematical expectation (2):

$$\hat{y} = 107{,}79236 - 97{,}874061 \cdot \mathrm{H} \quad (1)$$

$$\hat{y} = -611{,}182635 + 1077{,}442810 \cdot H \quad (2)$$

Table 1 shows the quality metrics of the obtained linear models for the methods of converting the input and output stream of packets when the medians and mathematical expectations are equal.

Table 1. Linear regression model quality metrics

Quality Metrics	mathematical expectation is equal	if the medians are equal
Determination coefficient R2	0.584792	0.49081
RMSE Regression Root Mean Square Error	130.908538	14.42016
Mean absolute error MAE	96.808209	9.95253
Estimated amount of the fine	55.710275	4.97626
Estimated loss	48.404104	4.976265

The obtained value of the coefficient of determination for flows matched by mathematical expectation suggests that 58% of the cases of changes in the Hurst exponent lead to a change in the queue size within the linear model.

The obtained value of the determination coefficient for flows compared by the median suggests that only about 49% of cases of changes in the Hurst exponent lead to a change in the queue size within the linear model.

Transforming a packet stream using median equality is less well described than transforming using expectation. This is due to the fact that the spread of buffer memory values when using the equality of medians is greater than when using mathematical expectations. However, the implied penalty and implied loss of the equal median method are much lower than those of the equal mean method.

Linear machine learning model in rectifying space. In general, the results obtained are unsatisfactory for practice, therefore, in the simplest case, it makes sense to consider other methods using the methods of linearization of nonlinear dependencies. As a result, the nonlinear dependence can be reduced to a linear one, and then the least squares method can be used.

Machine learning model based on hyperbolic regression. For hyperbolic regression, the relationship between H and $\hat{y}$ can be described as follows:

$$\hat{y} = b_0 + \frac{b_1}{H}.$$

Linearization of the hyperbolic equation is achieved by replacing $\frac{1}{H}$ it with a new variable, which we denote by z [7, 8]. Then the hyperbolic regression equation will take the form $\hat{y} = b_0 + b_1 z$.

Using the least squares method, we obtain the regression equations for the input and output flows compared by the median (3), for the flows compared by the mathematical expectation (4):

$$\hat{y} = 875{,}438 - \frac{489{,}379}{H} \quad (3)$$

$$\hat{y} = -38{,}443 + \frac{52{,}524}{H} \quad (4)$$

Table 2 shows the quality metrics of the obtained hyperbolic regression models for the methods of converting the input and output stream of packets when the medians and mathematical expectation are equal in relation to the initial data .

Table 2. Metrics of the quality of the hyperbolic regression model

Quality Metrics	if the mathematical expectation is equal	if the medians are equal
Determination coefficient R2	0.453263	0.53129
RMSE Regression Root Mean Square Error	150.218740	13.83514
Mean absolute error MAE	110.511548	9.29888
Estimated amount of the fine	63.841249	4.64944
Estimated loss	55.25577	4.649444

The obtained value of the coefficient of determination for flows matched by mathematical expectation suggests that about 45% of the cases of changes in the Hurst exponent lead to a change in the queue size. This is much worse than the value of the coefficient of determination of the linear model.

The obtained value of the coefficient of determination for flows compared by the median suggests that about 53% of the cases of changes in the Hurst exponent lead to a change in the queue size. This is better than the value of the coefficient of determination of the linear model.

The transformation of a stream of packets using the equality of the median for this model is described better than the transformation using the mathematical expectation.

The estimated penalty and the estimated loss of the equal median method are also significantly better than the equal mean method.

In general , the results obtained are unsatisfactory for practice, and for this reason it makes sense to consider another hyperbolic regression model:

$$\hat{y} = \frac{1}{b_0 + b_1 H}.$$

Using the least squares method, we obtain for this model the regression equations for the input and output flows compared by the median (5), for the flows compared by the mathematical expectation (6):

$$\hat{y} = \frac{1}{(-0{,}029806 + 0{,}0894069 \cdot \mathrm{H})} \tag{5}$$

$$\hat{y} = \frac{1}{0{,}039996 - 0{,}039720 \cdot H}. \tag{6}$$

Table 3 shows the quality metrics of the modified hyperbolic regression model for the methods of transforming the input and output packet streams with the equality of medians and mathematical expectation in relation to the original data.

Table 3. Quality metrics of the modified hyperbolic model

Quality Metrics	if the mathematical expectation is equal	if the medians are equal
Determination coefficient R2	0.591293	0.60839
RMSE Regression Root Mean Square Error	223.798030	14.24760
Mean absolute error MAE	77.543626	8.97085
Estimated amount of the fine	39.537133	6.14195
Estimated loss	28.189645	6.141958

The obtained value of the coefficient of determination for flows matched by mathematical expectation is about 59%, which is somewhat better than the linear model.

The obtained value of the coefficient of determination for flows compared by the median is about 61%, which is better than the linear model.

The transformation of the packet stream using the median equality for this model is described slightly better than the transformation using the mathematical expectation.

The estimated penalty and the estimated loss of the equal median method are also significantly better than the equal mean method.

Power regression. In the case of power regression, the relationship between H and $\hat{y}$ looks like:

$$\hat{y} = b_0 H^{b_1}.$$

This equation is non-linear in coefficient b_1 and belongs to the class of regression models that can be brought to a linear form with the help of transformations [7]

$$\ln y = \ln b_0 + b_1 \ln H.$$

The exponential function is intrinsically linear, so estimates of the unknown parameters of its linearized form can be calculated using the classical least squares method. The regression equations for the input and output flows compared by the median (7), for the flows compared by the mathematical expectation (8) have the form:

$$\hat{y} = 16{,}37597 * \mathrm{H}^{-1{,}97664} \quad (7)$$

$$\hat{y} = 401{,}143661 \cdot H^{3{,}596636} \quad (8)$$

Table 4 shows the quality metrics of the obtained power regression models for the methods of converting the input and output packet streams when the medians and the mathematical expectation are equal in relation to the initial data.

Table 4. Quality metrics of the power regression model

Quality metrics	if the mathematical expectation is equal	if the medians are equal
Determination coefficient R2	0.699138	0.61908
RMSE Regression Root Mean Square Error	128.675573	13.94731
Mean absolute error MAE	72.823850	8.94776
Estimated amount of the fine	53.042530	5.418426
Estimated loss	51.394345	5.418426

The obtained value of the coefficient of determination for flows matched by mathematical expectation is 70%, which is much better than the coefficient of determination of the linear model.

The obtained value of the coefficient of determination for flows compared by the median is 61%, which is much better than the coefficient of determination of the linear model.

The transformation of the packet stream using the equality of the median for this model is described worse than the transformation using the mathematical expectation. However, the estimated penalty and the estimated loss of the equal median method are also significantly better than the equal mean method.

Exponential regression. For exponential regression, the relationship between H and $\hat{y}$ has the form:

$$\hat{y} = b_0 e^{b_1 H}.$$

This equation is non-linear in coefficient b_1 and belongs to the class of regression models, which are reduced to a linear form with the help of transformations [7, 8]:

$$\ln \hat{y} = \ln b_0 + H \ln b_1.$$

The exponential function is intrinsically linear, so estimates of the unknown parameters of its linearized form can be calculated using the classical least squares method. The regression equations for the input and output flows compared by the median (9), for the flows compared by the mathematical expectation has the form (10):

$$\hat{y} = 225{,}66610 \cdot \mathrm{e}^{-2{,}68865\,\mathrm{H}} \quad (9)$$

$$\hat{y} = 2{,}926343 \cdot e^{5.089127 \cdot H} \quad (10)$$

Table 5 shows the quality metrics of the obtained exponential regression models for the methods of transforming the input and output packet streams when the medians and the mathematical expectation are equal in relation to the initial data.

Table 5. Quality metrics of the exponential regression model

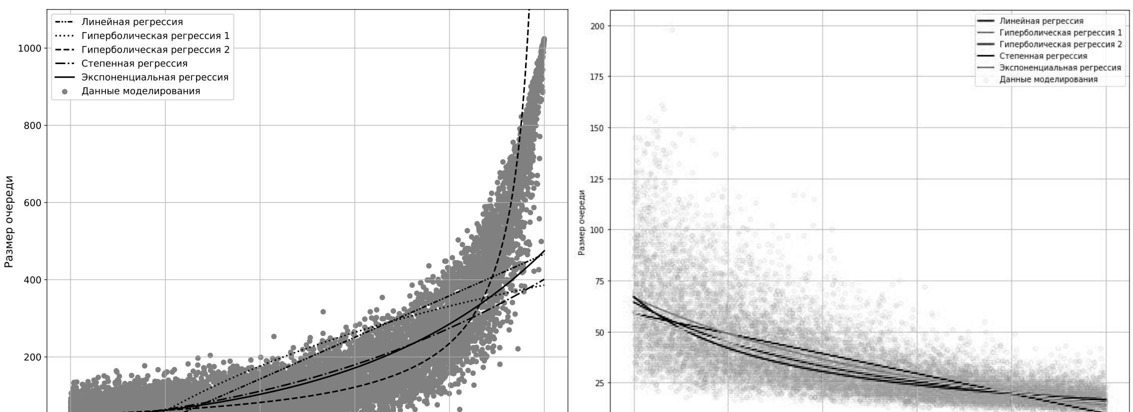
Quality Metrics	if the mathematical expectation is equal	if the medians are equal
Determination coefficient R2	0.745779	0.60997
RMSE Regression Root Mean Square Error	112.443773	14.18827
Mean absolute error MAE	65.199678	9.04531
Estimated amount of the fine	46.768626	5.52332
Estimated loss	45.25324	5.5233289

The obtained value of the coefficient of determination for flows matched by mathematical expectation suggests that about 74% of cases of changes in the Hurst exponent lead to a change in the queue size within the framework of the exponential model, which is the best result when using the methods of paired regression analysis.

The obtained value of the determination coefficient for flows compared by the median suggests that about 61% of the cases of changes in the Hurst exponent lead to a change in the queue size within the framework of the exponential model .

Let's carry out a comparative analysis of the results obtained for the methods of converting the input and output stream of packets when the medians and the mathematical expectation are equal . Let's build graphs of regression equations (Figure 4). Obviously, for flows matched by mathematical expectation , exponential regression and power regression most closely describe the relationship between the Hurst exponents and the buffer volume.

For streams matched by median, exponential regression is also used, power regression most closely describes the relationship between Hurst exponents and buffer volume



a) b)

Figure 4. Comparative analysis of the results of paired regression analysis
a) when the mathematical expectation of the input and output flows is equal b) when the medians of the input and output flows are equal

Isotonic regression. Let's train the isotonic regression model using the scikit - learn package of the Python 3 programming language [9-11]. Let's build graphs corresponding to the model built using isotonic regression for the methods of converting the input and output stream of packets when the medians and the mathematical expectation are equal (Fig. 5)

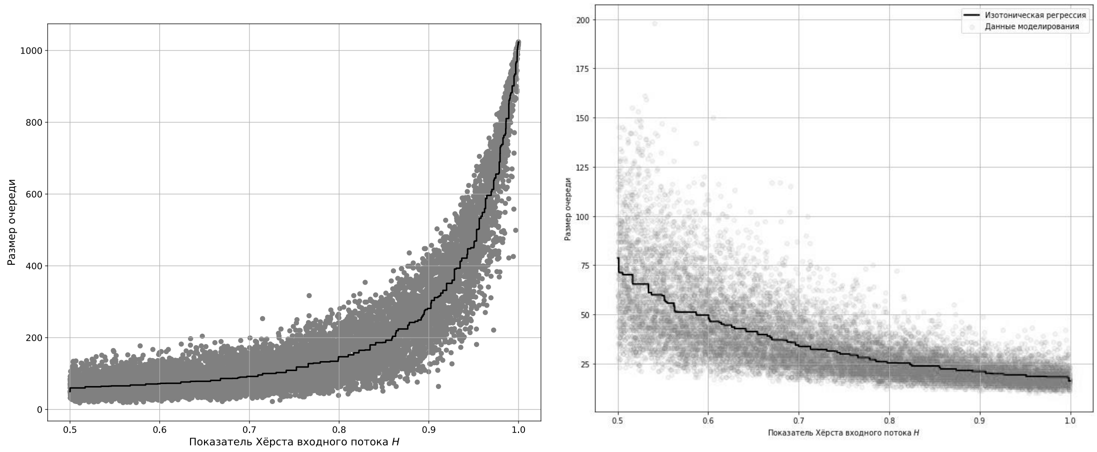


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Figure 5. Construction of an isotonic curve in relation to a data set

Table 6 shows the quality metrics of the obtained regression models for the methods of converting the input and output packet streams when the medians and the mathematical expectation are equal in relation to the initial data.

Table 6. Isotonic regression quality metrics

Quality metrics	the mathematical expectation is equal	if the medians are equal
Determination coefficient R2	0.928199	0.54490
RMSE Regression Root Mean Square Error	54.437567	13.63279
Mean absolute error MAE	39.500659	9.06566
Estimated amount of the fine	21.269167	4.53284
Estimated loss	19.75032	4.5328338

The obtained value of the determination coefficient for flows compared by mathematical expectation suggests that about 92% of the cases of changes in the Hurst exponent lead to a change in the queue size within this model, which is much better than models built on the basis of pair regression methods. At the same time, the penalty value for isotonic regression is two times less than the corresponding value for pairwise regression.

The obtained value of the determination coefficient for flows compared by the median suggests that about 54% of the cases of changes in the Hurst exponent lead to a change in the queue size within this model, which is much worse than models built on the basis of paired regression methods. At the same time, the amount of the fine and the expected amount of losses for isotonic regression is slightly less than the corresponding value for pairwise regression.

Support vector machine. Let's train the model based on SVR . The non-linear nature of the relationship between the Hurst exponent and the queue size indicates the need to choose a radial basis kernel for the SVR model . This model was trained using the scikit - learn package of the Python 3 programming language [9, 12]. On fig. 6 shows the graphs of the relationship between the queue size and the Hurst exponent corresponding to the trained SVR model for methods of converting the input and output stream of packets when the medians and the mathematical expectation are equal

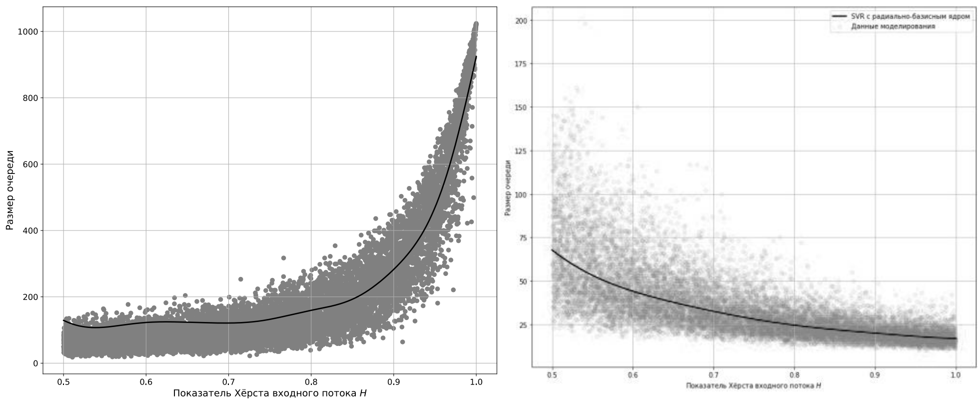

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Figure 6. Graph corresponding to the trained model by the support vector machine method

Table 7 shows the quality metrics of the obtained models using SVR for the methods of converting the input and output packet streams when the medians and the mathematical expectation are equal .

Table 7. Quality metrics of the support vector model

Quality Metrics	if the mathematical expectation is equal	if the medians are equal
Determination coefficient R2	0.901167	0.52283
RMSE Regression Root Mean Square Error	63.868307	13.95936
Mean absolute error MAE	52.506259	8.91937
Estimated amount of the fine	18.374489	5.59611
Estimated loss	15.43061	5.5961137

The obtained value of the coefficient of determination for flows matched by mathematical expectation is about 90%, which is slightly worse than that of the method using isotonic regression. However, the penalty for this method is less than in the case of isotonic regression.

The obtained value of the coefficient of determination for flows matched by median is about 52%, which is slightly worse than that of the method using isotonic regression and worse than that of models built on the basis of paired regression methods. The penalty for this method is greater than for isotonic regression.

Based on the nature of the relationship between the queue size QS and the Hurst exponent H , it is advisable when using SVR to evaluate not the value of QS , but the value of $\ln(QS+1)$, thus passing to the rectifying space.

Let's train the model based on SVR using the scikit-learn package of the Python 3 programming language [9, 12]. On fig. Figure 7 shows the dependency graphs of the queue size and the Hurst exponent corresponding to the trained support vector model with the transition to the rectifier space for the methods of transforming the input and output packet stream with the equality of medians and mathematical expectation.

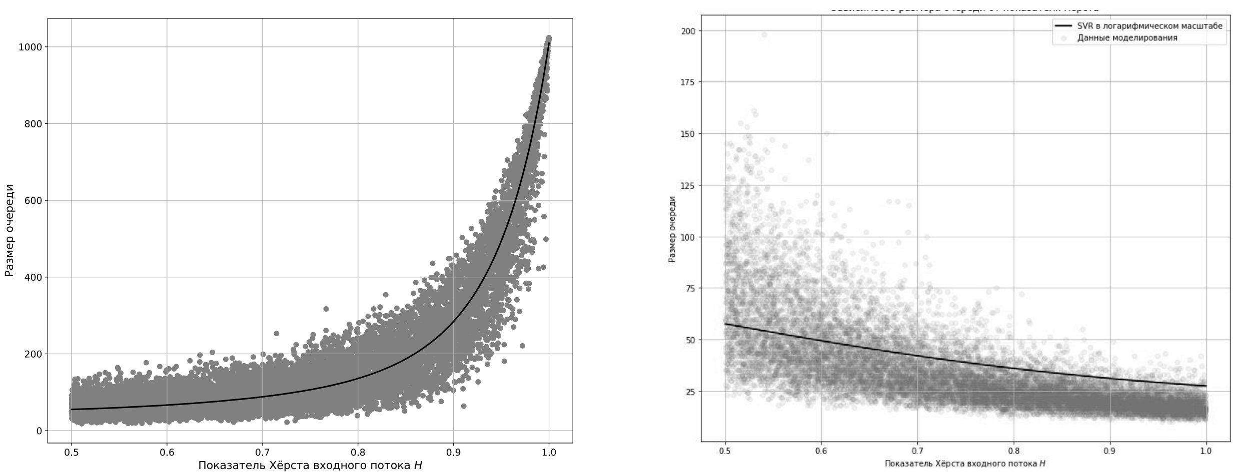

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Figure 7. Graph corresponding to the trained model by the support vector machine method in relation to the data set

Table 8 shows the quality metrics of the resulting model using SVR on a logarithmic scale for the methods of transforming the input and output packet streams with equal medians and mathematical expectation in relation to the original data.

Table 8. Quality metrics of the support vector machine model on a logarithmic scale

Quality Metrics	if the mathematical expectation is equal	if the medians are equal
Determination coefficient R2	0.923960	0.36051
RMS error RMSE regressions	56.021631	16.16018
Mean absolute error MAE	39.583393	12.87457
Estimated amount of the fine	21.724137	3.58006
Estimated loss	19.950616	3.580060

The obtained value of the coefficient of determination for the flows compared according to the mathematical expectation is about 92%, which practically coincides with the isotonic regression method. However, the value of the penalty in this case is less than for the SVR method , so the transition to the direct space did not lead to an improvement in the quality of training based on the values of the introduced quality metric, which is the penalty.

The obtained value of the coefficient of determination for flows matched by median is about 36%, which is much lower compared to the isotonic regression method and much worse than the models built on the basis of pair regression methods. However, the amount of the fine and the estimated amount of losses in this case, less than for the SVR method .

Comparative analysis of models. The results of the study are presented in a comparative table. 9 to evaluate and select the best method for predicting the queue size by the value of the Hurst exponent for the methods of converting the input and output packet streams when the medians and the mathematical expectation are equal .

Based on the data of the pivot table, it can be concluded that the best predictive ability based on the introduced quality metric for the method of converting the input and output packet streams when the mathematical expectation is equal is the model built using the support vector machine.

For the method of converting the input and output stream of packets with equal medians, the best results were obtained using power regression.

Within the framework of this study, we can conclude that the method of transformation using the median is better described by linear laws, and the method of transformation using the mathematical expectation by nonlinear laws.

Table 9. Comparative characteristics of regression methods at $0.5 < H < 1$

	Estimated amount of the fine		Estimated loss		Performance	
	mat. expected	median	mat. expected	median	mat. expected	median
Linear Regression	55.710275	4.976265	48.404104	4.976265	0.952730	0.995140
Hyperbolic regression 1	63.841249	4.649445	55.25577	4.649444	0.946039	0.995459
Hyperbolic regression 2	39.537133	6.141958	28.189645	6.141958	0.972471	0.994001
Power Regression	53.042530	5.418427	51.394345	5.418426	0.949810	0.994708
Exponential Regression	46.768626	5.523329	45.25324	5.5233289	0.95580	0.994606
Isotonic regression	21.269167	4.532848	19.75032	4.5328338	0.980712	0.995573
SVR	18.374489	5.596114	15.43061	5.5961137	0.984931	0.994535
SVR on a logarithmic scale	21.724137	3.580060	19.950616	3.580060	0.980516	0.996503

Conclusions. Thus, eight models have been studied that allow predicting the queue size when converting an input stream with a Pareto distribution to an output stream with an exponential distribution, depending on the Hurst exponent of the input stream, based on machine learning methods for converting the input and output stream of packets with equality medians and mathematical expectation .

Since the value of losses in the general case does not give any information about the efficiency of using the queue in the process of traffic conversion, a penalty is introduced to assess the quality of the resulting model, which takes into account not only the value of losses, but also the irrational use of buffer memory.

Each model was studied using the following quality metrics: coefficient of determination, regression mean square error, mean absolute error, penalty value, expected loss value.

The best in terms of the selected quality metrics for the methods of converting the input and output stream of packets when the mathematical expectation is equal are the models that use the methods of isotonic regression and support vectors.

For methods of transforming the input and output stream of packets with equal medians, linear models are the best.

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