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# RESEARCHING THE EFFICIENCY OF ARTIFICIAL NEURAL NETWORK CONFIGURATIONS AND ARCHITECTURES FOR FORECASTING ELECTRICITY CONSUMPTION OF RAILWAYS

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The efficient forecasting of electricity consumption in railway systems is critical for optimizing energy usage, reducing costs, and enhancing sustainability.

The study on the efficiency of artificial neural network architectures for forecasting electricity consumption in railways holds significant relevance in addressing the pressing challenges faced by Ukrainian Railways and the broader transportation sector. Accurate electricity consumption forecasting is vital for optimizing energy resources, reducing operational costs, and enhancing the sustainability of railway systems.

Different criteria can be used to assess the accuracy of an artificial neural approach to forecasting. A popular criterion for the quality determination of artificial neural network (ANN) training is the Mean Squared Error (MSE), the average of the squared difference between the resultant and target values, which can be determined by the equation [1]:

$$MSE = \frac{\sum_{i=1}^{N} \varepsilon^2}{N} = \frac{\sum_{i=1}^{N} (X_i - Y_i)^2}{N},$$

where $\varepsilon$ – is the training error; $X_i$ and $Y_i$ – are the expected and actual outputs of the ANN. Lower values are better. Zero means there is no error.

If the training error $\varepsilon$ for the entire set of input data does not exceed the set limit, or the predefined number of iterations is reached, the training process is completed.

The Bayesian regularisation algorithm has the best performance in [2], so all further researchs was conducted using it, and MSE was used as a criterion for the quality of the trained ANN.

At the initial stage of the experiment, the Feed-forward architecture of forward data propagation and backward error propagation was used, which is described as the most suitable for predicting electricity consumption.

With this architecture, the ANN is trained by specifying the input data to be processed and the target values of the time series, which are the norm for forecasting. After training, the ANN selects the weighting coefficients in such a way that the standard deviation of the output values from the reference values is minimal.

The speed of its operation is one of the advantages of this architecture. During the experiment, it showed fairly good forecasting results, but different each time. Indeed, the disadvantages of such a network include the impossibility of using the weighting coefficients obtained during the initial training for re-training, which leads to different solutions for the same data set and does not contribute to an increase in accuracy, since the ANN is trained from scratch each time.

Taking this drawback into account, the experiment is conducted on another time series forecasting architecture, which is a nonlinear autoregressive model with external inputs (NARX).

With this ANN architecture, it is necessary to set both input and target values of the function. The data at the input, passing through the network, is processed according to the weighting coefficients, and then re-enters the network input, thereby replacing itself with the backward propagation of errors, which makes it possible to apply the weighting coefficients obtained after the first training when re-training the ANN. In turn, this increases the accuracy of the ANN.

The ANN is created in the following configuration. The input layer consists of neurons, the number of which corresponds to the total amount of retrospective data: hourly air temperature, three types of rolling stock moving along the electrified section according to the established schedule, and non-traction load. The output layer contains neurons that characterise hourly electricity consumption.

The number of hidden layers and elements in them was chosen experimentally. This was done so that the minimum forecasting error was achieved for different input and output data sets.

As a result of the experimental research, the best MSE value is obtained for the NARX architecture and it is equal to 0.0020052, which is better than the previous result (MSE = 0.0021625) [2].

The findings of this research highlight the potential benefits of adopting ANN-based forecasting for railway electricity consumption. ANNs can capture complex relationships in the data, allowing for more accurate and adaptive predictions.

Moreover, their ability to incorporate external factors such as weather conditions and traffic volumes enhances forecasting accuracy.

In conclusion, this research provides valuable insights into the efficiency of Artificial Neural Network architectures for forecasting electricity consumption in railways. ANNs offer a promising approach to enhance the precision of electricity consumption forecasts, ultimately leading to improved energy management, cost savings, and reduced environmental impact in railway operations. Further research can explore real-time data integration and advanced ANN architectures to advance this field.

Conclusions. The Feed-forward and NARX architectures showed similar results. In practice, the NARX architecture proved to be more productive for forecasting railway electricity consumption. The ANN based on the NARX architecture responded better to an increase in the data sample and has more prospects for practical application, provided that further data is collected for its training. The experimental research of the NARX configuration revealed a significant dependence of the model's behaviour on the number of neurons in the input layer. Determining these architectural elements in an optimal way is a critical and complex task.

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## References

1. Dharmendra Kumar Mishra, Dwivedi A. K. D., Tripathi S. P. (2012). Efficient algorithms for load forecasting in electric power system using artificial neural network. *International Journal of Latest Research in Science and Technology*, *1 (3)*, 254-258. [in English].

2. Haidenko O. S., Holub H. M. (2018). Prohnozuvannia spozhytoi elektroenerhii metodamy nejromerezhevoho modeliuvannia [Electric power consumption forecasting by methods of neural network modeling]. Collection of scientific works of the State University of Infrastructure and Technologies. Series Transport Systems and Technologies, 31, 196-201. [in Ukrainian].