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UNIVARIABLE SHORT-TERM FORECAST OF NODAL ELECTRICAL LOADS OF ENERGY SYSTEMS

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Abstract

The paper proposes the architecture of deep learning neural network for short-term nodal electrical load forecasting. The neural network combines the recurrent module LSTM (Long short-term memory) and the multilayer perceptron on the top. Input and output of the network connected with shortcut connection. In multilayer perceptron used scaled exponential linear unit (SELU) function as a nonlinear transformation in hidden neurons. A comparative analysis of two approaches to the short-term prediction of node loadings of the grid is conducted. In the first approach, a separate model based on the artificial neural network eResNet is built for each load node. In the second approach, vector prediction of the values of the nodal load is performed using the proposed neural network. The second approach makes it possible to exploit the relationship between the loads in the nodes and reduce the number of computational operations required to build the model, especially at a large number of nodes. Recurrent network showed slightly better result when forecasting horizon was 24 hours, but eResNet showed more accurate forecast with longer horizons. References 16, figure 1, tables 3.

Key words: nodal electrical load, short-term forecasting, artificial neural network, recurrent network

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