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Application of Artificial Neural Network (ANN) for Short-Term Load Forecasting (Case Study on National Control Centre (PHCN) Oshogbo, Osun State, Nigeria)

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Abstract: Load forecasting is essential for efficient decisions in power systems design and operation. It is very important to know the electric load trend or evolution in order to ensure a high planning and decision making efficiency. A capital importance is given to short-term load forecasting in this research. Artificial Neural Network (ANN) which is considered multivariable, nonlinear and non-parametrical model was used. An attempt is made to forecast the short-term hourly load for a large power system by applying the method of ANN. Weekday and monthly patterns were considered. The weekday patterns include Monday-Saturday loads while the monthly patterns include January-June loads. Historical data obtained from the National Control Center (NCC) of Power Holding Company of Nigeria (PHCN), Oshogbo was used to demonstrate the effectiveness of the proposed approach. The ANN developed has four layers: an input layer, two hidden layers and an output layer. The inputs to the ANN were the hourly load demand for the full day (24 h) while the outputs obtained is the load forecast for a given day i.e., the predicted hourly load demand for the next day. On performance evaluation, the mean absolute percentage error was found to be 2.087%. Hourly load demand was predicted for a full week with a high degree of accuracy.

Key words: ANN, load forecasting, load demand, performance evaluation, artificial neural network, Nigeria

INTRODUCTION

Electric load forecasting is an important part of power system operation in that it serves to predict the system expected power demands. It thus plays an important role in economic and financial development, expansion and planning. With load forecasting, series of decisions can be made pertaining to operation plans, security studies and how to maximize the energy being generated in a power system.

Load forecasting is divided into short-term, mid-term and long-term load forecasting. Short term load forecasting involves forecast of load within a short period of time from 1 h-1 day or week. It is important for various applications such as unit commitment, economic dispatch, energy transfer scheduling and real time control (Hippert *et al*., 2001). Mid-term load forecasting may be considered over an interval ranging from 1 month to 5 years.

It is used for instance in planning for enough fuel purchase for power plants after electricity tariffs are calculated (Gavrilas *et al*., 2001). In long-term load forecasting, the forecast is for a longer period of time. Long-term load forecasting covers from 5-20 years or more. It can be up to several years or several decades and it is used by planning engineers and economists to determine the type and size of generating plants that will be needed to minimize both fixed and variable costs (Kandil *et al*., 2002). Earlier techniques for hourly load forecasting which were considered unsuitable for real time on-line load forecasting as they were time consuming include decomposition method, multiple regression model method (a statistical method), stochastic time series approach, adaptive load forecasting, exponential smoothing, Kalman filtering technique, etc. Other applied methods include econometric models, fuzzy logic, expert systems, etc. (Alfares and Nazeeruddin, 2002).

The conventional methods and statistical based approaches do not yield good results. In conventional schemes, load forecasting is based on mathematical models to find solutions. However, power systems have many uncertainties in practice. Those mathematical models provide only for specific situations of the power systems under respective assumptions. Due to these assumptions, the solutions to those problems are not trivial. Hence, there exist some limitations for the mathematical model based schemes. To overcome this limitation, neural network has been investigated in a lot of areas of power systems for reliable and high quality power supply at low cost. With the application of neural network, the historical data can be used to train the network for load forecasting without selecting any

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models. Neural networks aim to perceive and comprehend the significance of the data with which they are trained. Artificial Neural Networks (ANN) are characterized most adequately as computational models, the operation of which is based on parallel processing with particular properties such as the ability to adapt or learn to generalize or to cluster or organize data. Before ANN techniques are developed, a large amount of training data is required to train the network.

This training data is often hard to obtain and may not be a good representation of the total data set. A major advantage of ANN is that the domain knowledge is distributed in the neurons and information processing is carried out in parallel distributed manner. However, the disadvantage of using artificial neural network is that it can only be used to forecast load within the extent to which it was trained. In this study, use is made of a supervised artificial neural network for the hourly load forecasting of the daily load.

MATERIALS AND METHODS

The supervised training approach was considered. With supervised learning, the artificial neural network must be trained before it becomes useful. In supervised training, both the inputs and outputs are provided (Anderson and McNeill, 1992). The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back into the system.

The training process starts by initiating the desired topology for the artificial neural network. This involves initiating the number of layers input, hidden and output layers, the number of neurons per layer, the number of presentation cycles and the type of activation functions in the hidden and output layers.

A simple architecture feed-forward Artificial Neural Network is proposed for short-term load forecasting in this study. Feed-forward neural network architecture can be described either by continuous time model or by discrete time model (Cirstea *et al*., 2002). The network is trained using a back propagation learning algorithm. The training is done in a supervised manner that is a desired output is given for every input vector and the discrepancy between the actual output computed by the network and the desired output is measured by an error function which is to be minimized. While using the back propagation training algorithm the network is presented with a time series of daily load and thus made to predict the next values. The predicted values and the actual values are compared resulting in the Mean Square Error (MSE) which is propagated back through the feed-forward links.

The proposed neural network architecture: Four-layer architecture is proposed here: an input layer with twenty neurons, two hidden layers the first with twenty neurons, the second with fifteen neurons and an output layer with six neurons. The transfer functions used for the four layers were tangent sigmoid transfer function (tansig), tansig transfer function, linear transfer function (purelin) and purelin transfer function, respectively. The four layered architecture is unveiled by looking under the mask of Fig. 1 and 2. Signal propagation is allowed only from the input layer to the first hidden layer from the first hidden layer to the second hidden layer and from the latter to the output layer (Fig. 3). However, the output of the neural network is compared to the target and an error is computed. This error is then fed back (back-propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output.

Training: The network was trained based on the historical load data obtained from the National Control Centre (NCC) Oshogbo. Training was done using back-propagation with adaptive learning rate (The MathWorks, 2008). In order that the neural network is not subjected to saturation, there was need to normalize the data hence, the inputs were preprocessed using the normalizing technique. The hyperbolic tangent sigmoid transfer function (tansig) (Samarasinghe, 2007) was

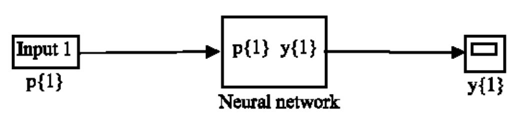

Fig. 1: The ANN architecture (Masked)

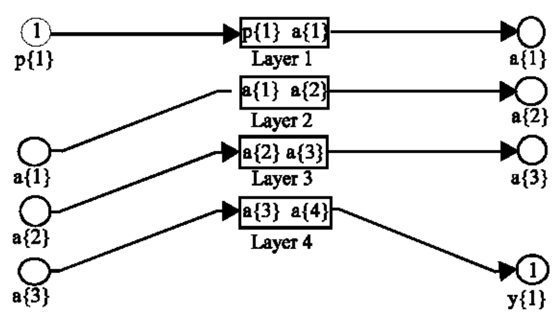

Fig. 2: The four layer ANN architecture

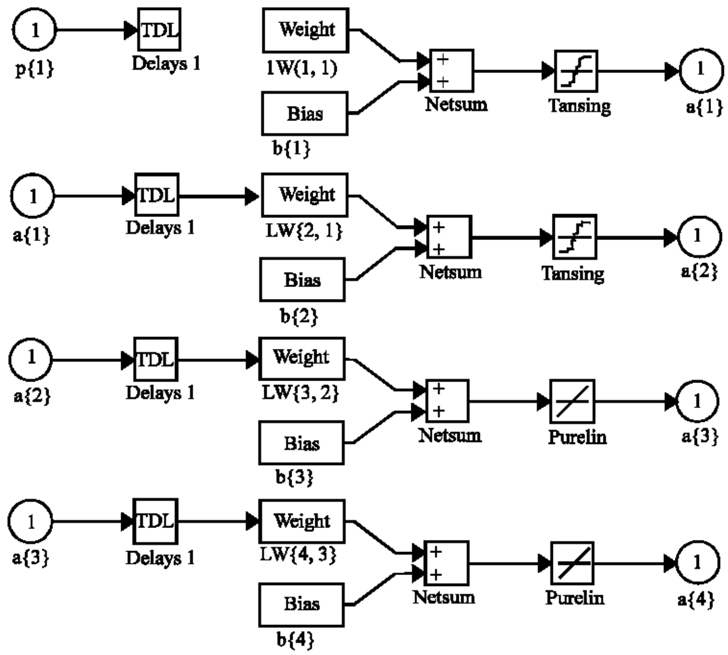

Fig. 3: The ANN architecture showing individual layer's interconnections (weights and biases)

used to squash the output from the first layer into a range -1-1. A four layer neural network was found to be adequate: an input layer, two hidden layers and an output layer. The input layer has twenty neurons with a tang-sigmoid activation function, the first hidden layer has twenty neurons and is also activated with tansig transfer function and the second hidden layer (third layer) has fifteen neurons and is activated with a linear transfer function, purelin. The output layer has six neurons with a linear activation output function, purelin.

RESULTS AND DISCUSSION

The numerical simulations were done using MATLAB version 7.4.0.287 (R2007a). The ANN algorithm yielded the following graphs: the performance curve, the regression graph and the disparity graph.

The performance curve shown in Fig. 4 shows the behaviour of the network during training, validation and testing. The performance function is the mean square error of the network output. Epoch shows the presentation cycles of the set of training vectors to the network and the calculation of new weights and biases.

The results obtained from testing the trained network are presented here. Figure 5-16 show plots of target load and forecast load (ANN Forecast) in MW against the 24 h of the day. The ANN model's forecast followed the actual load pattern more accurately throughout the forecasted period.

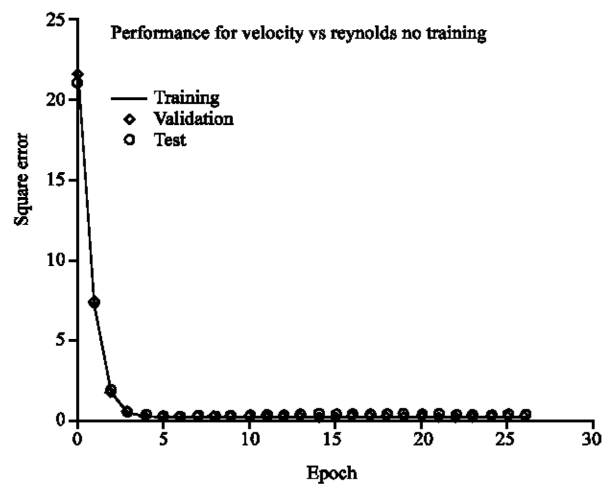

Fig. 4: Performance curve

Performance evaluation: A satisfactory convergence was achieved while using the following network training parameters: learning rate = 0.01, epochs = 200, network training goal = 0.0000001, no. of layers = 4, no. of neurons in the input layer = 20, no. of neurons in first hidden layer = 20, no. of neurons in second hidden layer = 15, no. of neuron in output layer = 6 and network performance parameter = trainlm.

The performance goal was met using: TRAINLM, Epoch 0/200, MSE 23.7134/1e-007, Gradient 1610.28/1e-010, TRAINLM, Epoch 26/200, MSE 1.02009e-009/1e-007, Gradient 0.00991879/1e-010.

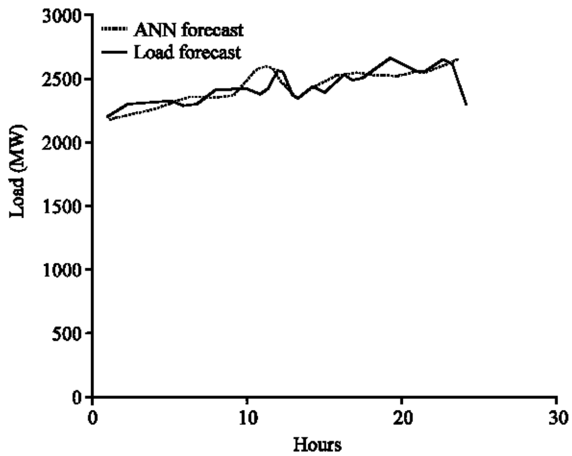

Fig. 5: Monday load forecast

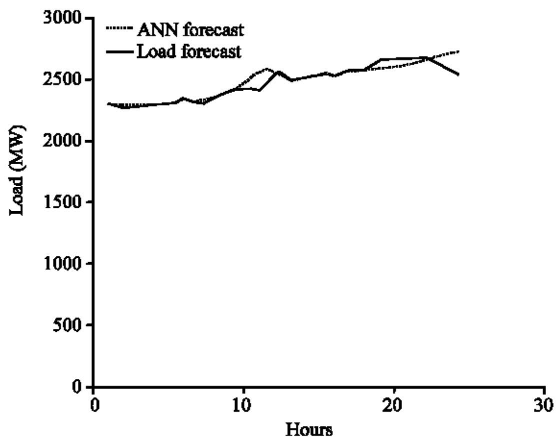

Fig. 6: Tuesday load forecast

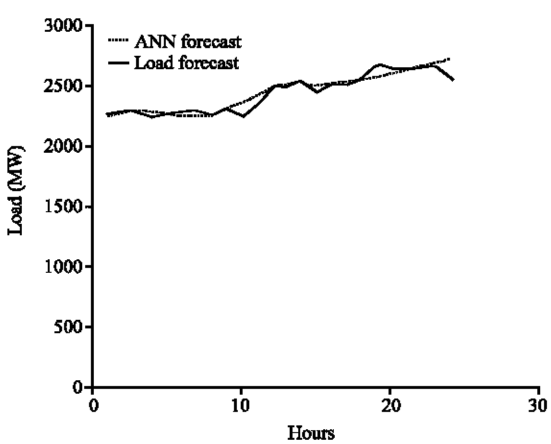

Fig. 7: Wednesday load forecast

The regression graph of Fig. 17, shows the relationship between the ANN output load and the targeted output load. R = 0.97789 indicating that the degree of correlation between the two outputs is approximately 98%. The disparity graph shown in Fig. 18

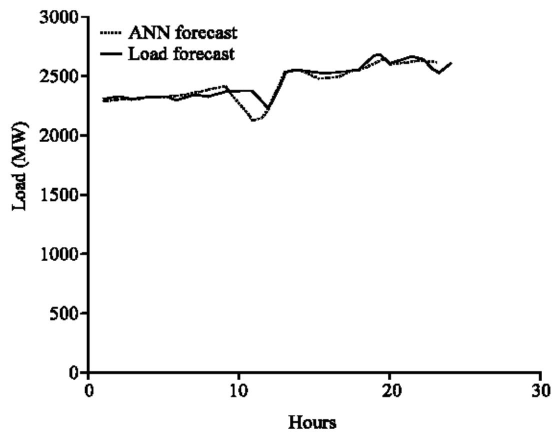

Fig. 8: Thusday load forecast

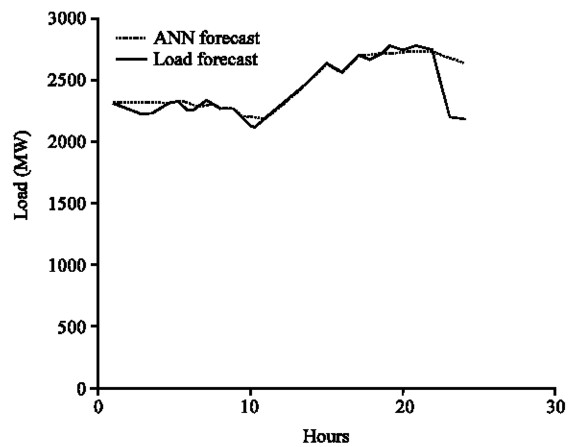

Fig. 9: Friday load forecast

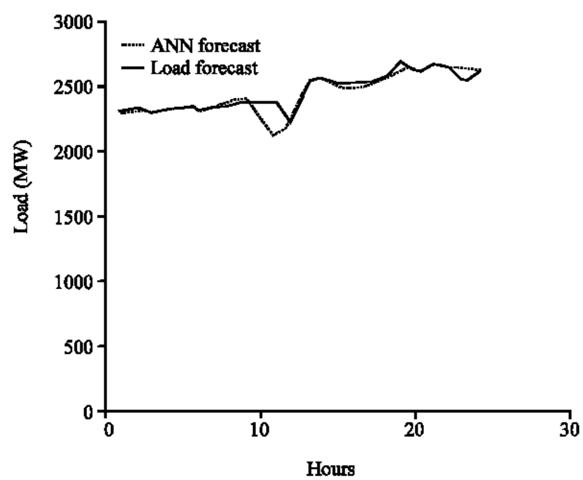

Fig. 10: Saturday load forecast

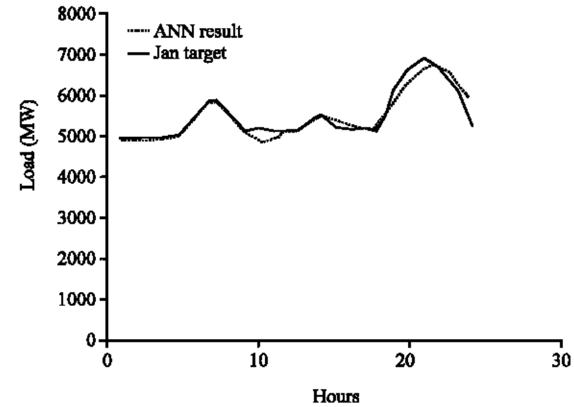

Fig. 11: January load forecast

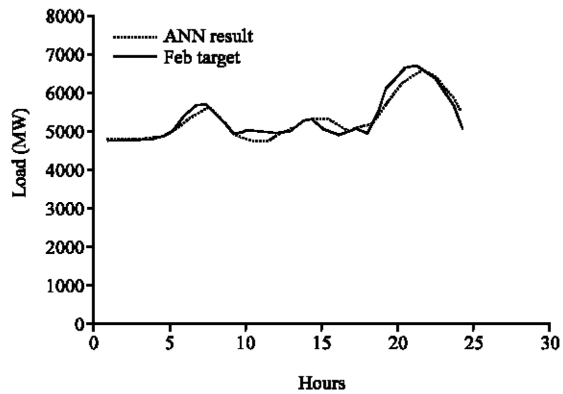

Fig. 12: February load forecast

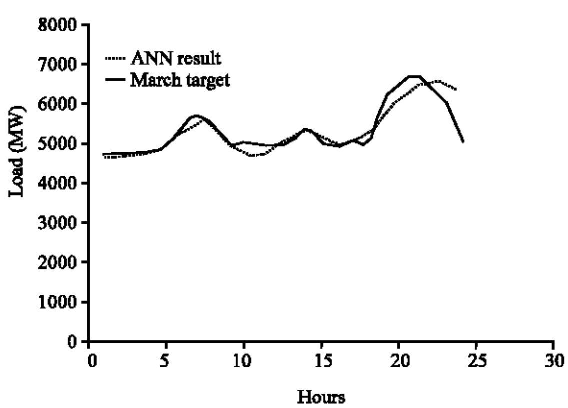

Fig. 13: March load forecast

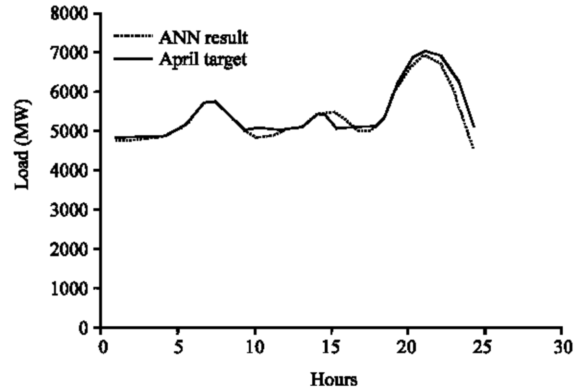

Fig. 14: April load forecast

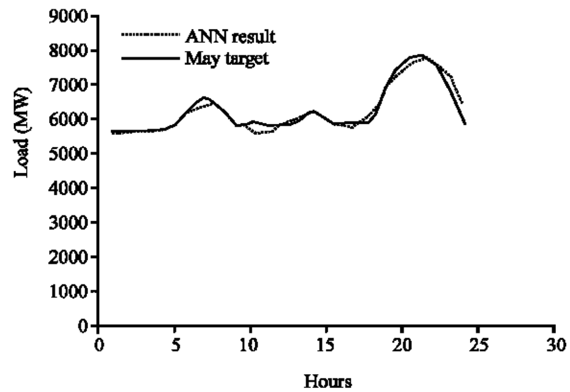

Fig. 15: May load forecast

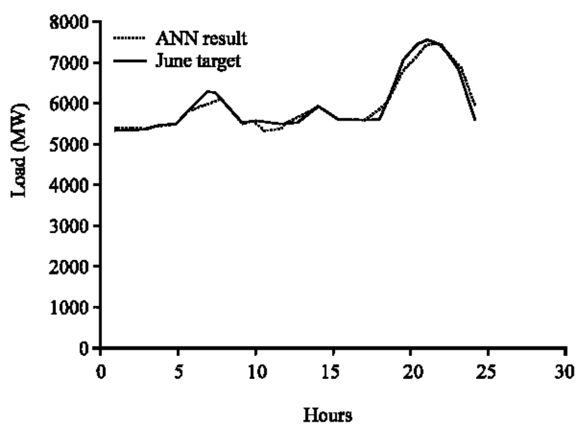

Fig. 16: June load forecast

shows the discrepancy between the targeted output load in MW and the ANN output load in MW. The Fig. 18 shows a fairly good mapping between the two outputs. The graphs for the daily load forecast are shown in Fig. 7-12.

The Fig. 7-12 show the closeness between ANN forecast and load forecast for each day. Figure 13-18 show the monthly load forecast from January to June. It can be seen from Fig. 13-18 that the ANN results closely match the targeted values. The performane of the model can be evaluated from the value of the measn absolute percentage error which was calculated to be 2.087% after comparing the forecasted load with the actual load data.

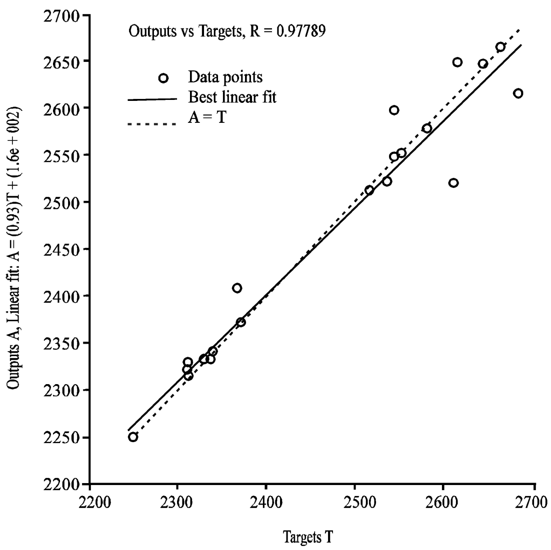

Fig. 17: Graph showing the regression between actual loads (A) and forecasted loads (T)

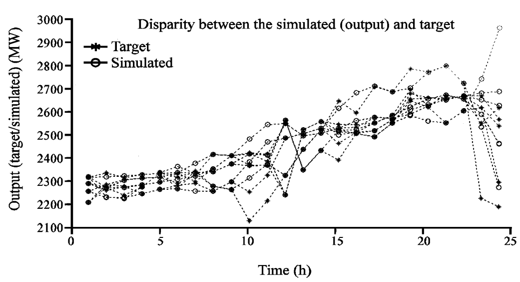

Fig. 18: Graph showing the disparity between simulated and targeted result

CONCLUSION

An ANN-based short-term load forecasting method that uses a four-layer feed-forward neural network and a back-propagation training algorithm is presented here. The results obtained from carrying out this research confirm the relevance and efficiency of neural networks in load forecasting in general and in the energy management of the Power Holding Company of Nigeria (PHCN) in particular. From the tested data, it is obvious that the neural network can train any set of data to produce a predicted one. Starting from a pair of input-output vector, ANN has been shown to estimate a relationship between inputs and outputs. It has thus been proven that ANN is capable of numeric approximation of any continuous function with the desired accuracy as well as being computationally fast. The Mean-Square Error (MSE) decreased much more rapidly with time resulting in a more pronounced improvement and the mean absolute percentage error was found to be 2.087%. The acceptability and suitability of this network can be confirmed for load forecasting with a high degree of accuracy. Though the effect of weather parameters are already being considered to a large extent, in various research works as in (Chow and Leung, 1996) the diurnal variations in temperature, pressure and other weather conditions could be incorporated into future ANN studies in load forecasting.

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