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APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR SHORT-TERM PREDICTION OF CONTAINER TRAIN FLOWS IN DIRECTION OF CHINA – EUROPE VIA KAZAKHSTAN

Summary. International container transport plays an important role in the exchange of goods between China and Europe, and accordingly, the efficiency of the transportation increases with the organization of special container lines (land and sea). Owing to its geographical location, the territory of Kazakhstan has become one of the main international landlines for passage of container cargo in recent years. Priority is given to solution of such problems as reduction of cargo delivery time, simplification of customs operations, setting attractive and competitive tariffs, ensuring a high degree of cargo safety, development of transport infrastructure, assessment of the transit potential of railway network of the country, and predicting future cargo flows. This article shows the use of artificial neural networks (ANN) for predicting container train flows in the direction of China – Europe. For this purpose, a three-layer perceptron with a learning algorithm, based on the back-propagation of the error signal, was used. A concrete example shows how the ANN training process is conducted and how the adjustable parameters are selected.

1. INTRODUCTION

Kazakhstan is the largest landlocked country in the world. However, its geographical location on the path of a growing land trade flow between Europe and Asia provides a number of transport and logistics advantages. Developing the transit potential with a modern infrastructure, Kazakhstan is not afraid of having no access to the sea. The policy of the country is not to be late and seek to benefit from the development of China. This is the largest country in the world that has huge resources. Kazakhstan adheres to a modern philosophy of great benefits, rather than the concept of a great game. Therefore, it is working on the revival of the Great Silk Road [1].

Given these prospects for the rapid growth of cargo flows from China to Europe using a transit corridor passing through the territory of Kazakhstan, the tasks of assessing the potential of the railway network of the country and predicting the volumes of cargo transportation with the purpose of improving the transport infrastructure acquire special importance.

There are many methods for forecasting the volume of transportation of goods and passengers. For example, the article by Mrówczyńska et al [2] considered a comparison of the three methods of artificial intelligence: Winter's method for seasonal problems – a multiplicative version, harmonic analysis and harmonic analysis aided by the artificial immune system.

One of the most effective ways of forecasting traffic is the use of ANN. In particular, in the article by [3], the ANN was used for route and destination prediction in intelligent transport systems. In the article by Amita et al [4], ANN was used for forecasting of the bus travel time. In the article by Ma et al [5], ANN was used for speed prediction in large-scale transportation networks. Thus, it can be argued that ANN is successfully applied to solve various transport applications.

This article shows the application of ANN for short-term predictions of cargo flows in the China – Europe transit corridor. The practical importance of this study is to illustrate the methodology for adjusting the parameters of the neural network, as well as the use of real statistics on the flow of container trains in this direction of cargo transportation. The program was written in Matlab, and the prediction values of the cargo flow were obtained, which are well within their actual values.

2. CONTAINER TRANSPORTATION

At present, the countries of Southeast Asia have become the ultimate world factory for production of a wide range of products from various industries. This is owing to various economic reasons, the main of which is cheap labor. According to the information from the article [6], the majority of the world's ships work on providing shipping services through container routes between the ports of Europe and Asia (Singapore, Shanghai, Hong Kong and Shenzhen are leading by a large margin).

In fact, container shipping is the most effective way of transporting goods in Eurasian transit. The container ensures safety of cargo, standardization of sizes, reduction of costs for packaging of goods, facilitation of loading and unloading operations, and unification of transport documentation and forwarding operations [7]. Analysis of the cargo flow in EU – EAEU – China indicates transportation of goods by land in 20- and 40-foot containers as the most prospective [8].

Transportation through Kazakhstan has significantly led to fall in price in dollars in the last two years - the depreciation of the tenge helped: the competitiveness increased accordingly. At present, freight transportations on land routes on the China – Europe axis are economically less efficient than the sea routes, but the short distance routes, to Moscow, the Ural and Kazakhstan, have room for opportunities in cost reduction.

According to experts, container transportation of goods with a high cost per kilogram of weight can be promising, if goods are put in a container worth \$50-60 thousand [8].

To realize the potential of land routes, consistent efforts to develop container traffic and to eliminate bottlenecks in the infrastructure of Kazakhstan are needed.

The main goal for all interested parties is to solve internal problems of transport and logistics infrastructure, containerization of economies, and optimization of industry regulation, customs administration, etc. This will lead to intensive growth of interregional cargo transportation, increase regional cohesion, and improve the logistics position of regions that do not have access to the sea, as well as the whole of Central Asia [8, 9].

To realize the potential for container transit growth of 1.7 million TEU, the following initiatives are needed:

- strengthening of marketing and sales functions in China to establish direct relations with shippers, explaining the advantages of rail transport with a small difference in price and shorter delivery terms, compared with sea transport;
- ensuring a reduction in the cost of transportation for the shipper jointly with all countries participating in the transit corridor to be on a competitive level of sea transportation;
- increase the coefficient of return load to an average level for each direction through the intensification of efforts of selling to shippers in Europe;
- optimization of the cost of transportation through further introduction of a cost reduction program with higher objectives of saving and optimizing [10] the flow distribution, taking into account the use of electrified tracks and areas with the least load to reduce the requirements for enhancing the capacity;
- strengthening of positions in consolidation and deconsolidation of cargoes to increase control over flows;

- preservation of competitive delivery terms in 7-10 days when the volume of transit significantly increases to the target levels; and
- ensuring quality monitoring of the implementation of planned activities for the development of transit transport operations in conjunction with the involved structural units and subsidiaries [11].

Shippers are beginning to use land routes more actively, reacting to changes in the price environment.

Development of “Silk Road Economic Belt” (SREB) program will facilitate progress in the Kazakhstan economy and development of its “containerization”. Currently, the system of the JSC “Kazakhstan Temir Zholy – Cargo Transportation” (JSC “KTZh-CT”), container transportation accounts for only 2% of the cargo turnover and 6% of the value of sales. The unrealized potential of containerization is largely related to infrastructure constraints. Transport and logistics infrastructure has a small reserve of transit capacity. With the growth of cargo flows, its efficiency will be reduced, and this will affect the preferences of shippers.

To solve this problem, it is necessary to create modern container terminals on the territory of Kazakhstan. At the same time, it is necessary to build and reconstruct railways (and to a lesser extent road networks), which will enable the increase of the total transit capacity of Kazakhstan by 3-5 times, depending on the directions. According to expert assessments, the construction of 3-4 basic infrastructure facilities (modern container hubs) will allow Kazakhstan to increase transit capacity by more than 2 times and reduce the cost of internal logistics by 40% [8].

3. EXPRESS CONTAINER TRAIN

In the sphere of worldwide cargo transportation, container transportation accounts for more than 55% of the total volume of cargo transportation, and according to experts, in the near future, this figure will increase up to 70%. Statistics confirm that the most progressive technological form of organization of container transportation is container trains [12].

Express container trains follow to the destination with minimum stops and without remarshalling. Transportation by express container trains allows to reduce the time of delivery of cargoes and to eliminate the marshalling and division of trains at marshalling yards, thereby ensuring the speed and safety of delivery of the goods to the buyer [13].

The organization of express container train service through the territory of the Republic of Kazakhstan is a new type of container transportation for Kazakhstan, which is effective and promising. Its advantages over transportation by other means of transport are obvious. These are, first of all, more attractive and competitive tariffs, a significant reduction of transportation time, implementation of express delivery to the destination, simplified procedures of border crossing and customs clearance, and a high degree of security for the transport of goods. The conclusion is obvious: organization and development of container transportation in the country is one of the most pressing issues regarding improvement of the transportation system for the near future [12, 13].

For Kazakhstan, development of container transportation and its compliance with international standards could cause the growth of investments in the railway industry, more efficient distribution of financial and material resources of the transport industry, accelerated establishment, and technical development of transport lines, including those entering international corridors. Container transportation could attract large transit cargo flows to the country and intensify competition between railcar and container transportation, which will maximize the transit transport potential and increase the competitiveness of the transport industry [12].

In this respect, according to experts from the source [14], the future lies in the development of technology of scheduled traffic. This will enable real competition for road transport, especially on lengthy routes. Methodological studies dedicated to the development of intermodal and multimodal transport are very significant [20].

4. PREDICTING CONTAINER FLOWS

Prediction of container flows is the most important tool for developing effective management decisions regarding the selection of an optimal development strategy; determining the required technical equipment; planning the requirement of material, labor, and financial resources; conducting activities to attract customers, etc. Thus, a solution for the developing a system for demand forecasting of cargo transportation in modern conditions has become particularly relevant. In this regard, it is necessary to develop a modern methodology for demand forecasting of cargo traffic using the latest mathematical methods and models and their adaptation to the specifics of the transport services market. In addition, the need to use developments in forecasting in actual practice imposes certain requirements on the selection of a mathematical tool: it must combine the merits of other methods and at the same time be distinguished by simplicity and clarity in application and be closely based on the information available to the railway transport.

Short-term prediction is an integral part of the strategy “Kazakhstan-2050”, which is currently being implemented, on developing transit potential and increasing transit transport operations through Kazakhstan by twofold by 2020, and by tenfold by 2050 [15]. The objective of the project is to increase transit cargo turnover by attracting containerized cargoes between China, Europe, the Middle East and Russia as a segment with the highest growth potential. For an unbiased assessment of changes in the dynamics of container flows, as well as prospects for the development of the network, it is necessary to predict a number of criteria indicators of transit potential, namely, the volume of container trains passing through the railway network of the Republic of Kazakhstan.

5. PREDICTION USING ARTIFICIAL NEURAL NETWORKS

At present, ANN is widely used in practice for solving various classes of tasks: prediction and approximation, pattern recognition and classification, decision making and control, etc. When modeling time series forecasting processes, multilayer perceptrons consisting of one layer of input neurons (sensory elements), one or several hidden layers of computational neurons (associative elements), and one layer of output neurons (responsive elements) are often used.

Furthermore, we will analyse a three-layer perceptron, where the hidden neurons form only one layer and assume that all neurons are characterized by the sigmoid activation function [17]. The input signals are fed to the sensor nodes, and these signals propagate in the forward direction from layer to layer, i.e., consistently pass through the input, hidden, and output layers of the network. We will analyse a fully connected perceptron, in which each neuron of the input layer is connected to each neuron of the hidden layer, and each neuron of the hidden layer is connected to each neuron of the output layer. Neurons of the input layer do not transform the data; in this layer, the input signal simply branches off and transfers to the neurons of the next layer.

At the output of the network, we receive the response of the system to the input vector of the signals fed to the sensor nodes of the network. The output signals of the neural network are compared with the desired response of the system and an error signal is generated. This signal propagates in the opposite direction: it passes through the output, hidden, and input layers and is used to learn the network to maximize the closeness (in statistical sense) of the response of the neural network and the desired response of the system. Such an error back-propagation algorithm [16] is widely used in neural networks. The training process can be repeated many times using different input signal vectors and corresponding actual responses of the system. The presence of hidden neurons facilitates the training process, allowing us to identify important properties and patterns in the input signals that are necessary for the formation of an output signal vector possessing the desired properties.

In the Matlab environment [18, 19], a program was written to predict the values of the weekly flow of container trains in the China – Europe direction (Tab. 1). The program enters the original data from an Excel file, in which the data are presented in two columns. Each row of the table consists of a date corresponding to the Sunday of each week, and the total number of trains per week. The Excel file used in the program contains data on the number of container trains for 69 weeks: for the period from

January 8, 2017 to April 29, 2018 (Fig. 1). Note that a significant decrease in the flow of cargo in February 2017 and 2018 is owing to the celebration of the New Year according to the Eastern calendar in China.

Table 1

Weekly number of container trains in the direction of China – Europe through Kazakhstan
for the period from 08.01.2017 to 29.04.2018

week	number of trains	Week	number of trains	week	number of trains	week	number of trains
1	21	19	22	37	35	55	23
2	20	20	21	38	32	56	21
3	19	21	20	39	32	57	26
4	18	22	22	40	29	58	31
5	3	23	23	41	28	59	28
6	6	24	24	42	29	60	1
7	14	25	25	43	29	61	11
8	17	26	22	44	35	62	31
9	23	27	28	45	37	63	28
10	26	28	24	46	36	64	29
11	30	29	28	47	34	65	29
12	27	30	26	48	38	66	31
13	27	31	24	49	29	67	30
14	23	32	25	50	28	68	28
15	27	33	28	51	28	69	31
16	25	34	26	52	27		
17	24	35	31	53	21		
18	18	36	31	54	21		

As a training interval for the network, a period was set from January 8, 2017, to April 1, 2018 (i.e., $T = 65$ values of the cargo flow are used for training). The beginning of the prediction interval was set from April 8, 2018 (the program gives forecasted values of the cargo flow for 4 weeks, starting from this date, i.e., for April 8, 15, 22 and 29, 2018). Note that the beginning of the prediction interval lies outside the training interval, i.e., in the training process, the program does not have information about the values of the flow in the prediction interval. In the program, training of the neural network is conducted according to the algorithm for back-propagation of the error signal [16].

To describe the structure of the neural network used, we must specify: n_1 , the number of neurons in the input layer; n_2 , the number of neurons in the hidden layer; and n_3 , the number of neurons in the output layer. In this example, the following values were used: $n_1 = 8$, $n_2 = 8$, and $n_3 = 4$, i.e., we predict 4 values of the cargo flow, using the previous 8 values (also we form 8 additional (hidden) values).

The training process consists of two nested loops. The training epochs E are produced in the outer loop, each epoch consists of L inner loops. Each internal training loop is as follows. Starting from the beginning of the training interval, a template consisting of $n_1 + n_3$ sequential data is selected. Based on the n_1 flow values, a forecast is made for the following n_3 weeks. Then, the deviations of the predicted values from their actual values are calculated, and taking into account this error, the weight matrices and bias vectors used in the back propagation algorithm are corrected. Then, the template of

$n_1 + n_3$ data is shifted one week ahead and the next internal training loop begins, etc. until the end of the training period. In the next epoch, training begins again from the start of the training period. In this example, we repeat $E = 10\,000$ training epochs.

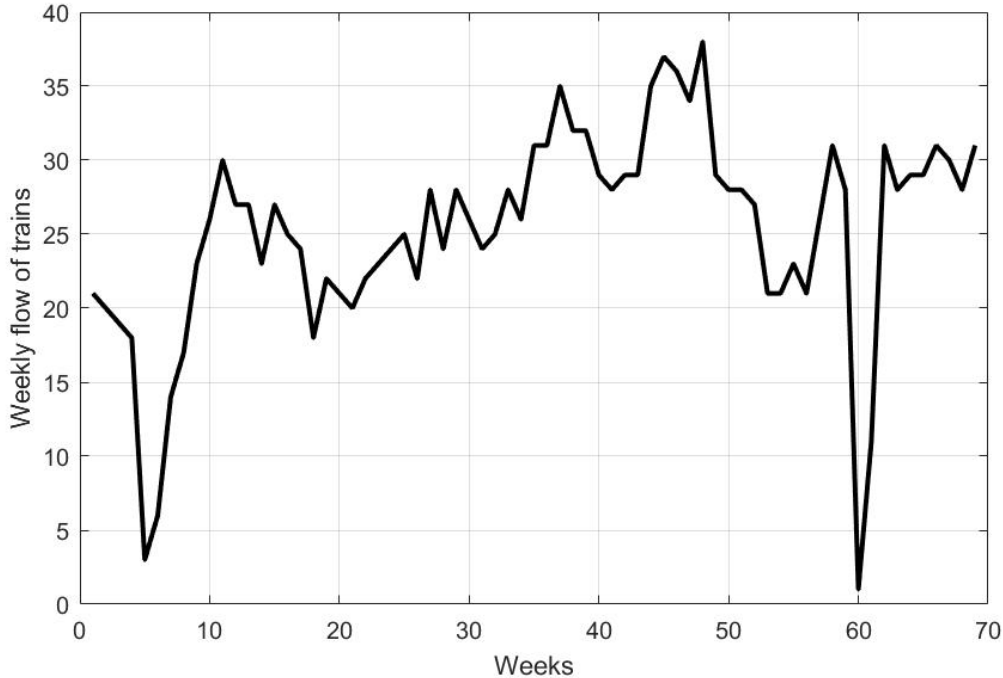


Fig. 1. Weekly number of container trains in the China – Europe direction from 08.01.2017 to 29.04.2018

To show how the neural network training process is going, a trial prediction is performed at the end of each epoch, and ε , the mean absolute percentage error (MAPE) of prediction, is calculated according to the following formula:

$$\varepsilon = 100 \cdot \left(\frac{1}{n_3} \sum_{i=1}^{n_3} \frac{|P_i - F_i|}{F_i} \right), \quad (1)$$

where P_i are predicted values and F_i are actual values of the cargo flow ($i = \overline{1, n_3}$).

The program written in Matlab plots a graph of the MAPE $\varepsilon(k)$, depending on the epoch number k . According to the received graph, it is possible to adjust network learning parameters.

The neural network learning algorithm implemented in the program is characterized by two selectable parameters: the learning rate η and the momentum constant α , which can take values ranging from 0 to 1. Below, using the neural network to predict the cargo flow values, we show how the network is configured.

The best values of the parameters η and α are selected based on the multi-criteria decision making problem. The following set of indicators can serve as criteria for assessing the acceptability of parameters:

- 1) Property of monotony of the learning process (it is desirable that the prediction error decreases monotonically as the number of the training epoch increases).
- 2) Stability of the learning process (prediction error should converge to a certain limiting value, i.e., when the values of the epoch number are sufficiently large, we should receive almost the same error values); at that, the learning process will be represented by an almost horizontal line for large values of the epoch number.
- 3) Minimizing the number of training epochs required to achieve the prediction error limiting value with some specified accuracy.
- 4) Minimize the limiting value of the prediction error.

The monotony and stability of the training process allow the reduction of the number of epochs necessary for training the neural network. Training can be interrupted ahead of time as soon as the prediction error becomes sufficiently close to the limiting value, i.e. when the learning process comes to an almost horizontal area.

Numerical experiments were carried out on the computer to study the dependence of the prediction accuracy on the parameters of the neural network: on the learning rate η and the momentum constant α . For different pairs of values (η, α) , where η varies from 0.1 to 1.0 in increments of 0.1 and α varies from 0.0 to 1.0 in increments of 0.1, prediction was performed using the constructed neural network and the corresponding values of the MAPE (Eq. (1)) were determined. The results of the numerical calculations are presented in Tab. 2.

Table 2
The MAPE ε for different values of the learning rate η and the momentum constant α

		α										
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
η	0.1	3.50	3.42	3.37	3.32	3.29	3.27	3.26	3.25	3.26	3.27	3.28
	0.2	3.26	3.29	3.33	3.37	3.43	3.48	3.54	3.64	3.81	3.99	4.15
	0.3	3.43	3.51	3.59	3.75	3.97	4.17	4.34	4.46	8.99	9.18	9.36
	0.4	3.64	3.79	4.03	4.22	4.36	9.18	9.44	9.70	9.96	10.24	10.54
	0.5	3.84	4.04	4.20	9.33	9.66	10.01	10.38	10.78	11.18	11.60	12.04
	0.6	4.03	4.17	9.63	10.07	10.54	11.04	11.55	12.09	12.66	13.28	13.95
	0.7	4.23	9.82	10.38	10.97	11.59	12.23	12.93	13.68	14.47	15.25	15.95
	0.8	4.45	10.55	11.26	11.99	12.78	13.63	14.52	15.37	16.08	16.60	16.83
	0.9	10.55	11.38	12.23	13.15	14.13	15.08	15.87	16.41	7.27	7.60	7.94
	1.0	11.31	12.27	13.30	14.37	15.33	16.02	7.19	7.56	7.95	8.32	8.67

As can be seen from the table above, the lowest value $\varepsilon_* = 3.25\%$ is obtained with the learning rate $\eta = 0.1$ and the momentum constant $\alpha = 0.7$. Fig. 2 shows the learning process corresponding to these values of network parameters. The learning process satisfies the conditions of monotony and stability. With the increase in the number of the training epoch k , the MAPE $\varepsilon(k)$ gradually decreases and converges to the limiting value ε_* . For comparison, Fig. 3 shows the learning process with $\eta = 0.7$ and $\alpha = 0.3$. As can be seen from the figure, with these parameter values, the learning process of the network does not have the properties of monotony and stability.

While operating the program, the following information is displayed in the Matlab command window (Fig. 4): initial data and training intervals, initial prediction date, architecture of the used neural network (the number of neurons in the input, hidden and output layers: n_1 , n_2 and n_3), the values of the learning parameters (learning rate η and momentum constant α), number of training epochs (E) and the time spent for training, as well as the results of prediction (predicted and actual values of the cargo flow: P_i and F_i , ($i = \overline{1, n_3}$)), and MAPE ε (%).

Since the cargo flow, measured by the number of container trains, can take only integer values, the program rounds the predicted flow to integers. As can be seen from the results of the program (Fig. 4), the predicted values of the cargo flow for 4 weeks ahead are well within their actual values (the MAPE $\varepsilon = 2.45\%$). In the case where the prediction interval is outside the range of the initial data, the program issues prediction values of the cargo flow, but does not print their actual values and does not calculate the MAPE ε , because in this case there is no possibility of comparing the predicted and actual values.

In addition to selecting learning parameters, another important issue is determining the number of training epochs. Setting too many epochs E will not only require a large amount of computer time for

training process, but it can also lead to accumulation of calculation errors. For the values of the training epoch $k > 10\,000$, there is no significant improvement in the prediction; furthermore, the MAPE $\varepsilon(k)$ begins to grow for sufficiently large values of k . So, in the provided example, the selection of the number of training epochs $E = 10\,000$ can be considered quite acceptable.

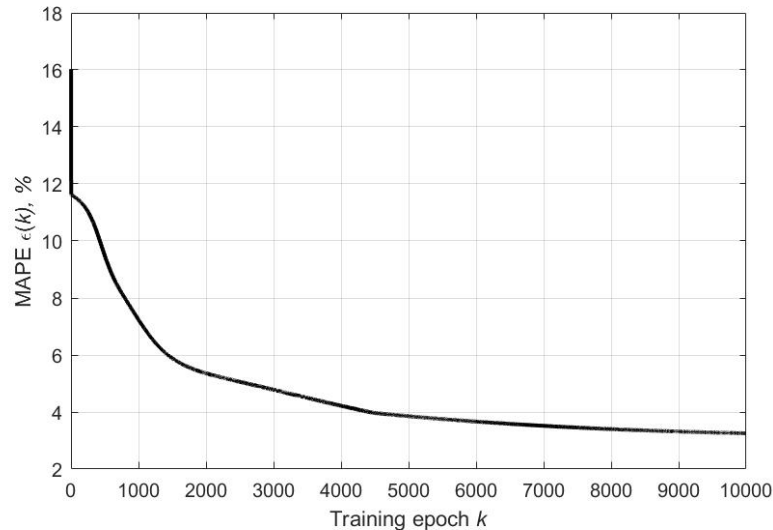


Fig. 2. Learning process with $\eta = 0.1$ and $\alpha = 0.7$

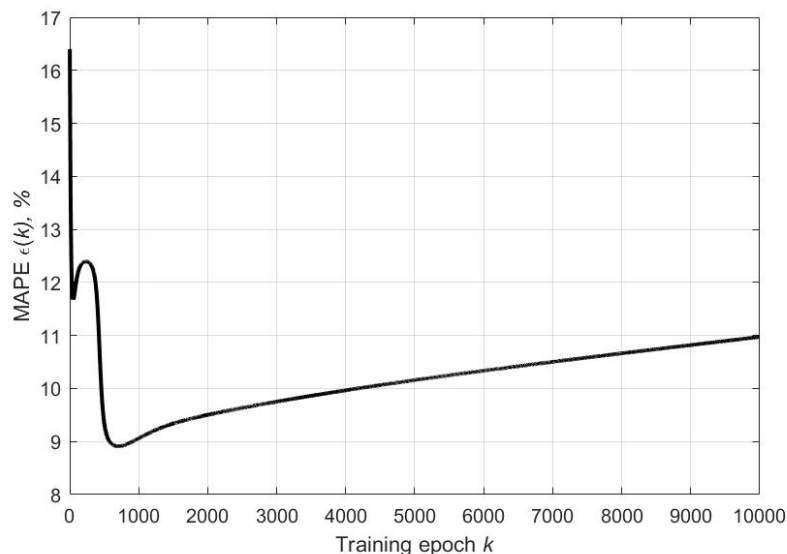


Fig. 3. Learning process with $\eta = 0.7$ and $\alpha = 0.3$

Thus, for the present task of predicting the container cargo flows, the following network structure was chosen: number of neurons in the input, hidden and output layers were taken equal to $n_1 = 8$, $n_2 = 8$ and $n_3 = 4$ respectively; number of training epochs $E = 10\,000$; learning rate $\eta = 0.1$; and momentum constant $\alpha = 0.7$. The constructed neural network provides a fairly accurate prediction of the cargo flow values with the MAPE $\varepsilon = 2.45\%$.

6. CONCLUSION

The current stage of development of Kazakhstan's market economy has not yet led to sufficient inter-sectoral coordination and forecasting of traffic flows on the basis of marketing, as well as to the

effective identification of necessary technical equipment, and planning of material, labor and financial resources. Effective functioning of the transport system, meeting the requirements of the volume of traffic flows, depends largely on a reliable forecast of the needs for its development, recruitment and rational sequence of activities that allow them to meet.

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Prediction of China - Europe container flow

Start date of the initial data interval: '08.01.2017'

End date of the initial data interval: '29.04.2018'

Given start date of the training interval: 08.01.2017

Given end date of the training interval: 01.04.2018

Given start date of the prediction interval: 08.04.2018

Number of neurons in the input layer (input)= 8
Number of neurons in the hidden layer (hidden)= 8
Number of neurons in the output layer (output)= 4
Learning rate (eta) = 0.1
Momentum constant (alpha) = 0.7
Number of training epochs (E) = 10000

Start of training process
End of training process
Time spent for training = 64.058 sec.

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                PREDICTION RESULTS
    Date          Prediction    Fact
08-Apr-2018         31          31
15-Apr-2018         29          30
22-Apr-2018         28          28
29-Apr-2018         29          31
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MAPE = 3.25%

After rounding the prediction to integer values
MAPE= 2.45%

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Fig. 4. Calculation results in the Matlab command window

Forecasting the increase in traffic volumes, against the backdrop of the backward development of the transport sector and the disproportions in its development, predetermine a threat to the economic growth and competitiveness of the transport system and the development of the country's economy as a whole, opportunities to realize the transit potential of the country.

An artificial neural network consisting of three layers (a three-layer perceptron) was used in this article to solve the problem of predicting the flow of container trains. It should be noted that the

accuracy of the prediction depends on the successful selection of the network architecture (number of hidden layers, number of neurons in each layer), as well as the network learning method. Here we applied a back-propagation learning algorithm, which allows us to reuse the initial data on the time series in a loop, each time changing the weight matrices and bias vectors, used to compute the predicted values.

In the article, special attention is paid to the choice of custom parameters used in the learning algorithm. A specific example shows how to select such parameters as the learning rate η and momentum constant α . For different pairs of values (η, α) , numerical calculations were performed and the values of the parameters $\eta = 0.1$ and $\alpha = 0.7$, which correspond to the minimal MAPE $\varepsilon_* = 3.25\%$ and ensure convergence of the iterative training process (Fig. 2), were found. For some values η and α the properties of monotonicity and the stability of the training process can be violated, for example, for $\eta = 0.7$ and $\alpha = 0.3$ (Fig. 3). Therefore, the choice of acceptable values for custom parameters in the learning algorithm is important for predicting with using ANN.

It should also be noted that an increase in the number of training epochs E in some cases may not lead to a significant improvement in the forecast, and if the values E are too large, the MAPE $\varepsilon(k)$ may begin to increase with growth k owing to the accumulation of computational errors. Moreover, the increase E leads to a considerable amount of CPU time, as in the iterative training process, the matrixes of weights and the displacement vector used in the back-propagation algorithm are repeatedly transformed. Thus, the choice of the optimal structure of a neural network and the tuning of its parameters requires a large number of computer experiments.

For the time series containing data on the weekly flow of container trains in the direction of China – Europe, the prediction task using a neural network with a learning algorithm based on the back-propagation of the error signal was analyzed. The results of numerical calculations show the effectiveness of this method for short-term prediction tasks.

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