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STUDY OF METHODS FOR PREDICTING THE RECEIPT OF CONTAINER FLOWS FROM SHIPPERS TO THE RAILWAY TERMINAL STATION

ДОСЛІДЖЕННЯ МЕТОДІВ ПРОГНОЗУВАННЯ НАДХОДЖЕННЯ КОНТЕЙНЕРОПОТОКІВ ВІД ВАНТАЖОВІДПРАВНИКІВ НА ЗАЛІЗНИЧНУ ТЕРМІНАЛЬНУ СТАНЦІЮ

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Abstract. *The paper considers a tool, a neural network of the LTSM architecture, which is quite appropriate to use for forecasting the intensity of random flows, which represent the processes of the arrival of containers at railway terminal stations in the system of intermodal transportation.*

Keywords: *railway terminal stations, road transport, container flows.*

Introduction.

The arrival of container flows at the terminal railway station from shippers is a complex stochastic process that has many uncertainties. A part of the transportation way of containers can take place both by road transport, for example, from the shippers to the railway terminal station, and by rail - transportation from the railway terminal station to the port or border station. There is a need for a thorough study of container flows in order to build a management model with the interaction of several types of transport for the timely delivery of goods in containers according to the principles of logistics, with minimal costs [1].

To ensure the possibility of making high-quality management decisions, the use of only statistical data of container arrival processes, such as, for example, mathematical expectation and variance of the interval between container arrivals, is insufficient.

Thus, in order to be able to use the container flow management model, first of all, the dynamics of container flow parameters is required.

Main part.

The main characteristic of container flows is the intensity function. But considering the arrival of containers at the station as non-stationary random flows, the intensity of the flow can represent a time dependence.

On the basis of the above mentioned, representation of such data can be in the form of so-called time series. Time series represent statistical material collected at certain periods of time which have the values of one or more parameters.

Figure 1 shows a scheme for representing the intensity of a random flow as a function of time using a numerical sequence.

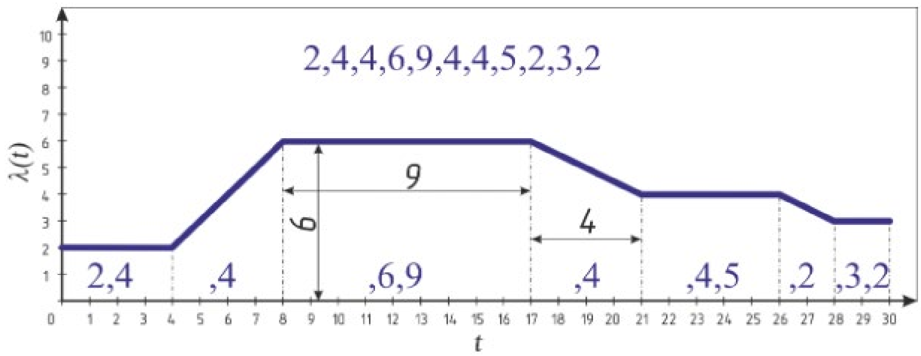

Figure 1 - Encoding scheme of the random flow intensity function in the form of a numerical sequence

According to this scheme, the intensity function can be represented by a numerical sequence. The dependence curve is approximated by a broken line, which has horizontal sections corresponding to constant levels of intensity, and sloping sections corresponding to transitional levels when moving from one constant level to another. Thus, the function is coded by a set of data in which numbers are sequentially placed that determine the constant level of intensity, its duration and the duration of the transition period that follows it. Such triples of numbers can be repeated indefinitely, as shown on the figure. In addition, this method of coding is compact, because to represent, for example, a section corresponding to a constant level of intensity or a time interval in which there are no events at all, it allows spending only one number of the sequence, regardless of the duration of this interval.

Analyzing various forecasting models of time series, it was found out that there is a fairly significant number of them, which are listed in Table 1.

Recurrent neural networks based on modules of long short-term memory (long short-term memory; LSTM) are considered the most successful modern neural architecture for forecasting time series models [2].

Neural networks of the LSTM architecture are considered universal because, given a sufficient number of neurons, they can approximate any function with a given level of accuracy, that is, simulate computational processes of any complexity. Such calculations are possible after taking the learning process and forming a matrix of weights of connections between neurons, which can be interpreted as a knowledge base and as a computer program. Neural networks of the LSTM architecture can be considered the least versatile of the entire class of recurrent neural networks.

Table 1- Classification of the main types of models for forecasting time series

Models based on classical methods	Models based on trust networks	Models based on neural networks
1. Exponential smoothing	1. Models based on Bayesian networks	1. Autoregressive models based on neural networks
2. Decomposition, seasonal decomposition	2. Deep trust networks with restricted Boltzmann machines	
3. Integrated model of autoregression and fluctuating average (ARIMA) seasonal version of SARIMA		3. Models based on neural network architecture using long-short-term memory cells
4. Dynamic linear models		
5. Trigonometric model based on Box-Cox transformations, errors based on autoregression, fluctuating average, trends and seasonality (TBATS)		

However, these neural networks are capable of implementing deep learning technology [3] and are most suitable for the tasks of data processing, classification, and prediction of time series, in particular irregular time series that do not have clear parameters and a constant step size, time series, the key events of which are distant by significant aperiodic distances, the forecasting of which using neural networks of any other architecture is ineffective or practically impossible.

The task of forecasting time series using neural networks is solved due to their properties such as the ability to generalize and find hidden dependencies [3]. This statement applies to models based on “deep learning” networks. Neural networks of the “deep learning” direction, are much more complex than neural networks of the traditional “machine learning” direction. In the process of learning, they do not need to indicate certain features of the data directly, they are able to highlight them themselves. In fact, they themselves create functional structures that are able to draw logical conclusions. However, to do it, they may require significantly larger amounts of data, computing power, and training time for networks created using machine learning technologies [4].

The neural network of the LTSM architecture is a tool that is quite reasonable to use for forecasting the intensity of random flows, which represent the processes of container arrivals at railway stations, which are terminal points in intermodal container transportation systems. As it was shown above, networks of this type can effectively solve the problems of forecasting time series. Time series refers to sequences of data that are put in order on the time axis. Thus, time series are sequences of data with discrete time. However, it is usually also implied that these data correspond to points on the time axis that are equidistant from each other.

LSTM networks have a rather complex structure. The main component of neural networks of long-short-term memory is not a single neuron or a layer of neurons, but memory cells that include various components, including neurons of different types. An important component of the LSTM architecture network is the pipeline of the main flow 1 (Fig. 2), which can also be called the memory pipeline. It is a memory cell, any element of which can be deleted or changed at any iterative step of learning or network operation, and can retain its value for a long time. At the same time, this memory pipeline is one of two channels for the passage of signals that are translated from one cell to another or from one iteration step to another, experiencing a minimum level of interaction with the structures of the cell. The signal stored and transmitted by this memory pipeline is called “cell state”. It allows the network to store for an almost unlimited period of time information about previous elements of the numerical sequence of data and network states.

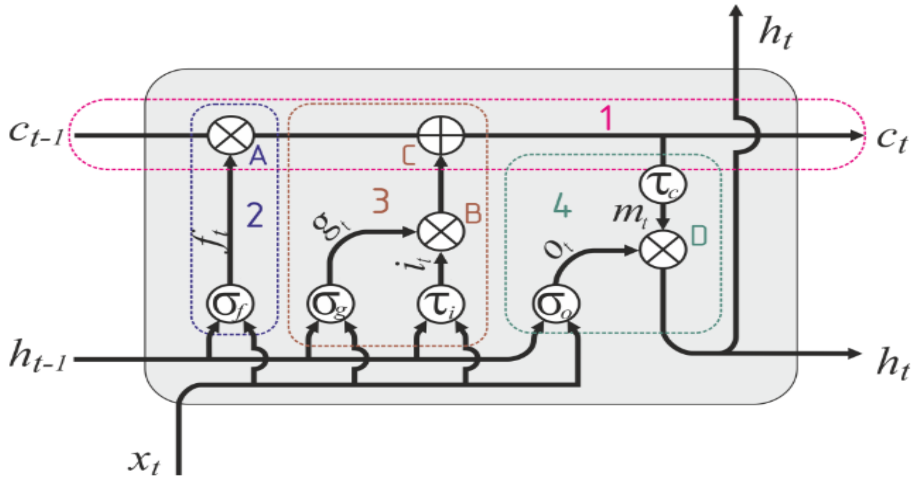

Figure 2 - Scheme of the functioning of a neural network cell of LSTM architecture

A forecast model based on a recurrent neural network was implemented to predict the function of the intensity of container flows in the Matlab environment. The architecture of the model is shown on Figure 3.

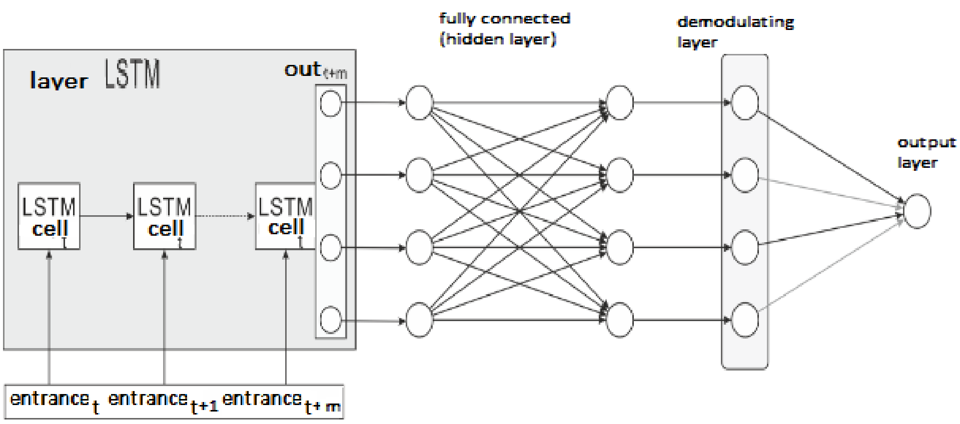

Figure 3 - Architecture of a model based on a recurrent neural network for forecasting the flow intensity of container arrivals

The neural network consists of 40 cells in the LSTM layer, 80 neurons in the fully connected layer, and 20 neurons in the demodulating layer. Figure 3.5 shows the dynamics of the learning speed of the constructed neural network. The network is configured in such a way that during the learning process this parameter is adjusted to the level of 0.0005, which corresponds to a high level of accuracy of the model. But at the same time, this parameter value significantly slows down the learning process.

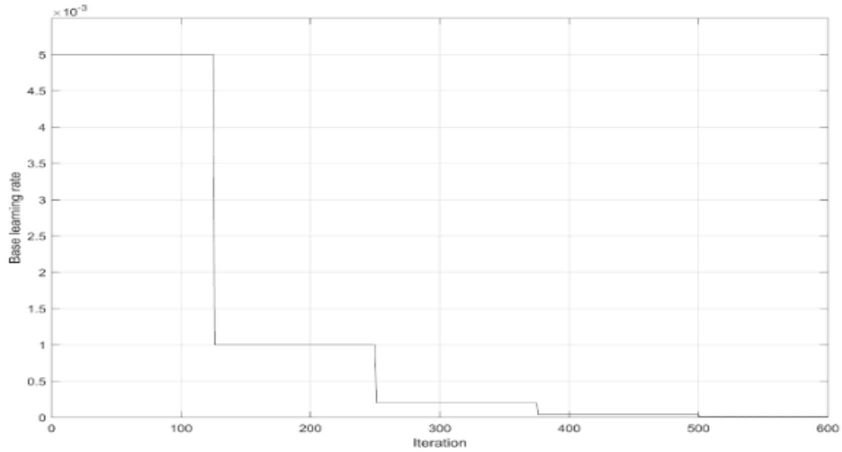

Figure 4 - Learning speed dynamics of the constructed neural network

The method of reproducing the intensity function proposed above, which was used to encode and interpret data of actual intensity and predictive dependence, is convenient in the conditions of the necessity to encode parameters of rarefied flows and search for dependencies of events remote in time. To solve the problem of managing the process of accumulation of containers, the primary interest is not the direct form of the dependence of the flow intensity function, but the integral function from it. Under such conditions, the comparison of area elements under the graphs of predicted and actual intensities, which correspond to equal intervals on the time axis, will be more accurate. Graphs of the actual and predicted intensities with the specified values of the segment areas are shown on Figures 5a and 5b, respectively.

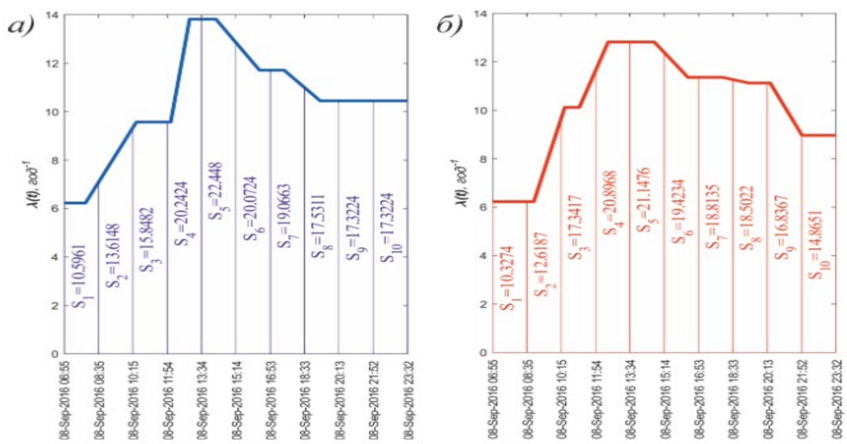

Figure 5 - Graphs of the actual - a) and predicted - b) flow intensity with the indicated values of the areas, which correspond to the number of flow events at equal time intervals

Conclusions.

The developed model for forecasting the intensity of the flow of container arrivals based on recurrent neural networks of deep learning was implemented as a software product in the Matlab environment. As a result of the simulation conducted on real data, it was found out that the forecast error is within 6%, which allows the developed forecast model to be attributed to class of high-precision models. This result is due to the application of the developed model of a layer of long-short-term memory elements as part of the architecture, which provides the possibility of finding hidden dependencies and connections between data substructures even if they are separated by long time intervals.

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Анотація. *В статті були досліджені методи прогнозування надходження контейнеропотоків на залізничну термінальну станцію. Виявлено, що для прогнозування моделей часових рядів найбільш успішною сучасною нейронною архітектурою вважаються рекурентні нейронні мережі на основі модулів довгої короткострокової пам'яті. Для прогнозування функції інтенсивності контейнеропотоків в середовищі Matlab була реалізована прогнозна модель на основі рекурентної нейронної мережі. У результаті проведеного на реальних даних моделювання було встановлено, що похибка прогнозу знаходиться у межах 6%, що дозволяє віднести розроблену прогнозну модель до класу високоточних моделей. Даний результат обумовлений застосуванням у складі архітектури розробленої моделі шару з елементів довгої короткострокової пам'яті, які забезпечують можливість знаходження прихованих залежностей та зв'язків між субструктурами даних навіть якщо вони віддалені часовими інтервалами значної тривалості.*

Ключові слова: *залізничні термінальні станції, автомобільний транспорт, контейнеропотоки.*

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