Запропоновано метод прогнозування очікуваного часу прибуття (ETA) вантажної відправки з урахуванням визначення тривалості руху вантажного поїзда дільницею для залізниць з системою руху поїздів без дотримання розкладу відправлення. Характерною особливістю залізниць з такою системою руху є складність передбачення стадій перевізного процесу, що вимагає розробки дієвих методів прогнозування. На основі кореляційного аналізу визначено залежність загальних макрохарактеристик поїздотоку та індивідуальних параметрів вантажного поїзда на його тривалість руху на дільниці. Запропоновано представити залежність прогнозної тривалості руху поїзда залізничною дільницею від наступних факторів: інтенсивність, щільність руху поїздопотоку на дільниці, частка пасажирських поїздів в межах загального поїздопотоку, довжина поїзда та його маса брутто.

На основі порівняльного аналізу за показниками точності та адекватності декількох методів регресії для прогнозування ETA вантажної відправки вибрано регресійну модель на основі штучної нейронної мережі – MLP. Для пошуку структури MLP застосовано метод перехресної перевірки, який передбачає оцінювання достовірності математичної моделі за критерієм точності – MAE та адекватності – F-тестом. Знайдено структуру MLP, яка складається з пятьох скритих шарів. Проведено прогнозування тривалості руху поїзда в парному напрямку руху на дільниці Основа-Люботин. Для даного прогнозу значення MAE скло 0,0845, що є достатньо високою точністю для задач такого типу та підтверджує ефективність застосування MLP для рішення задачі прогнозування ETA вантажної відправки.

Дані дослідження дозволяють в перспективі розробити автоматизовану систему прогнозування ETA вантажної відправки для залізничної системи зі змішаним рухом та відправленням вантажних поїздів без дотримання нормативного розкладу

Ключові слова: залізнична мережа, логістика, очікуваний час прибуття, машинне навчання, штучна нейронна мережа

FORECASTING THE ESTIMATED TIME OF ARRIVAL FOR A CARGO DISPATCH DELIVERED BY A FREIGHT TRAIN ALONG A RAILWAY SECTION

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1. Introduction

Under current economic conditions, railroad companies-carriers must solve complex tasks on adapting an operating model of railroad freight transportation to the requirements of consignees. The market of transport services increasingly faces the need for personalized mobility and logistics solutions that ensure lower risks in the transportation process. As practice shows, the technological process of cargo transportation by railroads has a lot of serious drawbacks, the main of which is the lack of predictability of the duration of operations execution in the process of transportation [1]. The high degree of uncertainty in the execution of a transportation process is particularly characteristic of the railroad system of Ukraine (AT "Ukrzaliznytsya"), which

belongs to railroads with a system of trains traffic not complying with a departure schedule. The lack of information about the traffic time of a cargo dispatch included in the composition of trains leads to a mismatch between the plan of transportations and actual operational conditions. There are failures to meet the terms of unloading wagons and to supply empty wagons for loading, which are due to errors in determining a timely arrival of these wagons. That increases the turnover time of freight cars, causing damages to cars' owners, and increases the costs of logistics for consignees due to larger reserves required to meet demand [2].

In this connection, there is a need at present to construct a system for transportation planning with a possibility to predict the stages within a transportation process, which would make it possible to track stages in the transportation

process of cargo dispatch. One of the directions to improve a system of planning is the implementation of a function of periodic notification about the status of a cargo dispatch in a train, which includes the estimated time of arrival at the destination (ETA). Given that the duration of train traffic is affected by different factors, information about which is limited in existing automated systems of transportation management, the possibility of applying any expert methods for the prediction of transportation process is greatly complicated. There emerges that task on implementing a method for predicting a cargo dispatch ETA, which could be easily automated and scaled for a problem of large dimensionality.

Thus, it is a relevant task to construct a method for predicting the expected time of arrival of a cargo shipment included in a mixed train in order to reduce the risks posed by train flows, meant to follow the plan of delivery but transported by a railroad system where the schedule of freight trains departure is not obeyed.

2. Literature review and problem statement

Under conditions for the digitalization of transportation processes there is a possibility to handle large amounts of data, which could be applied for constructing more efficient systems to plan transportation with the possibility to predict stages in a transportation process. One of the functions that underlie modern successful planning systems is the function for predicting the expected time of arrival (ETA) [3]. This has led to the emergence of research aimed at the development of methods to improve the accuracy of forecasting the expected time of arrival (ETA) in many transportation sectors.

Quite a lot of studies on the prediction of ETA are performed in the automotive and aviation industries [4–6]. To improve the information system that notifies passengers about the expected time of arrival of buses to stops along a route, artificial neural networks have been successfully applied [4]. Paper [5] reports a system of ETA forecasting, which is based on different regression models and recurrent neural network (RNN), the results from which are selected based on several indicators for accuracy. The results obtained confirm that the proposed system of forecasting generates more accurate predictions with a much smaller standard deviation than existing systems in EUROCONTROL. Authors of [6], in order to predict a 4D trajectory of aircraft routes at a terminal maneuvering area, have used the new hybrid model that processes data based on clustering and Multi-Cells Neural Network (MCNN) to predict ETA. Comparing the obtained results with the forecasts constructed using a Multiple Linear Regression (MLR) has proven the effectiveness of the proposed hybrid machine learning model. Based on the above findings, we can conclude that the application of machine learning methods to predict ETA is effective, however, the constructed prediction models cannot be applied to railroad transportation.

Very little attention has been paid to solving the task on predicting the execution time of cargo dispatches at the railroad network of Ukraine and similar networks [7–9]. Paper [7] used an artificial neural network (ANN) of the perceptron type in order to determine time points of arrival of freight trains at technical stations. The authors recommended to use such input parameters for the model as the time and date (day of week, month) of train departure from a nearby technical station, as well as the mass of the train and the type of a locomotive. Given the conditions of freight trains departures without complying with the schedule, the information about the departure time and the type of a locomotive can be obtained only under an operational mode. This affects the accuracy of forecasting, and prevents the application of the constructed model for tactical forecasting tasks. To determine the track of arrival, a mathematical model based on ANN has been applied [8]. A given mathematical model solves the problem on classification in terms of selecting a variant of freight train arrival under an operational mode and does not make it possible to predict the duration of the train arrival under conditions of change in the operational work of a railroad station. Resolving such a task is addressed in work [9], which proposed using a neural-network model to solve the task on choosing the track of train arrival at a shunting station, which makes it possible to take into consideration the forecast of train arrivals and the forecast of development of events at a receiving park. The authors stress the effectiveness of application of the artificial neural network for forecasting tasks, however, the study was not directly focus on forecasting a cargo dispatch ETA. The research that is maximally close to the set task on ETA forecasting is reported in [10]; ot addresses modelling of scenarios for moving cargoes along the Ukraine's railroad system supply chains. The authors constructed the algorithm that generates the scripts of delivery events in order to determine the control time points according to technological norms and practical experience. The disadvantage of this approach to predicting the duration of dispatch is the lack of a possibility to account for changes in the operating conditions at railroad stations and to take into consideration the characteristics of a transportation process on order to improve the forecasting accuracy. There is no information regarding the accuracy of the proposed method.

In the field of global railroad transport, of interest is research [11], which points to the importance of ETA forecasting in order to improve the efficiency of railroad transportation in the United States, and reduce costs. The functions of ETA notification make it possible to enhance the level of customer service and to further implement the automated planning of transportation. It has been proposed to use the algorithms of machine learning, built using the operational data on the railroad CSX Transportation, in order to construct a system of ETA notification in real time. The research proved the possibility to improve the accuracy of ETA forecasting when using a vector support regression model and the model of deep neural networks. The greatest accuracy was demonstrated by the ensemble method of machine learning, Random Forest. However, the disadvantage of this approach is the large amount of memory to store the derived models. In addition, there is a tendency of the algorithm to retrain under conditions of handling data with much noise, which is quite typical for a railroad transportation system where a departure schedule is not obeyed.

Paper [12] addresses the development of methods for forecasting trains traffic in time and space under an on-line operation mode. The constructed methods are proposed for a future consultative system of railroad transport dispatch. The author stresses the importance of using methods for predictive reasoning and machine learning. In article [13], similar tasks on predicting the arrival time of a train were solved in a different field – improvements to the operation of traffic signals near the highway-rail grade crossings

(HRGC). The results confirm the importance of application of prediction methods in the construction of industrial dispatching systems. Research [14] addresses the impact of crossings in the Melbourne metropolitan area, Australia, on the overload in a network of automobile flows. At the macro level of analysis of dependences, the relationship between the frequency of trains, the percent change in traffic time and the magnitude of a flow of cars has been established. The derived equation can predict changes in the time of cars flow traffic considering the number of railroad crossings and the frequency of trains.

This confirms the effectiveness of applying data characterizing a transportation process at the macro level. Thus, one of the directions to improve a method of ETA prediction for a railroad system where trains do not comply with a departure schedule is to take into consideration the macrocharacteristics of train flows traffic at a railroad station and to establish a dependence of the time required for a freight train to travel along a railroad section on operational conditions.

Scientific achievements are actively implemented into industries; thus, the project F-MAN that implied the construction of a wagon fleets management system for the railroad network in the European Union has successfully employed an ETA prediction module [15]. ETA calculation depends on notifications about the location of a wagon sent by its onboard devices and is based on the constructed cumulative probability distribution functions for the time that a wagon would require to reach its destination. The module for calculating ETA is based on innovative concepts and algorithms that are able to improve and adjust effectiveness during operation of the system (self-learning algorithms).

The association RailNetEurope (RNE), which brings together European operators of railroad infrastructure, actively introduces experimental projects aimed at implementing the functions of ETA prediction for trains in international traffic [16]. The examples of implementing the systems of ETA forecasting in the railroad network of the European Union confirmed the relevance of research in that article. However, the EU's railroads have a less degree of uncertainty in comparison with railroad systems similar to AT "Ukrzaliznytsya" where there is a system of freight trains traffic that does not comply with a schedule of departures. This requires the development of new forecasting methods, which would take into consideration the specificity of a transportation process, as well as limited information.

The task on improving the function of ETA prediction has received much attention in all transportation sectors. To improve the accuracy of ETA forecast, a variety of methods are used, which make it possible to account for factors inherent to the examined processes. However, there are almost no studies addressing the construction of methods for the prediction of the expected time of arrival of a cargo dispatch for the railroads with a system of trains traffic without complying with the timetable of departures, where the specificity of transportation organization dictates a considerable uncertainty of the transportation process. Lately, the methods of machine learning have been commonly used to forecast ETA. To improve the accuracy of forecasting under conditions of significant uncertainty, one should take into consideration information about the macrocharacteristics of train flows traffic at a railroad station. All this necessitates research in the respective field, which is the basis for the automation of a cargo dispatch ETA forecasting aimed to reduce the risks in a transportation process.

3. The aim and objectives of the study

The aim of this study is to construct a method for the prediction of the expected time of arrival of a cargo dispatch that would take into consideration determining the time that it would take for a freight train to travel a station. That could improve the quality of predicting a transportation process and, as a result, the planning efficiency for railroads with a system of freight trains traffic where the timetable of departures is not obeyed.

To achieve the set aim, the following tasks have been solved:

– to analyze the macrocharacteristics of train flows traffic along a railroad section and to establish dependences of time that it takes for a freight train to travel a section on operating conditions;

– to perform a comparative analysis of regression methods to predict the time that it would take for a freight train to travel a railroad section;

– to formalize a mathematical model to predict the time that it would take for a cargo dispatch in a mixed train to travel a section;

– to check the accuracy and adequacy of the constructed mathematical model for forecasting the time that it would take for a freight train to travel a section.

4. Features in the prediction of the expected time of arrival under conditions when trains depart without observing the schedule

Implementation of the function of ETA prediction (estimated time of arrival) at a railroad network requires taking into consideration the specificity of organization of the operating model of a railroad system. A given function must be implemented for each cargo dispatch – for a single car, a group of wagons, or a route, which corresponds to the number of cars within the complete train. Given that a network has a large number of dispatches, the task is to implement a method of forecasting, which could be easily automated and scaled for a problem of large dimensionality. The function of ETA prediction should provide a forecast from a station where a train is formed to the station of destination, which requires taking into consideration the topology of a railroad network and the technology of transportation. A technological process of the freight train traffic implies scheduled stops of the train at technical service stations (sorting or sectional stations) in order to change locomotives or locomotive crews and for technical and commercial inspections of cars to ensure traffic safety. For cargo dispatches that require the calculation of ETA, the direction and the category of a train by which they would be delivered are known in advance. This information is defined by a train formation plan that is compiled and approved for each freight year [17]. That makes it possible to define the route of a cargo dispatch in advance and specify those sections and stations for which it would be required to predict the duration of travel. Though the graph of a railroad system is highly branched and has loops, a route of the examined wagons can be mapped linearly, by listing consistently all the technical stations at which the train is to stop. Fig. 1 shows a schematic of the selected route for a cargo dispatch from a forming station to the station of destination, which for this cargo is a transfer to maritime transportation.
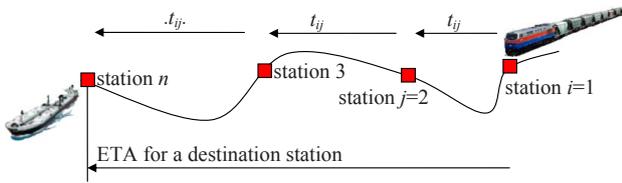
Fig. 1. Schematic of linear decomposition of a route in order to predict the expected time of arrival of a train at the destination station

The total route duration can be divided into two components – the time that trains spend at technical service stations and their traffic along railroad sections between them. Operating conditions and factors that affect the time that cars spend at stations and the time when they run differ and require separate study. It is proposed to investigate the factors and construct a mathematical model to predict the time that it would take for a freight train to travel a railroad section in order to calculate the expected time of arrival at a technical station along the route.

5. Original data and study into conditions of trains travelling along railroad sections

5. 1. Studying the macrocharacteristics of train flows traffic at a railroad section

As practice shows, the time that it takes for a train to travel a railroad section does not coincide with the planned duration, regulated by the timetable of trains. According to research [18, 19], the railroad systems, specifically AT "Ukrzaliznytsya", where the principle of traffic is based on dispatching freight trains "when ready" without observing the schedule of regulatory timetable of trains, are characterized by considerable uncertainty. Thus, there is a deviation of the actual time of traffic from the planned one that reaches 20–40 %. This can be explained by the inability to determine the local velocity of a train in line with a standard schedule, based on the traction calculation of traffic duration, which considers the motion of a single train along the section without accounting for the interdependence of trains in a flow [20]. However, even adding the reserves of time does not make it possible to compensate for the arising deviations from the planned traffic. This, to a greater extent, is due to the problems of mutual influence of trains when their flows increase at railroad sections. The network of AT "Ukrzaliznytsya" most commonly employs a system of interval traffic of trains along a section, called "auto-lock", which refers to systems based on the principle of delimitation of intervals between trains "fixed block signaling". Under such conditions, increasing the number of trains at a section increases the time that it takes for a train to travel a section due to the unsynchronized load on block sections. As a result, trains move to the yellow and red traffic light signals, which requires a decrease in speed. According to existing regulations, the train running to the yellow signal must move at lower speed than to green [18]. In addition, the time that it takes for freight trains to travel a railroad section depends on numerous factors.

These include setting a temporary traffic speed limit in order to provide for "windows" needed for repair and modernization of the infrastructure. As swell as the length and weight of trains, which affect the execution of operations of crossing and overtaking. The most important factor is the unaccounted-for processes of interdependence of trains when their number in a flow increase.

Given the difficulties related to predicting the time that it takes for freight trains to travel a section, in this study we propose exploring the macrocharacteristics of the process of train flows' interdependence at a railroad section. For solving the task on analyzing patterns in the organization of trains traffic, an important role belongs to the fundamental diagram of a traffic flow [21]. According to this approach, a train flow can be considered a continuous medium, and its macrocharacteristics can be described by the relation of a flow's speed and density and the intensity of train traffic, which is called the fundamental expression of the transport flow or a train flow

$$\lambda_{ij}(\rho_{ij}) = \rho_{ij} \cdot \nu(\rho_{ij}), \tag{1}$$

where $\lambda_{ij}(\rho_{ij})$ is the intensity of traffic, trains/hour; ρ_{ij} is the flow density, trains/km; $\nu(\rho_{ij})$ is the local speed of trains traffic, km/h. All three quantities in expression (1) are bound via a complicated relationship, and, therefore, research aimed at establishing these dependences could predict the time that it takes for a train to travel a section considering the individual parameters for a train and the macro-parameters for the traffic of a general train flow.

To search for an effective method for predicting the expected time of arrival of a freight train, in the current work we propose conducting an experimental study along the section Osnova-Lyubotyn (Ukraine). It is one of the most loaded railroad sections at Kharkiv railroad node of the regional branch "Southern Railroad" at AT "Ukrzaliznytsya". This section is a point along the routes of train flows with exported and transit cargoes, which are transported to/from the railroad stations at Odesa region. The scheme of section Osnova-Lyubotyn is shown in Fig. 2. The section Osnova-Lyubotyn has an operational length of 32.2 km, two tracks, powered by direct current.
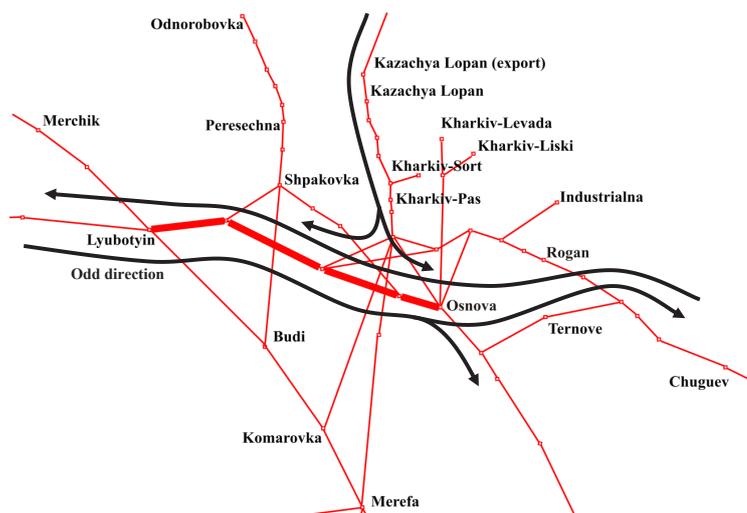

Fig. 2. Graph of the railroad junction at Kharkov node of the regional branch "Southern Railroad" at AT "Ukrzaliznytsya", which combines railroad sections along the direction Osnova-Lyubotyn

The experimental study is based on actual data on operation along the section Osnova-Lyubotyn at the railroad network AT "Ukrzaliznytsya" over a period of maximum volume of transportation in July–September, 2017. Fig. 3 shows the dependence of daily intensity, density, on time that it takes for a freight train to travel along the section Osnova-Lyubotyn in an even direction.
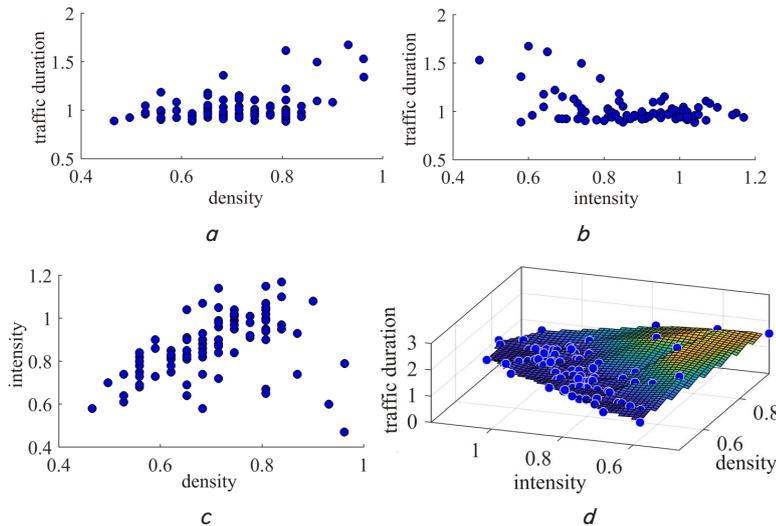

Fig. 3. Interdependence between the intensity, density, and duration of train flow traffic along the section Osnova-Lyubotyn in an even direction: *a* – dependence of daily average duration of train traffic in the density of trains at a section; *b* – dependence of daily local speed on intensity; *c* – dependence of intensity on density; *d* – 3D dependence of intensity, density, and traffic duration

Under conditions of the mixed model of a railroad section operation, the speed of a freight train, and, as a result, the duration of traffic, are affected by the proportion of passenger trains within an overall train flow. Fig. 4 shows the dynamics of change in the share of passenger traffic within an overall train flow over 24 hours, as well as average over 24 hours, for three months (July–September, 2017) along the section Osnova-Lyubotyn.
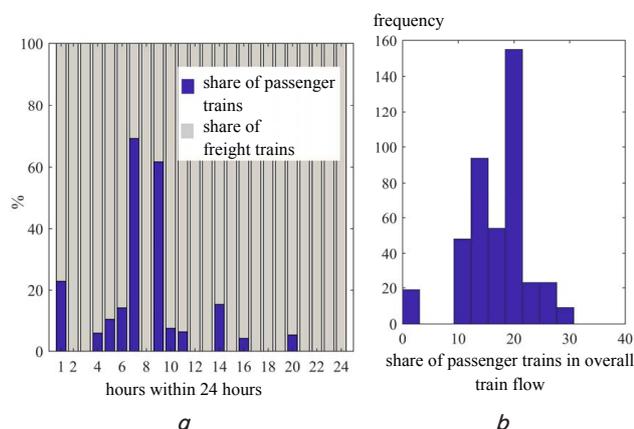

Fig. 4. Dependence of the number of passenger trains on the overall train flow at the section Osnova-Lyubotyn: *a* – dynamics of change in the share of passenger traffic within the overall train flow over 24 hours; *b* – dependence of frequency on the percent share of passenger traffic on average over 24 hours

Our analysis of the dynamics of change in the share of passenger traffic within the overall train flow within 24 hours testifies to the irregularity in the traffic of passenger trains. Fig. 4, *a* shows a significant increase in the share of passenger trains in the morning hours. This can be explained by the location of the section Osnova-Lyubotyn near a big passenger station, Kharkiv-Passenger. It should be noted that in the railroad systems of mixed traffic a priority is given to passenger trains that run in line with the regulatory timetable. The fact that passenger trains obey the schedule when freight trains depart without observing the schedule leads to the increased delays of the latter at a section. Given that the greatest frequency of passenger trains is on average 20 % within the overall train flow over 24 hours, one can make an assumption about the impact of a given factor on the traffic duration of a freight train.

5. 2. Analysis of operational parameters affecting the time that it takes for a freight train to travel along a railroad section

In addition to the general macrocharacteristics of a train flow, the duration of a train traffic is affected by its individual settings. One of the most essential parameters for a train, which depend on the constraints for infrastructure and define its operating conditions for passing along a section, is a conditional train length (the number of cars in a train) and its weight gross. To theoretically substantiate the accepted factors that affect the total time that it takes for a train to travel a section, in this work we proposed to investigate correlation connections among these factors for an effective parameter. For the sample size (N=425), we calculated correlation coefficients by Pearson. The determined correlations are significant at the level $p<0.05$. Fig. 5 shows the calculated correlation matrix by Pearson [22].

A data analysis reveals (Fig. 5) that all variables demonstrate positive correlation and are statistically significant. According to the assessment of the tightness of connections based on the "Chaddock table", relationships can be characterized as moderate and weak. This can be explained by the nonlinearity of dependences and the weakly-structured statistical data that can be evaluated rather poorly by the Pearson correlation. In addition, there are no any other readily available data that could make it possible to describe the process related to a freight train running along a section. Under such conditions, it is appropriate to construct a mathematical model for predicting the expected time of arrival of a freight train based on available information.

According to the above, in the current work it is proposed to represent the dependence of a predicted time that it takes for a train to travel along a section t_{ij} on the following factors: the intensity of traffic, the density a traffic train flow along a section, the share of passenger trains within the overall train flow, the conditional length of a train (the number of cars in a train) and its gross weight. According to the specified factors, the implicit mathematical model for predicting the time that it takes for a train to travel along a railroad section can be described by a dependence of the following form

$$t_{ij} = f\left(\lambda_{ij}, \rho_j, \phi_{ij}, m_{ij}, Q_{ij}\right), \tag{2}$$

where t_{ij} is the time that it takes for a train to travel along a railroad section, limited by technical sections, respectively, i and j, h; λ_{ij} is the intensity of trains traffic along a section, h^{-1}; ρ_{ij} is the density of train flow at a section, trains/km; ϕ_{ij} is the proportion of passenger trains within the overall train flow, %; m_{ij} is the conditional train length (the number of cars in a train), cond. wag.; Q_{ij} is the gross weight of a train, tons.

var1 – conditional train length, wagons
var2 – train gross weight, tons
var3 – train flow intensity, hours^{-1}
var4 – density, trains/km
var5 – share of percentage trains, %
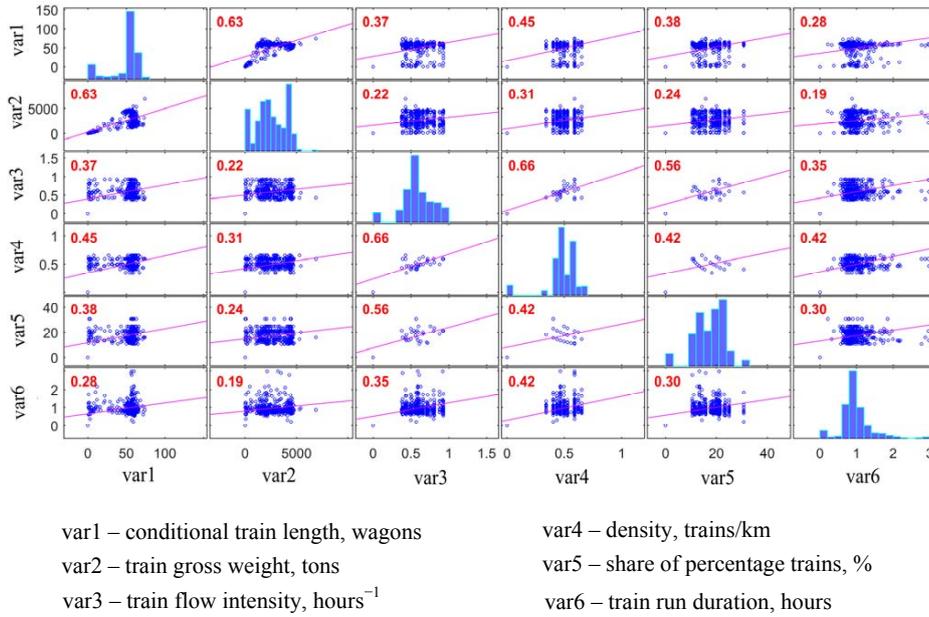var6 – train run duration, hours

Fig. 5. Correlation matrix by Pearson to analyze the influence of a train's individual parameters and the macrocharacteristics of a train flow on the time that it takes for a train to travel along the section Osnova-Lyubotyn

6. Search for a method to predict the time that it takes for a freight train to travel along a railroad section

At the first stage of the search for a method to predict the time that it takes for a freight train to travel along a railroad section, in this work we compared several methods of regression analysis to search for dependence (2). To assess quality of the built models, we used a mean absolute error (MAE), the value for coefficient of determination R^2 and a Fisher criterion [22]. Comparative analysis of regression methods to predict the time that it takes for a freight train to travel along a railroad section is given in Table 1.

Table 1

Comparative analysis of regression methods to predict the time that it takes for a freight train to travel along a railroad section

Method	Mean absolute error, MAE	Value for coefficient of determination R^2	F-test
Linear regression model	0.09559373	0.4648786	78.18613485
Regression model based on a neural network	0.09185588	0.596569902	131.4408072
Ridge regression model	0.09942611	0.443689963	75.91870887
Bayesian ridge regression model	0.09582799	0.464744424	75.91870887

Based on the specified indicators (Table 1), the worst among the selected methods has proven to be a multiple linear regression model [22], which confirms the above conclusions regarding dependence (1), which describes complex non-linear processes of section operation. The most appropriate method was a regression model based on the artificial neural network, a multi-layer perceptron, MLP. Given that the comparative analysis employed the neural network with standard default settings, in order to improve the accuracy of predictions it is appropriate to adjust the architecture of an artificial neural network so that it matches the examined problem, which we solve.

7. Design of the architecture of an artificial neural network to predict the time of freight train traffic

An artificial neural network (ANN) refers to the methods of machine learning (ML) [23]; it has parallel computing structures, consisting of nonlinear elements in terms of computing – neurons [24]. This makes it possible to establish non-linear dependences over a rather short time, which is ensured by its scalability. High adaptability and the uniformity of analysis and design of ANN are relevant under conditions of industrial application within the existing AT "Ukrzaliznytsya" network "Unified Automated Control System of Cargo Transportation". However, such shortcomings of ANN as a lack of transparency, complicated choice of architecture, and strict requirements to a training sample, require research into the feasibility of ANN application for a task on predicting the time that it takes for a freight train to travel along a section.

The current work employs the basic type of a neural network for the construction of a prognostic model – a multi-layer perceptron (MLP) that uses the method of learning with a trainer [25]. The principal diagram of the model for predicting the time that it takes for a freight train to travel along a section based on MLP is shown in Fig. 6.
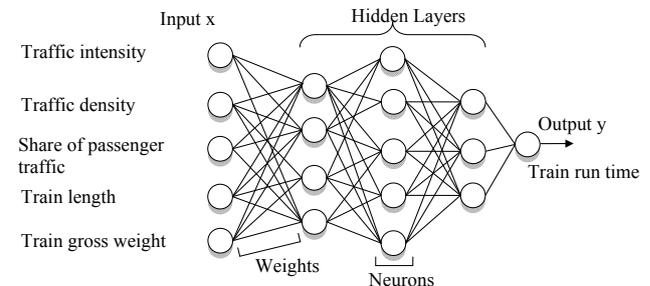

Fig. 6. Principal diagram of the model for predicting the time that it takes for a freight train to travel along a section based on MLP

To define the structure of MLP, we have applied a cross-validation method. A given method implies the reliability estimation of a mathematical model based on the criterion of accuracy – MAE, and adequacy – F-test. The sample of data $N=425$ was divided into a training set, 60 % of the total number, and a testing set. The testing set was randomly selected from the overall data set. MLP was adjusted using an error backpropagation algorithm. The method of learning with a trainer for a mathematical model of forecasting based on MLP is implemented cyclically through learning based on a training set, which is structure of the following form

$$<input\ X_1^\kappa,...,\ X_n^\kappa - output\ Y_1^\kappa>,$$

where κ is the number of the sample within a training sample.

After learning, there is a check of the model based on a testing set that has a similar structure.

7. 1. Results of predicting the time that it takes for a freight train to travel along a railroad section

We defined the structure and carried out checking processes for accuracy and adequacy of the predictive neural network automatically in the Python environment. The results of cross-validation based on operational data along the section Osnova-Lyubotyn in an even direction are shown in Fig. 7. While implementing the method of cross-validation the algorithm used 4,417 iterations. To test the adequacy of the neural network, the estimated values for Fisher statistics (F-test) were compared with the permissible ones (F-perm=2.42). The trend equation for MAE is negative; it has the following parameters $y=-1.18e-05x+0.326$, a trend equation for calculating the values for Fisher statistics takes the form $y=3.9e-0.5x+3.38$.
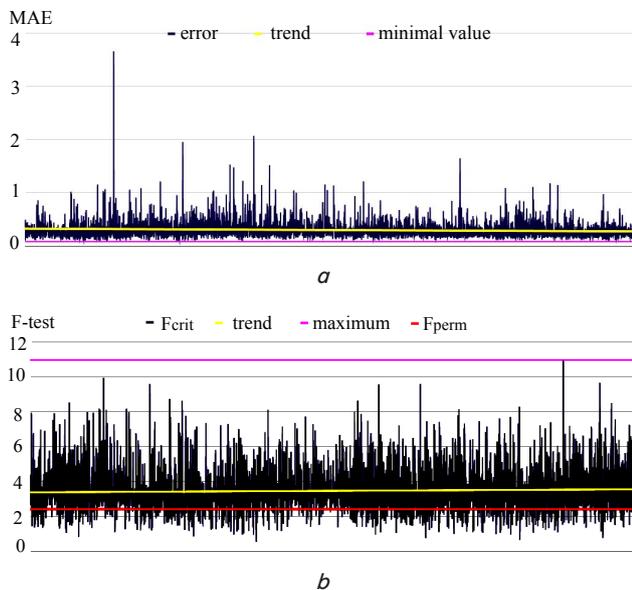

Fig. 7. Results from cross-validation: a — dependence of mean absolute error on the number of checking iterations; b — dependence of Fisher criteria on the number of checking iterations

Based on the method of cross-validation, we have defined the structure of MLP with six hidden layers of the network that have the following numbers of neurons: the first layer –

5 neurons, the second – 10, the third – 5, the fourth – 5, the fifth – 20, the sixth – 20. The neural network employed a sigmoid transfer function; the error backpropagation method was used as a configuration algorithm [24]. Based on the testing set, in the current work we predicted the time that it takes for a train to travel in an even direction along the section Osnova-Lyubotyn. For a given forecast, the value for MAE was 0.0845. Mean deviation does not exceed the error of 4.43 minutes, which is a rather high accuracy for problems of this type.
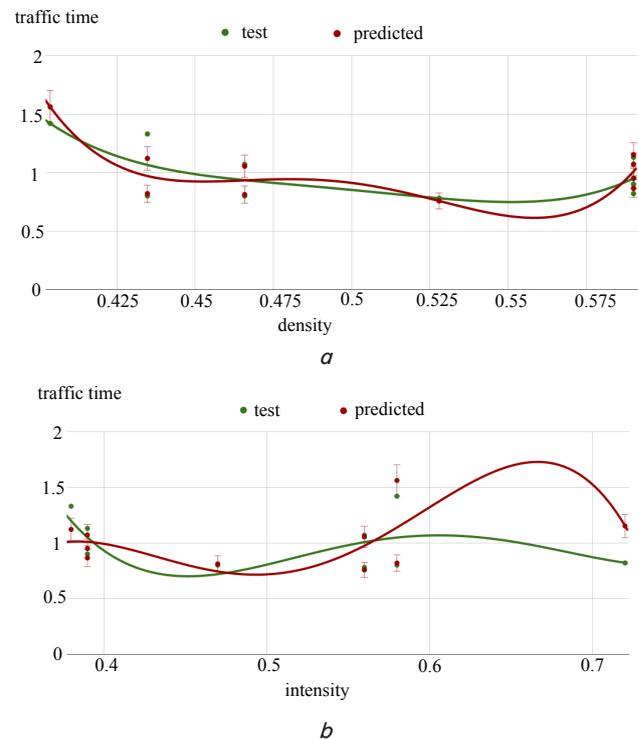

Fig. 8. Results of predicting the time that it takes for a freight train to travel along the section Osnova-Lyubotyn in an even direction based on MLP: a — dependences between the intensity and duration of traffic in the modelled and test values; b — dependences between the density and traffic duration in the modelled and test values

To confirm robustness of the obtained results, the proposed method of forecasting has been verified based on operational data at the section Osnova-Lyubotyn in a reverse (odd) direction. Based on analysis of practical operation of the examined section, one can argue that the traffic of trains along the section in the opposite direction does not fundamentally differ from even direction in terms of operational characteristics. That makes it possible, under conditions of limited amount of data, to "roughly" check the trained neural network. However, to improve the accuracy of ETA forecasting in the reverse direction, the further research implies constructing a separate neural network based on the proposed method. The results obtained have confirmed reliability of the built neural network and a possibility to apply it for predictions of this type.

8. Discussion of results of applying the constructed mathematical model for predicting the expected time of arrival

The obtained results from predicting ETA for a cargo dispatch delivered by a freight train along a railroad section

based on a multilayer neural network confirm the effectiveness of a given method. The disadvantage of classic methods of prediction, which were tested when solving the stated problem within the framework of the current research, is the need to adjust the model for each section. When applying the resulting neural network to predict ETA, a given drawback is eliminated. A neural-network structure can be easily trained and scaled for other railroad sections. The advantage of the proposed method is the possibility to use it under conditions of limited information about a transportation process, as well as accounting for changes in the operational conditions at a section. The combination of macrocharacteristics for train flows at a section and the individual parameters for a train has made it possible to improve the accuracy of forecasting the time that it takes for a freight train to travel along a railroad section compared when compared to the approach suggested in study [10].

The quality of forecasts derived from the trained MLP, verified for accuracy and adequacy, can be improved with the accumulation of the history of cargo dispatches delivered by mixed freight trains.

The constructed method of forecasting is the first stage in research aimed at designing a system of ETA forecasting for a cargo dispatch along the entire route. The research could prove useful when constructing an automated system for ETA forecasting for a railroad system with mixed traffic where the timetable of departures of freight trains is not obeyed. The proposed method of forecasting needs additional checking at other sections of a railroad network. In order to solve the set task comprehensively, the further research would tackle the construction of a mathematical model to predict the time that a cargo dispatch spends at technical sections.

9. Conclusions

1. We have examined operational conditions for a freight train that travels along a railroad section. It has been proposed, to improve the accuracy of forecasting the time that it takes for a train to travel along a section, to take into consideration, in addition to general macrocharacteristics of a train flow, the individual parameters for a freight train. To theoretically substantiate the accepted factors that affect the total duration of train run along a section, we performed correlation analysis. The calculated Pearson coefficients have positive correlation and are statistically significant. The relationships among the following factors have been established: the intensity of traffic, the density of train flow traffic along a section, the share of passenger trains within the overall train flow, the conditional length of a train and its gross weight, which all affect the time that it takes for a train to travel along a section.

2. To define a method for predicting the time that it takes for a freight train to travel along a railroad section, we compared several methods of regression analysis: a linear regression model, the regression model based on a neural network; ridge regression model; Bayesian ridge regression model. Based on such criteria of comparison as a mean absolute error (MAE), the value for coefficient of determination R^2, and F-criterion by Fisher, the most appropriate method chosen is the regression model based on an artificial neural network the type of a multi-layer perceptron, MLP, trained by a trainer.

3. To improve the accuracy of prediction, the current work has formalized a mathematical model based on the artificial neural network architecture design. To define the structure of MLP we applied a cross-validation method, which implies the assessment of reliability of a mathematical model based on the criterion of accuracy – MAE, and adequacy – F-test. The structure of the neural network has been established, which consists of five hidden layers. Our experimental study aimed at training a given neural network was based on historical data on trains traffic along the railroad section Osnova-Lyubotyn.

4. To verify the constructed mathematical model, we forecasted the time that it takes for a train to travel in an even direction along the section Osnova-Lyubotyn based on the testing set. For a given forecast, the value for MAE was 0.0845. Mean deviation does not exceed the error of 4.43 minutes, which is a rather high accuracy for problems of this type. The adequacy of the obtained prediction results has been tested by the Fisher criterion. The results derived have confirmed the reliability of the constructed neural network and a possibility to apply the constructed method for ETA prediction for a cargo dispatch delivered by a freight train along a railroad section.

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