Rural Area Short Term Load Forecasting: A Review

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Abstract— Demand forecasting is very necessary in now days. It is very useful to maintain the reliability of power or maintain uninterrupted power supply to various consumers. India is developing country here demand of power supply is higher as compare to other country. To maintain the supply it is necessary to forecast the demand for future expansion. The predictable method for short term load forecasting is mostly limited to electricity load data with monthly or annual granularity. This leads to forecasts with low down the accuracy. In this paper, a new technique for long term load forecasting with hourly resolution is propose. Demand forecasting is essential part of power system planning and operation. This paper presents the demand forecasting on basis of RMSE, Accuracy, MAPE (mean absolute percentage error). The data used for analysis collect from the HVPNL Dhadibana Ch. Dadri 220 KV substation for the year 2016-2018 and predication for different months or weeks for year 2020 using the neural network and regression method. The output/observation have presented in the form of table for easy comparison.

Keywords: Demand Response, Load Forecasting, Long Short-Term Memory

I. Introduction

When India is independents in 1947 the total generating capacity is 1362 MW and average power consumption is 16.3 units. Now it increases with exponential rate. Now days the total generating capacity is 1121 GW and consumption is 1273 units as soon Dec 2019. It is big challenge to the power companies to meet the demand of different consumers and take the profit by selection of good generating station i.e. nuclear, Hydro, Thermal which have less operating cost as well as capital cost with high efficiency.

In India almost all power companies are adopting deregulated their structure for better utilization of resources and proving choice and quality of service to the consumers at less rate of tariff. The forecasting of electricity load has great research field in electrical engineering under for new deregulated environment t because it helps in management of demand.

There are basically two types of prediction technique based on input data selection first is physical model and secondly is time series. The first model or technique require physical data for which forecast but other technique require only time series data of the load and input time lag for neural network. Training is selected on basis auto correlation function and partially ACF. This paper represents the short term load forecasting result basis on RMSE, MAPE and MAE. The data used for analysis of the 2017-2019 and prediction is done for the first four week of JAN 2020.

Load Forecasting can be carry off for long, medium and short term. Range of short term can be assumed from one hour to seven days, in spite of no explicit explanation of each time horizon [3]. In past few decades, the research have been carried out to develop various techniques of STLF, such as Statistical models, Artificial Neural Network (ANN) based models, fuzzy models and hybrid models. These methods are broadly categorized into Artificial Intelligence (AI) and Statistical approach.

Short Term Load Forecasting (STLF) is of paramount significance in unit commitment, exchange and scheduling of power for energy generation and Distribution Company, and Demand Response Management (DRM). To implement various DRM planning strategies, knowledge of the amount of future energy demand at residential level is required. Economically, the precise forecasting of load decreases the operating cost that prompts significant savings for the power companies. However, there are some challenging factors like seasonal effects (daily and weekly cycles, calendar holidays), meteorological conditions, and special events which make load forecasting a complex problem.

ANN has gained maximum attention by both industry and academia [4, 6]. ANN has also been executed in various powers utility applications such as failure forecast (with altering degree of success) for distribution system [4]. Due to its flexibility and the capability of handling non-linear data, it is highly utilized by several vendors in power industry [4],[6]. Although, as a black-box approach, the ANN models can deliver quite competent forecast but the accuracy of ANN, when combined with other AI-based techniques such as Fuzzy logic, has not been absolutely persuasive [4]. Further, there are some challenges, such as lack of interpretability and over fitting, in applying ANN to electric load modelling and forecasting [4].Most of the utilities still use similar day approach, one of the earliest techniques, for short term load forecasting due to its simplicity of implementation and adequate results [7]. The idea of STLF is to utilize the historical days as the fundamental reference. Historically, time series approaches such as Auto-Regressive Moving Average (ARMA) and Auto-Regressive Integrated Moving Average (ARIMA) have been used enormously by the utilities for STLF [4]. ARIMA bring short term accuracy for time series models but its interpretability is complex as compared to regression models [7], [8]. Multiple Linear Regression (MLR) is also one of the extensively used statistical techniques in electrical load forecasting [4], [9],This approach considers independent dummy variables, such as time of the day and day of the week, for electric power load shown as a linear function [4]. In Random Forest (RF), a generic form is considered which is capable of predicting the load demand of one day ahead by a step of half-an-hour. This model imparts precise results giving no importance to any specific day or the season [3]. The accuracy level of RF is as good as optimized ANN and Support Vector Machine (SVM) with no tuning required [3], [6],[11]. Further, poor option of parameters does not manipulate the forecasting accuracy severely [3].

II. TRANSMISSION SYSTEM

Electricity has been traded through bilateral contract and through power exchange. Currently there two major power transmission companies in Haryana these are power grid India limited and BBMB. Which are meet 69% of total demand and remaining 31% is supply by the state owned companies (i.e. HPGCL). In December 2019 the Average energy requirement is 3821 MW.

A. Energy Profile:-

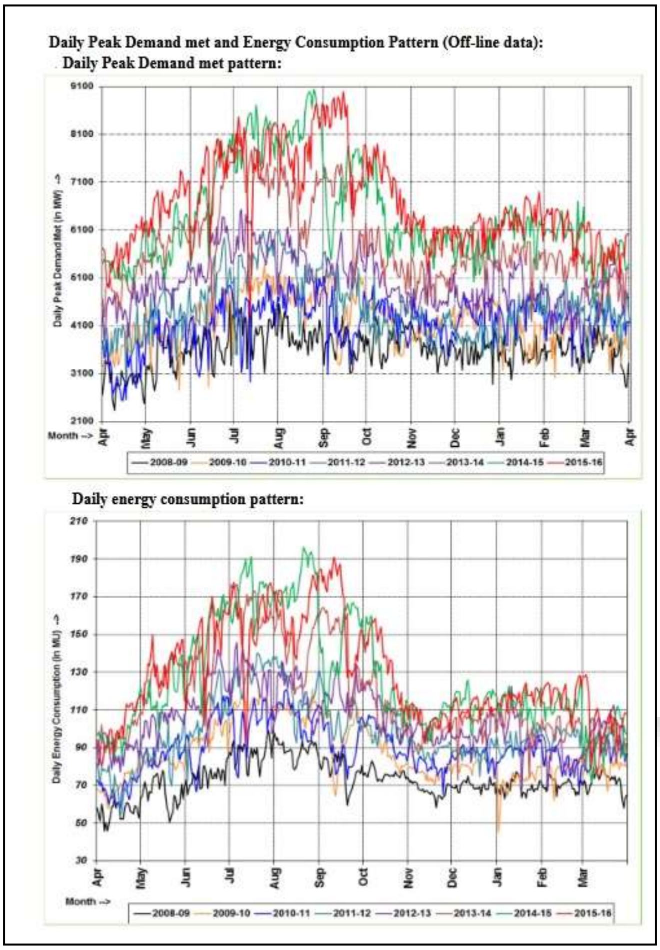

Fig. 2.1: Peak Demand/Power consumption

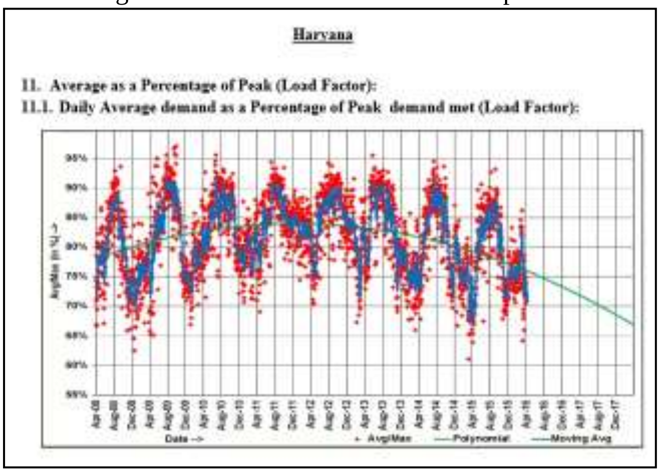

Fig. 2.2: Daily avg demand in percentage

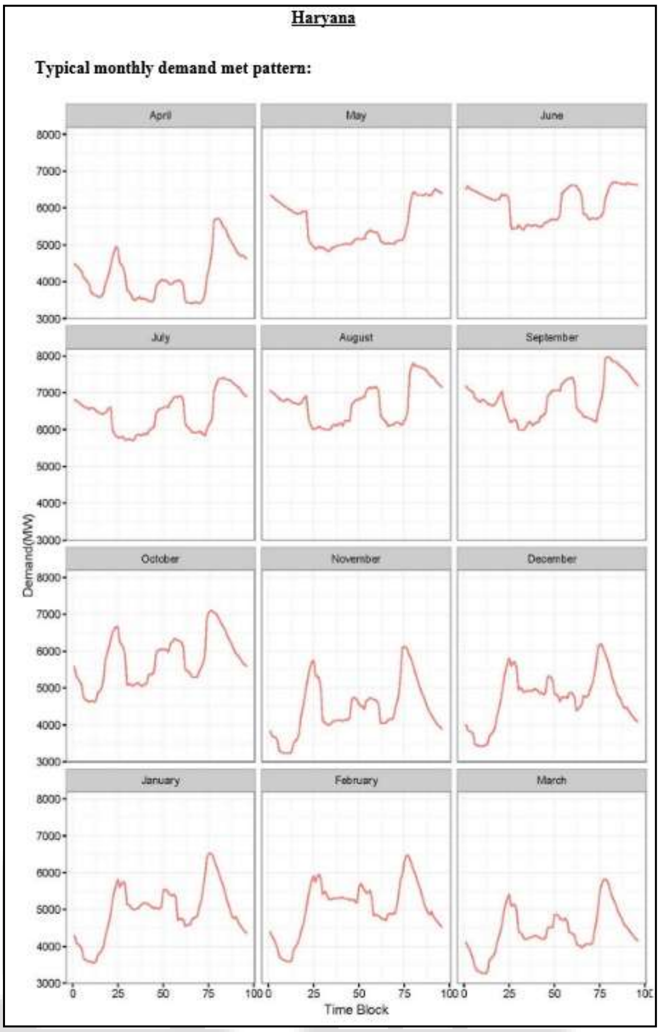

Fig. 2.3: Monthly Demand Pattern

III. ARTIFICIAL INTELLIGENCE

These non parametric model that map the input and output relationship without exploring the underplaying process. It is considered that AI model have the ability to study non linear and complex relationship that difficult to model with conventional model. These models are:-

1) Artificial model
2) Data mining model

A. Neural Network:-

It is a advance technique with faster output result. The predication architecture of this model having three layer input layer, output layer, and hidden layer. The input time series data pattern given to the input layer neuron of network the output of input layer is processed to the hidden layer through the weight and bias and output of hidden layer is used as an input and output layer of the neural network. To avoid the overtraining during the process and more accuracy only 744 hour’s data taken in account.

B. Train Data:-

The train data contain the data from 1 Jan 2019 to 31 Dec 2019 i.e. 9404 hours. This data contain (t-1) (t-2) (t-3)......................... (t-100) time lags data. This data is analysis by two type of prediction is done by the perform ACF (auto correlation) and without the ACF. With ACF result comes more accurately.

C. Test Data:-

Test data is data which prediction analysis. This data has contained 31*24=744 hours, in this no systematic approach followed. There are hidden layer used is twenty and input time lag are 100. There is single output neuron.

Pre-processing was done to forecast max, min, medium value of demand 3 auxiliary NN for forecast hourly demands. Georgilaly has repeated and adaptively trained. MLP-Bp, in which main NN prediction the hourly using forecast load information of auxiliary NN. In Reference (20) wt has been used to extract approximation and then these signal fed to an artificial algorithm based on NN to map influence of non linear factor. Reference () takes the less number of hidden layer and less number of time lags. Theses factor affect the output accuracy.

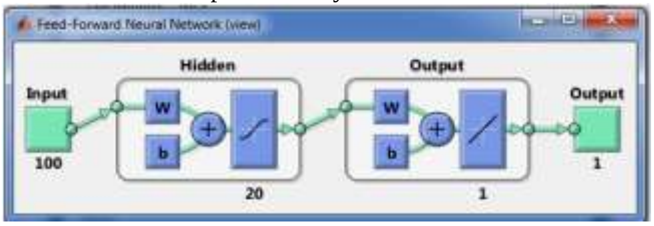

Fig. 3.2: Neural Network Feed Forward

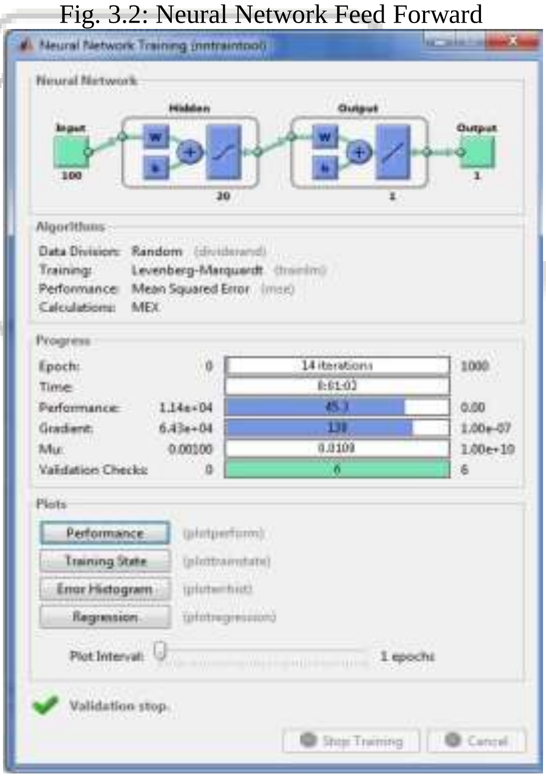

Fig. 3.1: NN tool performance

D. Basic Steps Neural Network to Perform Predication

- Structure of NN employed for the present work.
- For the training of network training algorithm is used with tangential sigmoid and linear activation function for each year hour of days.
- One data has been trained with one month moving average testing algorithm for whole year max epoch set equal to 1000.
  1) Time=00.00.43
  2) MU=0.00100
  3) No. Of iteration=14
- Forecast value found at output. It compare with Actual value.

The performance of model also tested by MAPE, RMSE and MAE.

MAPE is Also define as;-

$$\frac{1}{N}\sum_{t=1}^{N}\frac{ABS(Actual_t - Forecast_t)}{Actual_t} * 100\%$$

RMSE

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2}$$

MAE

$$\text{Mean absolute error} = \frac{\text{Sum of all absolute errors}}{\text{No of errors } (n)}$$

$$= \sum_{i=1}^{n} \frac{X_i - X}{n}$$

IV. OBSERVATION

The observation is done by analysis the input and output. The power demand is less than 10 MW its mean that the demand of reactive power is more as compare to true power and its predication is very nearly to the actual value. If true power nearly to zero and current having large magnitude its mean a fault occur at transmission line with low power factor. These are affecting the output result during the forecasting,

The peak load demand is maximum at 14:00, 15:00 hours and 23:00 and 1.00 hours. During the 14:00 and 15:00 hours domestic consumer demand is increase using of air conditioner, heaters or other domestic appliances. During the night hours domestic demand is decreases and excess amount of energy supply to industrial consumer through pool operation. In other hand less power demand during 5:00 and 6:00 hours.

The Power (demand) curve substation:-

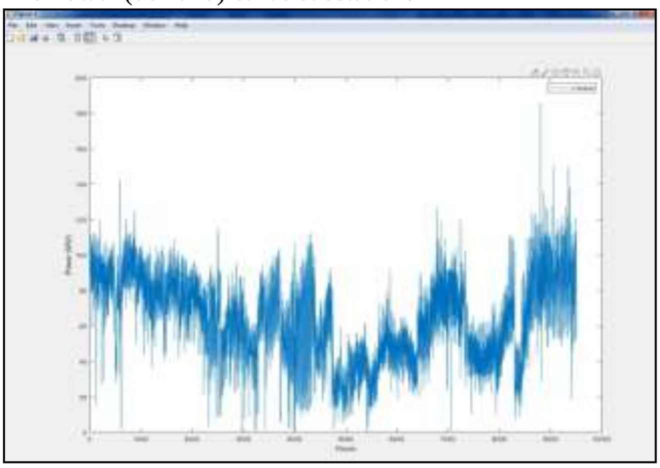

Fig. 4.1: Result

The demand forecasting carried out using MATLAB, R 2019, 3.0 versions, 6 GB RAM and Intel i5 processor. The data as input from 1st Jan to 31st Dec 2019 used as training data. MAPE and RMSE are carried out from different time duration. When the prediction done by without ACF only 100 time lags are used (t-1) to (t-100). After this ACF is done the time witch have correlation value less than 0.6 are ignored and higher value take for analysis. Due to this accuracy of result increase and MAPE value has been reduced. The ACF value which have more than 0.6 have excellent relationship and less value have poor relationship. The prefect ACF times are:

(t-1), (t-2), (t-5), (t-7), (t-1), (t-17), (t-31), (t-45), (t-52), (t-97), (t-98)

Before Auto correlation:
MAPE: - 0.084717
RMSE: - 10.76
Iteration=16
Performance=50.5
MU=0.0100
Time=0:00:48
Validation check=6

A. Graph:-

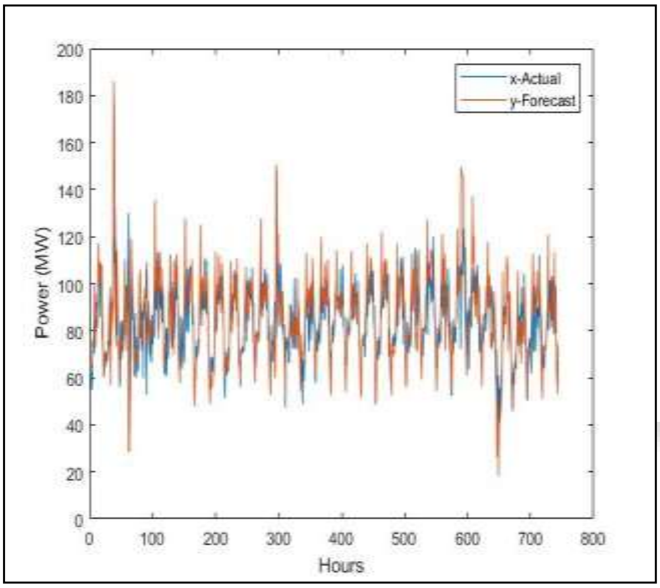

Fig. 4.2: Graph actual v/s forecast

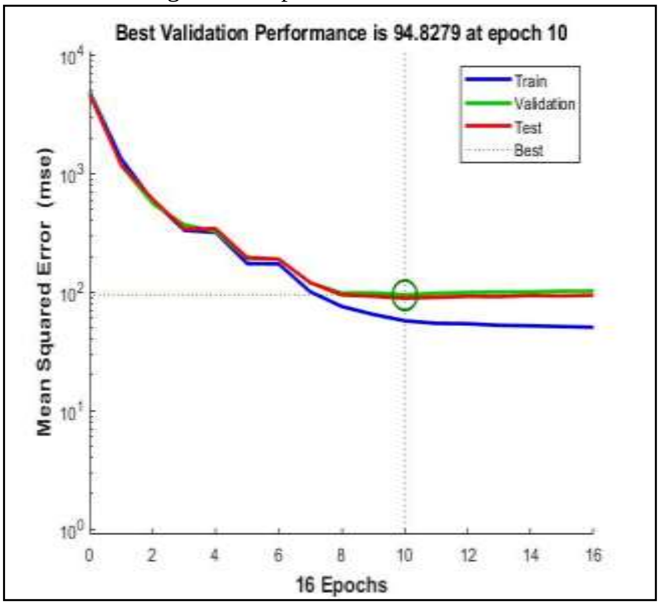

Fig. 4.3: Performance graph

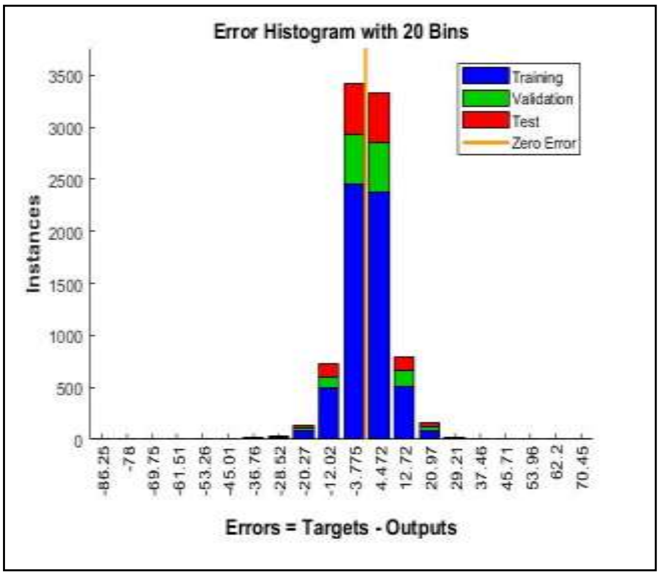

Fig. 4.4: Error Histogram

After Auto Correlation Function

MAPE=0.0711
RMSE= 10.59
Iteration= 13
MU=0.0100
Time=0:00:03
Validation Check=6

B. Graphs:-

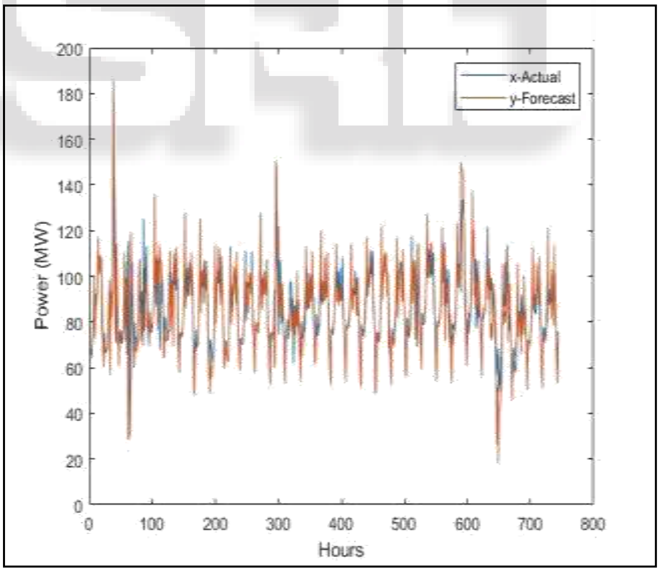

Fig. 4.5: Actual v/s Forecast

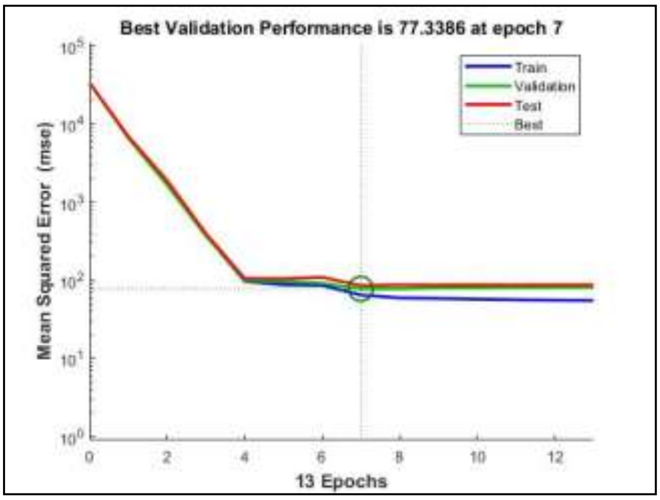

Fig. 4.6: Performance

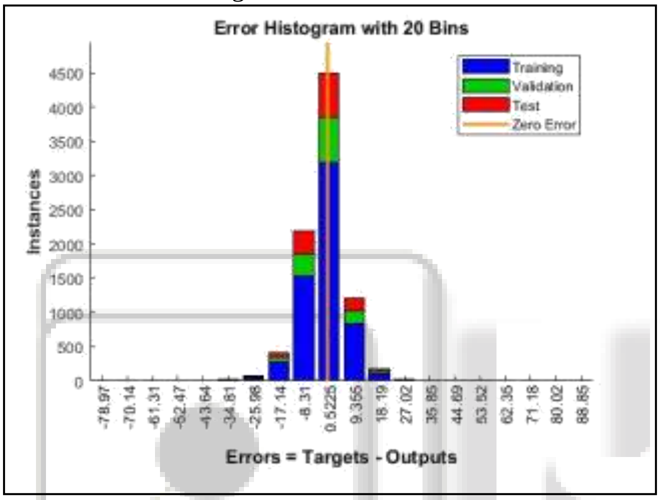

Fig. 4.7: Error Histogram

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