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SOLUTION OF THE TRANSPORTATION PROBLEM EMPLOYING INTELLIGENT TECHNOLOGIES

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Abstract*—The article presents a new method of predicting the time of completion of a transport task. The method is based on the created mathematical model of the transport task process and on artificial intelligence methods. The choice of the optimal transportation route is based on the conditions of a specific task. A new method of choosing the optimal route is presented, taking into account the influence of such factors as weather conditions, day of the week, time of day, condition of the road surface, presence of residential complexes and other factors. The purpose of the study is to optimize the method of building a transport route using neural networks. The work presents the improvement of the general method of optimizing the transport process, the development of a neural network training method for predicting the time of the transport process, the development of a simulation mathematical model of the transport process and the determination of the model parameters and the effectiveness of the method verification. Research methods: methods of mathematical modeling, simulation modeling, Monte Carlo method, methods of artificial intelligence based on neural networks.*

Index Terms—Logistics; transport logistics; model; simulation model; simulation; optimization; artificial intelligence; neural network.

I. INTRODUCTION

The research highlights the importance of developing optimal routes for goods transportation in order to accurately determine the necessary number of vehicles, transportation time, and costs. This approach also helps to minimize downtime and maximize the efficient use of vehicles in the transportation process. By creating modern and effective transportation projects that meet current requirements, the smooth execution of assigned tasks can be ensured. Implementing such projects in practice enables the timely and uninterrupted delivery of products. The development of optimal cargo transportation routes forms the foundation for effective collaboration between suppliers and consumers. The application of neural networks in the field of transportation is extensive and encompasses various tasks such as traffic forecasting, route optimization, traffic flow management, and car number recognition. Accurately predicting traffic flow patterns is crucial for effective traffic management systems. A smart approach to traffic flow forecasting, based on real-time data, has proven to be successful in providing accurate traffic predictions [1]. Deep learning neural networks are employed to forecast traffic flow conditions using real-time traffic data. The proposed supervised model is trained using a deep learning algorithm that utilizes real traffic data collected at five-minute intervals [2]. Promising results have demonstrated the effectiveness of a hybrid multi-agent system based on neural networks in solving large-scale traffic signal management tasks in a distributed manner [3]. The integration of data-driven applications with transportation systems plays a pivotal role in the latest advancements in transportation applications [4]. In addressing the problem of optimizing delivery routes, we have chosen a method based on the utilization of neural networks. This method takes into consideration various factors such as seasonality, day of the week, time of day, as well as the personal characteristics of the driver and forwarder in order to accurately predict transportation time [5].

The developed model utilized the Monte Carlo method for its implementation. The simulation of the model was conducted within the Matlab environment [6]. This model not only serves as a training tool for neural networks but also enables the analysis and optimization of the operations of a transportation enterprise [7].

II. PROBLEM STATEMENT

The objective of this research is to optimize the creation of transportation routes using neural networks. In order to achieve this goal, the following problems need to be addressed.

- Development of a general method for estimating the time required for transportation tasks using a neural network.
- Designing an algorithm for preparing the neural network.
- Development of data sets for training the neural network, utilizing a simulation mathematical model of the transportation process.
- Conducting numerical experiments to optimize the structure of the neural network and evaluate the overall efficiency of the proposed method.

III. PROBLEM SOLUTION

In general, the method for optimizing delivery routes consists of two distinct stages. During the first stage, an artificial neural network is trained to predict the time required for a task, using real route data and, if necessary, the results of mathematical modeling. Separate networks are trained for each type of route. This training process is conducted prior to the initial use of the network and is periodically repeated whenever new operational data becomes available or significant changes occur in the routes (such as road repairs or the emergence of new residential complexes nearby). During the second stage, all trained networks that represent the possible routes are simulated using the expected task parameters. The outputs of the networks provide estimated task times for each route variant. The route with the shortest time is selected as the recommended route. The input metrics for the network utilize parameters that can be easily obtained from the computer systems of the enterprise or from open sources.

As an input for the network, various metrics can be used, which can be easily obtained from computer systems within an enterprise or from open sources. Some of these metrics include the date of the transport task, the minimum time for each possible route under ideal conditions ($T_{drv}^{\min}$), the standard time for the implementation of operations related to the receipt and delivery of goods by the forwarder ($T_{frv}^{\min}$), and the driver ID. The date of the transport task can be further converted into two metrics: the day since the beginning of the year and the day of the week. Additionally, the network can be supplemented with additional metrics such as environmental temperature, precipitation, and so on.

To effectively utilize a neural network for problem-solving, it is crucial to train the network using prepared examples. During the training process, the parameters of all neurons in the network, including weights and biases, are gradually refined. For a more comprehensive understanding of the network structure, reference can be made to works [8], [9]. To evaluate the performance of the network, the closeness parameter Δt is calculated.

$$\Delta t = \sqrt{\frac{\sum_{i=1}^{N}\left(t_{n_i} - t_{e_i}\right)^2}{N}}, \tag{1}$$

where N is volume of the dataset, t_e, t_n are expected execution time and its neuron network prediction, i is number of an example in the data set.

When training the network and optimizing its structure, it is essential to consider the possibility of overlearning. To address this, the method of three datasets is employed [8]. Each dataset consists of the aforementioned metrics and the expected time for the execution of a transport task for a specific type of road. The first set, known as the training set, is used for network training. The training process is periodically paused, and the trained network's performance is simulated using the training set. Subsequently, the network is simulated using both the first and the second sets, known as the control sets, and the resulting simulations yield the parameters Δt_T and Δt_C, respectively. Initially, the values of these parameters decrease simultaneously. However, at a certain point, the value of the parameter Δt for the control set (Δt_C) may start to deviate.

However, at a certain point, the value of the parameter Δt for the control set (Δt_C) starts to increase, while for the training set (Δt_T) it continues to decrease. In this scenario, it can be concluded that the network is experiencing overlearning, indicating that the network has become too complex. If the overlearning effect is not present, the training process can continue. The third set, also known as the test set, is only utilized once at the end of the network preparation. As mentioned earlier, a minimum of two data sets are required for training. These sets should comprehensively represent all anticipated task conditions and their combinations. If the enterprise database already contains such information, the aforementioned forecasting method can be implemented using it.

However, if this condition is not met, the data for network preparation can be obtained through mathematical modeling methods. In such cases, the initial use of the model is based on certain a priori hypotheses. As data on performed routines accumulates, the model must be identified accordingly. Data sets are crucial for training neural networks. The development of the acquisition method involves utilizing a simulation mathematical model of the transportation process. The time required for cargo delivery is calculated as the duration from the start of the forwarder's work on cargo acceptance and registration to the moment when the cargo is fully delivered to the recipient. A general description of the mathematical model reveals that the transportation process is modeled using the Monte-Carlo Method.

Task execution time is calculated as

$$\hat{T}_{run} = \hat{T}_{drv} + \hat{T}_{frv}, \tag{2}$$

where $\hat{*}$ is a sign of a random variable that has a given distribution law; $\hat{T}_{drv}, \hat{T}_{frv}$ is the random time of the route and time for forwarder tasks fulfillment.

The time of the route is defined as

$$\hat{T}_{drv} = T_{drv}^{\min} \cdot \hat{k}_{drv} \cdot \hat{k}_{drr}, \tag{3}$$

where $\hat{k}_{drv}$ is coefficient determined by objective route factors; $\hat{k}_{drr}$ is coefficient, which is determined by subjective factors.

The value ($\hat{k}_{drv}$) depends on the problems solved by this model and can be defined in different ways. If it is necessary to simulate the transportation of goods on a specific given route (routes), the coefficient ($\hat{k}_{drv}$) can be calculated as

$$\hat{k}_{drv} = \hat{k}_{drv}^{rd} \cdot \hat{k}_{drv}^{twyd} \cdot \hat{k}_{drv}^{rds}, \tag{4}$$

where $\hat{k}_{drv}^{rd}$ is coefficient, which is determined by the road on which the route passes (depends on speed limits, road surface quality, etc.); $\hat{k}_{drv}^{twyd}$ is coefficient, which is determined by the specific hour of the route start, week day, year day (jams, decreasing of the maximal allowed speed, etc.); $\hat{k}_{drv}^{rds}$ is coefficient, which is determined according to the characteristics of the route depending on the season (ice, wet surface, fallen leaves, etc.).

The value of the coefficient $\hat{k}_{drr}$ is calculated as

$$\hat{k}_{drr} = \hat{k}_{ds} \cdot \hat{k}_{dl}, \tag{5}$$

where $\hat{k}_{ds}$ is coefficient that depends on the driver's skills (driving style, ability to independently find a way out of a critical situation, find and solve technical problems with the car, etc.); $\hat{k}_{dl}$ is coefficient that depends on the mental state of the driver (problems in the family, at work, the influence of the freight forwarder on the driver during the trip, etc.).

The value of the parameter $\hat{T}_{frv}$ is calculated as:

$$\hat{T}_{frv} = T_{frv}^{\min} \cdot \hat{k}_{fs} \cdot \hat{k}_{frv}^{twyd} \cdot \hat{k}_{frv}^{ds} \cdot \hat{k}_{fl}, \tag{6}$$

where $\hat{k}_{fs}$ is coefficient that depends on the skills of the forwarder (experience and style of work, etc.); $\hat{k}_{frv}^{twyd}$ is coefficient that is depends on the features and conditions of work at a particular time, day of the week and day of the year (availability of personnel, equipment for loading and unloading, etc.); $\hat{k}_{frv}^{ds}$ is coefficient that depends on the characteristics of work on a particular object; $\hat{k}_{fl}$, is coefficient that depends on the psycho-emotional state of the freight forwarder (conflicts in the family or at work, relations with the driver, etc.) [7].

It is important to note that these coefficients, which account for their respective influences on delivery time, should generally be equal to or greater than one. To illustrate the proposed approach, a model for delivering cargo along four routes by a single driver-forwarder pair has been developed. Table I provides the characteristics of each route, including the transportation time in ideal conditions.

TABLE I. CHARACTERISTICS OF ROADS AND ROUTE TIME

Characteristics of the route	**Transportation time in ideal conditions $T_{\mathbf{drv}}^{min}$, h**
Short route with a broken roadway covering	1.5
Short route, through residential complexes	1.5
Average route, speed limit and summer cottages near the road	2
Long route, good roadway covering, no residential complexes and cottages	2.5

For all scenarios, the time required for the forwarder to perform operations such as acceptance, delivery, and cargo registration is assumed to be $T_{drv}^{\min} = 0.5$ h.

The start time for each route is modeled using a uniform distribution within the range of 0 to 24 h. The value of each coefficient is calculated using the formula

$$\hat{k}_l = 1 + \Delta\hat{k}_l, \tag{7}$$

where $\Delta\hat{k}_l$ is a random parameter that determines the difference of the *i*th coefficient of the model from 1. All distributions and their parameters defining values of $\Delta\hat{k}_l$ were obtained using the method of expert evaluations.

In the context of a pair of freight forwarders and drivers working on all 4 routes, it was assumed that both individuals have a phlegmatic temperament. Phlegmatic individuals are known for being calm, reserved, and sometimes slow, with a consistent mood. They rarely express their emotions outwardly and possess a strong, balanced, and inert type of nervous system. Considering the temperament of this pair, the mathematical expectation of the parameters that characterize their work skills, which depend on each other, is denoted as $M\left(\Delta\hat{k}_{ds}\right) = M\left(\Delta\hat{k}_{fs}\right) = 0,$ standard deviation $S\left(\Delta\hat{k}_{ds}\right) = S\left(\Delta\hat{k}_{fs}\right) = 0.08.$ Additionally, the coefficients that are influenced by psychological state, family problems and mood also change in relation to each other. Based on this, we take $M\left(\Delta\hat{k}_{dl}\right) = M\left(\Delta\hat{k}_{fl}\right) = 0,\ S\left(\Delta\hat{k}_{dl}\right) = S\left(\Delta\hat{k}_{fl}\right) = 0.03.$ In model we assumed that the coefficients $\Delta\hat{k}_{ds}$ and $\Delta\hat{k}_{dl}$ have a normal distribution [7].

The first route, which is relatively short, has a worn-out and damaged road surface. As a result, drivers are compelled to reduce their speed while driving on this route. Moreover, the presence of ice or rain further decreases the speed. During weekdays (Monday to Friday) during peak hours (08:00–09:00 and 18:00–20:00), traffic congestion is common on this route. The second route is also short and passes through residential areas. It is characterized by traffic jams on Monday to Thursday, as well as on Saturday during peak hours. However, between peak hours and during nighttime, the road is usually clear. Traffic jams are typically not observed on Fridays and Sundays. The third route is of medium length and includes country settlements. From the end of April (April 30 – the 120 th day of the year) to the end of September (September 30 – the 373 rd day), there is a high probability of encountering traffic congestion on Fridays and Sundays (5 and 7 days of the week) during the hours of 18:00–20:00. For the rest of the time, the road is generally free from congestion. The fourth route is long and does not pass through residential areas or country settlements. This route offers a clear road with good surface conditions. However, delays may occur in the event of accidents or the formation of ice on the road. It is assumed in the calculations that the random variables $\Delta\hat{k}_{drv}^{twyd}, \Delta\hat{k}_{drv}^{rds}$ have the exponential distribution [7].

The moment of entering the zone of possible jam is calculated as

$$t_b = t + \frac{T_{drv}^{\min}}{2}. \tag{8}$$

Rush hours occur in the morning from 08:00 to 09:00 and in the evening from 18:00 to 20:00. The traffic congestion is most intense during the evening rush hour, as it is when the majority of people are returning home after work. To accurately assess the situation on the roads, it is necessary to analyze each day of the week separately. During weekdays, the roads experience more congestion during rush hours compared to the rest of the day and night. On Friday evenings, the roads are congested due to the high number of people leaving the city for the countryside or other out-of-town destinations. On weekends, the roads within the city are relatively free, while those in rural areas become more congested. It is important to note that all four routes in this study have the same cars operating under the same technical conditions and with identical technical features. The cargo being transported is also consistent in terms of type and quantity. Therefore, the influence of these factors can be disregarded in this research. The primary objective of this study is to determine the most optimal route for transporting goods based on the time of day, day of the week, and day of the year. To achieve this, various transportation options have been defined and are presented in Table II.

Parameter $\Delta\hat{k}_{drv}^{twyd}$ characterizes the speed variations based on factors such as traffic congestion, road conditions, and speed limits in residential areas. It provides insights into the specific characteristics of a route at a given time, day of the week, and day of the year, such as rush hour during summer weekends.

When driving on icy roads, drivers are compelled to reduce their speed, particularly when executing maneuvers. The impact of ice is also influenced by the presence of traffic congestion, as driving in a jam significantly decreases the car's speed and minimizes the effect of ice. The accepted mathematical expectation values for parameter $\Delta\hat{k}_{drv}^{rds}$ simulation in case of ice are shown in Table III, and in the absence of ice this parameter is 0. This parameter has an exponential distribution.

TABLE II. TRANSPORTATION VARIANTS OF TIME INTERVALS FOR THE ROUTS

Winter	Summer
- weekdays, 8:00-9:00; - weekdays, 9:00-18:00; - weekdays, 18:00-20:00; - weekdays, 20:00-8:00; - Friday, 8:00-9:00; - Friday, 9:00-18:00; - Friday, 18:00-20:00; - Friday, 20:00-8:00; - Saturday, 8:00-9:00; - Saturday, 9:00-18:00; - Saturday, 18:00-20:00; - Saturday, 20:00-8:00; - Sunday, 8:00-9:00; - Sunday, 9:00-18:00; - Sunday, 18:00-20:00; - Sunday, 20:00-8:00;	- weekdays, 8:00-9:00; - weekdays, 9:00-18:00; - weekdays, 18:00-20:00; - weekdays, 20:00-8:00; - Friday, 8:00-9:00; - Friday, 9:00-18:00; - Friday, 18:00-20:00; - Friday, 20:00-8:00; - Saturday, 8:00-9:00; - Saturday, 9:00-18:00; - Saturday, 18:00-20:00; - Saturday, 20:00-8:00; - Sunday, 8:00-9:00; - Sunday, 9:00-18:00; - Sunday, 18:00-20:00; - Sunday, 20:00-8:00.

TABLE III. MATHEMATICAL EXPECTATION OF THE PARAMETER $\Delta\hat{k}_{drv}^{rds}$

8:00–9:00	**9:00–18:00**	**18:00–20:00**	**20:00–8:00**
Short broken road			
Monday-Friday (1-5 days a week)			
0.015	0.07	0.02	0.2
Saturday-Sunday (6.7 days a week)			
0.1	0.03	0.025	0.15
Short road through residential complexes			
Monday-Thursday, Saturday (1-4, 6 days a week)			
0.01	0.07	0.02	0.2
Friday, Sunday (5.7 days a week)			
0.01	0.03	0.02	0.15
Middle road, speed limits, cottages			
Monday-Friday (1-5 days a week)			
0.015	0.02	0.01	0.15
Saturday-Sunday (6.7 days a week)			
0.1	0.18	0.15	0.2
Long road, few cottages, no residential complexes			
Monday-Thursday, Saturday (1-4, 6 days a week)			
0.15	0.15	0.15	0.2
Friday, Sunday (5.7 days a week)			
0.15	0.15	0.1	0.2

For coefficient $\Delta\hat{k}_{frv}^{twyd}$ it was assumed that it is close to 0 during working hours (from 08:00 to 17:00 on weekdays) and increases at night and on weekends due to the delay that occurs in the absence of employees in the warehouse, increasing the waiting time, etc.

Thus the forwarder phlegmatic works unhurried, but does not create errors and delays. For weekends (6–7 days of the week) and during non-working hours (from 18:00 to 08:00) $M\left(\Delta\hat{k}_{frv}^{twyd}\right)=0.15$ and $S\left(\Delta\hat{k}_{frv}^{twyd}\right)=0.08,$ and for working days during working hours $M\left(\Delta\hat{k}_{frv}^{twyd}\right)=0.03$ and $S\left(\Delta\hat{k}_{frv}^{twyd}\right)=0.05.$ These parameters have the normal distribution law.

The impact of the freight forwarder's interaction with a specific enterprise is not considered in the equation $\hat{k}_{frv}^{ks}=k_{frv}^{ks}=1.$

In the simulation, holidays are not taken into account. A numerical experiment is conducted to optimize the structure of a neural network and analyze its results. The experiment aims to evaluate the minimum size of the train set. During the experiment, the control set is fully utilized and consists of 365 points, representing the number of days in a year. Another training set is obtained using different initial values of pseudo-random number generators, also containing 365 points. However, this set is used to create samples of varying sizes. The size of the sets gradually increases, for example, 2 delivers per month resulting in 24 points, 4 delivers leading to 48 points, and so on. Neural network training is performed with each set, and the quality of learning, denoted as $\Delta t_T,$ is assessed after each training epoch using Levenberg-Marquardt's algorithm [10]. The maximum number of epochs is set to 70. A three-layer network with 20 neurons in the first layer and 10 neurons in the second layer is trained. This network size is considered sufficiently large to avoid overlearning. To determine the network's performance at this stage, the difference between Δt_T and Δt_C for the sets when the overlearning effect becomes apparent is calculated as

$$\Delta t=\left(\Delta t_{\text{contr}}-\Delta t_{\text{tr}}\right)\cdot 60, (\text{min}),\cdot \qquad (9)$$

where Δt_{tr}, Δt_{contr} are error of time estimation (hour) obtained for train and control sets, at the moment of the overlearning effect manifestation.

For a route duration of 1.5 hours, the value of Δt is found to be less than 1 minute. Similar results were obtained for the fourth route as represented in Fig. 1.

To determine the optimal network structure, a numerical experiment was conducted using a neural network with two layers. The input layer consists of neurons with a hyperbolic tangential activation function, while the output layer has a neuron with a linear function. The number of neurons in the input layer was gradually increased from a minimal value until the overlearning effect was observed. A maximum of 12 neurons were selected for this experiment, while the output layer always had one neuron. Both the training and control sets had a maximum size of 365 points, and the training was conducted three times for each case. Training is conducted 3 times for each case. The smallest value Δt_T was chosen. The results of optimizing the neural network size for the first route are presented in Fig. 2. It can be observed that the neural network with 4 neurons yielded the best results. However, increasing the number of neurons led to a faster and stronger occurrence of the overlearning effect, resulting in a deterioration of the quality parameter obtained for the control set. Similar findings were obtained for the other routes. Attempts to increase the number of iterations did not lead to an improvement in the results. The simplicity of the network structure may be attributed, in part, to the assumption of a step-like nature in the variations of the parameters used in the model.

The optimal neural network for optimizing the transportation route is shown in Fig. 3.

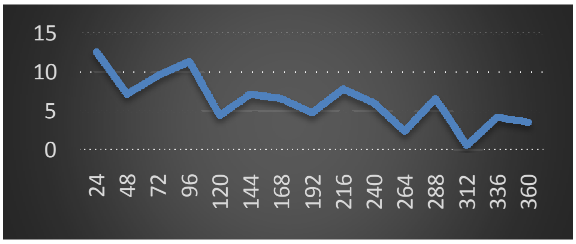

Fig. 1. Relation of value of Δt onto the number of transportations per year (the first route)

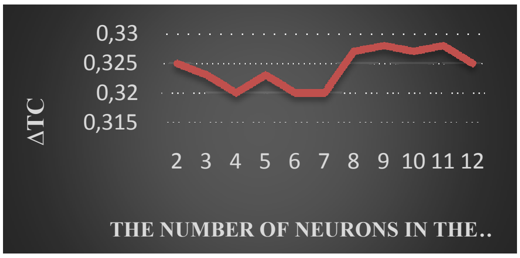

Fig. 2. Parameter Δt_C for the control sample of the first route

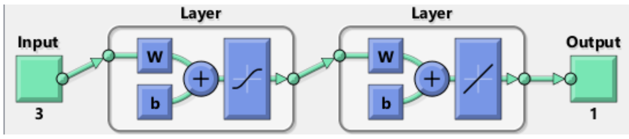

Fig. 3. The final two-layer neural network

After determining the optimal network structure, four distinct networks were trained to calculate the duration of a transportation task along four different routes.

IV. CONCLUSIONS

The method employed for route optimization involves estimating the time required to complete the task on various routes and selecting the route that offers the shortest duration. A neural network is utilized to estimate the required time for the task, which can be trained using either real data or simulation outcomes. This method takes into consideration several factors that influence the predicted time, including road conditions and characteristics, presence of settlements along the way, seasonal and weather conditions, as well as the driver's performance in different situations. A method has been devised to obtain the data necessary for training the neural network. This method relies on a simulation model of the process, enabling the simulation of transportation under different conditions. In order to estimate the task duration, a neural network with direct data transmission is employed, and the Levenberg-Marquardt method is selected as the training method. The training process involves three sets of data, where the first set is used for training and the quality of the network is evaluated based on the second set. The final assessment of the network's adequacy is determined by comparing its results with those of the third set.

Numerical experiments were carried out to determine the structure of the network. The network consisted of two layers, with a hyperbolic tangential function used as the activation function at the input layer and a linear function at the output layer. The training data set comprised more than 320 points, representing all seasons, start times of routes, and days of the week. The performance optimization method for the transportation process was examined. Various scenarios of goods transportation on different days of the week, times of day, and seasons were considered. A total of 32 different variants of cargo transportation were analyzed. The resulting method proved to be highly sensitive to external factors and offered the potential for optimizing the operations of transport companies.

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О. С. Якушенко, Д. О. Шевчук, І. А. Стенякін, А. О. Шишка Рішення транспортної проблеми з використанням інтелектуальних технологій
У статті представлено новий метод прогнозування часу виконання транспортного завдання. Метод базується на створеній математичній моделі процесу транспортного завдання та на методах штучного інтелекту. Вибір оптимального маршруту перевезення базується на умовах конкретного завдання. Представлено нову методику вибору оптимального маршруту з урахуванням впливу таких факторів, як погодні умови, день тижня, час доби, стан дорожнього покриття, наявність житлових комплексів та інші фактори. Метою дослідження є оптимізація методу побудови транспортного маршруту з використанням нейронних мереж. В роботі представлено удосконалення загального методу оптимізації транспортного процесу, розробка методу навчання нейронної мережі для прогнозування часу транспортного процесу, розробка імітаційної математичної моделі транспортного процесу та визначення параметрів моделі та ефективність перевірки методу. Методи дослідження: методи математичного моделювання, імітаційного моделювання, метод Монте-Карло, методи штучного інтелекту на основі нейронних мереж.
Ключові слова: логістика; транспортна логістика; модель; імітаційна модель; моделювання; оптимізація; штучний інтелект; нейронна мережа.

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