A Short-Term Load Forecasting Technique and Analysis Using Artificial Neural Network

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***Abstract* - This paper proposes a neural network approach for forecasting short-team loads. The basic objective of short team load forecasting is to predict the near future load. This paper uses techniques for artificial neural network base short team load forecasting. Historical load data were obtained from SLDC (State Load Dispatch Centre) Gotri Baroda, Gujarat and weather data were obtained from online weather site for the same period to train neural network. It is trained using two layer feed forward neural network and tested error was calculated as MAPE (Mean Absolute Percentage Error) and with error of about 0.9592% this paper was successfully carried out.**

I. INTRODUCTION

Short –Term Load forecasting is basically aimed at predicting system load with a leading time of one hour to seven day, which is necessary for adequate scheduling and operation of power systems. Thus, Load forecasting has also become an important component of energy brokerage systems. There is a 3-7% increase of load depends on the population growth, local area development, industrial expansion etc. [1].

Load forecasting is an important component of power system energy management system. Load forecasting means predicting the future load with the help of historical load data available. It is very important for the planning, operation and control of the power system. The accuracy of the forecast is crucial to any electric utility. Since in power system the next's day power generation must be scheduled every day, day- ahead short- team load forecasting (STLF) is a necessary daily task for power dispatch. Its accuracy affects the economical operation and reliability of the system greatly. The short team forecast are not only needed for control and scheduling for power system but also used as input to load flow study or contingency analysis i.e. for load management program. The short team forecasting is also primarily used for the generation dispatch, capacitor switching, feeder reconfiguration, voltage control and automatic generation control (AGC) [3].

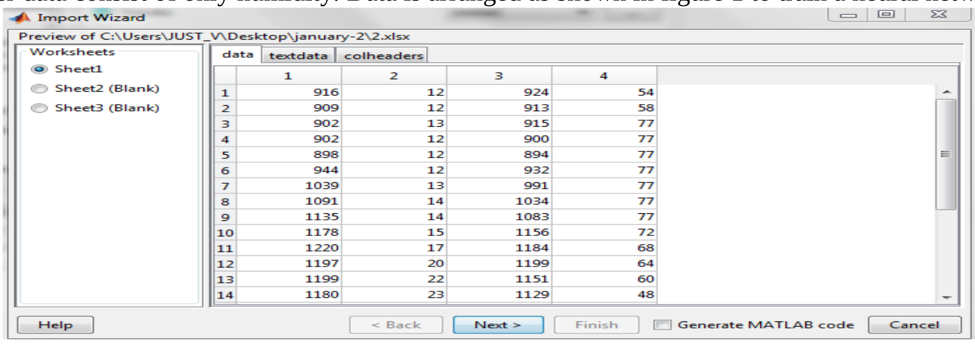
Short team load forecasting is the prediction of electrical load demand for a period varying from the next few minutes up to a week. Short team load forecasting plays a vital role in system operation and is the main source of information for all daily and weekly operations concerning generation commitment and scheduling. Short-team load forecast is also important for the economic and reliable operation of the power system. In order to achieve high forecasting accuracy and speed, it is required to know the factor that affects the load. Some of this factor is: the type and time of day, the weather conditions of the forecasting area, the season, etc. since most days have different load profiles, it is necessary to have a day type. Time of the day is an important factor in short team load forecasting. It is required to know the forecasting time of the day is different. Therefore, the relationships between this factors and the load demand need to be determined so that the forecast may be as accurate as possible.[4].

One of the major research areas in the field of electrical engineering which has been of great importance for many years is load forecasting. Load forecasting facilitates to maintain a balance between electricity supply and demand.[5]

II. METHODOLOGY

A. Data

There are two set of data namely load profile data and weather data. Load data is obtained from SLDC- Gotri Baroda and to weather data is obtained from online website for same period. Load data consist one hourly measurement of load for period of year 2014. Weather data consist of only humidity. Data is arranged as shown in figure 1 to train a neural network.



	1	2	3	4
1	916	12	924	54
2	909	12	913	58
3	902	13	915	77
4	902	12	900	77
5	898	12	894	77
6	944	12	932	77
7	1039	13	991	77
8	1091	14	1034	77
9	1135	14	1083	77
10	1178	15	1156	72
11	1220	17	1184	68
12	1197	20	1199	64
13	1199	22	1151	60
14	1180	23	1129	48

Fig.1 Arrangement of data set

B. *Load pattern analysis*

This table reading indicated by the 1st &2nd January reading of forecasted load, actual load and error. From SLDC- Gotri Baroda.

TABLE-1 SLDC-Gotri, Baroda reading

Forecasted load (MW) 1.1.14	Actual load (MW)	Diff . (MW)	Forecasted Load (MW) 2.1.14	Actual load (MW)	Diff. (MW)
916	924	-8	965	913	52
909	913	-4	949	892	57
902	915	-13	930	887	43
902	900	2	931	883	48
898	894	4	929	888	41
944	932	12	969	923	46
1039	991	48	1053	1018	35
1091	1034	57	1113	1076	37
1135	1083	52	1132	1078	54
1178	1156	22	1184	1141	43
1220	1184	36	1212	1188	24
1197	1199	-2	1208	1174	34
1199	1151	48	1187	1158	29
1180	1129	51	1168	1139	29
1174	1149	25	1179	1129	50
1180	1098	82	1147	1111	36
1170	1120	50	1143	1115	28
1198	1156	42	1167	1118	49
1230	1206	24	1231	1197	34
1206	1156	50	1192	1125	67
1177	1075	102	1104	1055	49
1080	1028	52	1049	1037	12
995	1000	-5	1011	980	31
982	930	52	983	943	40

This fig .1 is the load cave of 1st January 2014 and fig 2 Error plot for 1st January 2014.

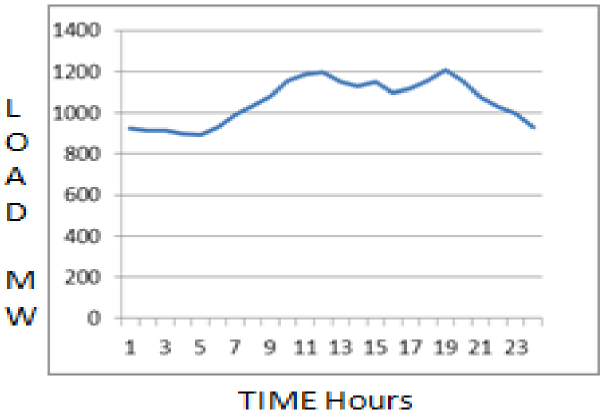


Fig.1 Load curve of 1st January 2014

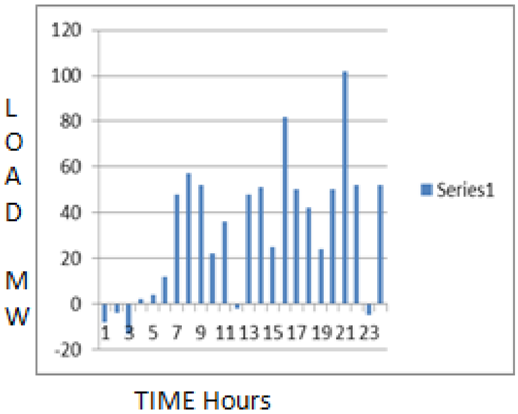


Fig 2 Error plot for 1st January 2014

This fig .3 is the load cave of 2nd January 2014 and fig 4 Error plot for 2nd January 2014

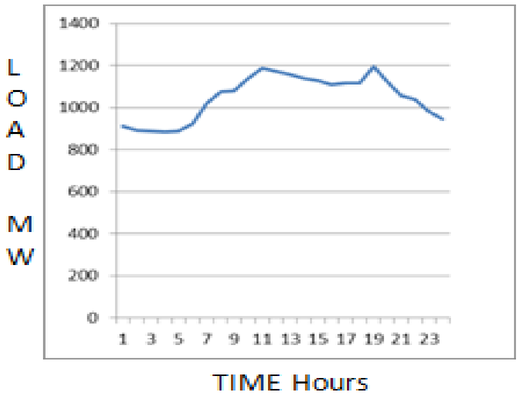


Fig.3 Load curve of 2nd January 2014

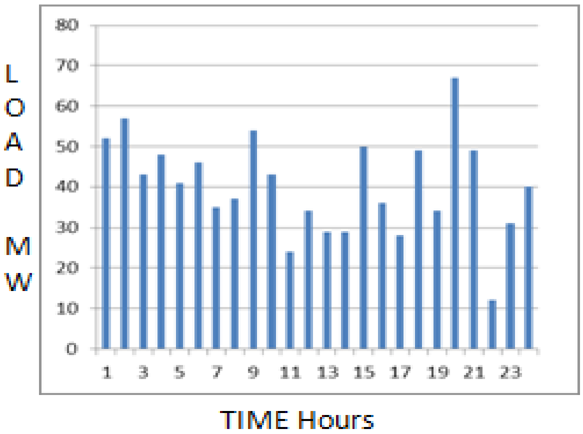


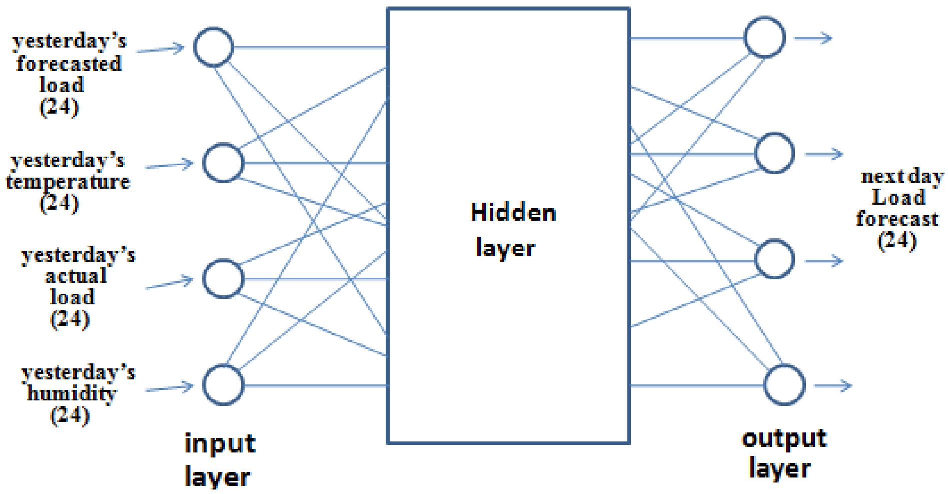
Fig.4 Error plot for 2nd January 2014

C. Neural network training

Neural network training using training sets. The input variables to the neural network are:

- Yesterday's forecasted load
- Yesterday's temperature data
- Yesterday's actual load
- Yesterday's humidity data

ANN Modal for STLF



forecast	error	actual	humidity
916	12	924	54
909	12	913	58
902	13	915	77
902	12	900	77
898	12	894	77
944	12	932	77
1039	13	991	77
1091	14	1034	77
1135	14	1083	77
1178	15	1156	72
1220	17	1184	68
1197	20	1199	64
1199	22	1151	60
1180	23	1129	48
1174	23	1149	61
1180	23	1098	57
1170	21	1120	64
1198	20	1156	68
1230	19	1206	68
1206	19	1156	68
1177	18	1075	73
1080	17	1028	72
995	18	1000	62
982	17	930	72

Previous day input data

actual
913
892
887
883
888
923
1018
1076
1078
1141
1188
1174
1158
1139
1129
1111
1115
1118
1197
1125
1055
1037
980
943

Next day target data

This all data is used for hourly data. The output of input layer. Hidden layer consist of 10 neurons with long sigmoid as activation function. The output of hidden layer is used as input for this layer. It consist of single neuron, with linier activation function From total number of samples 70% were used for training , 15% were used for validation and 15% were used for testing Neural network training tool is shown in figure Neural Network performance and regression plot and fit plot are shown in figure

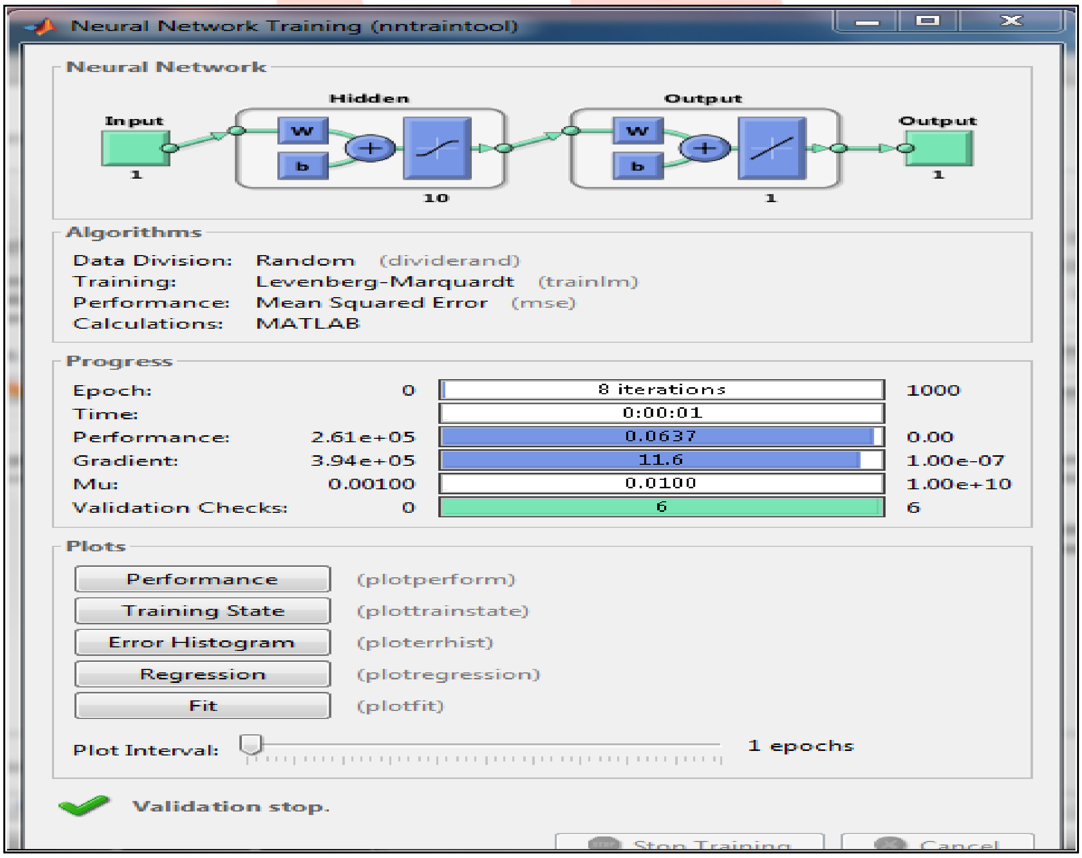


Fig 5. Neural Network training tool

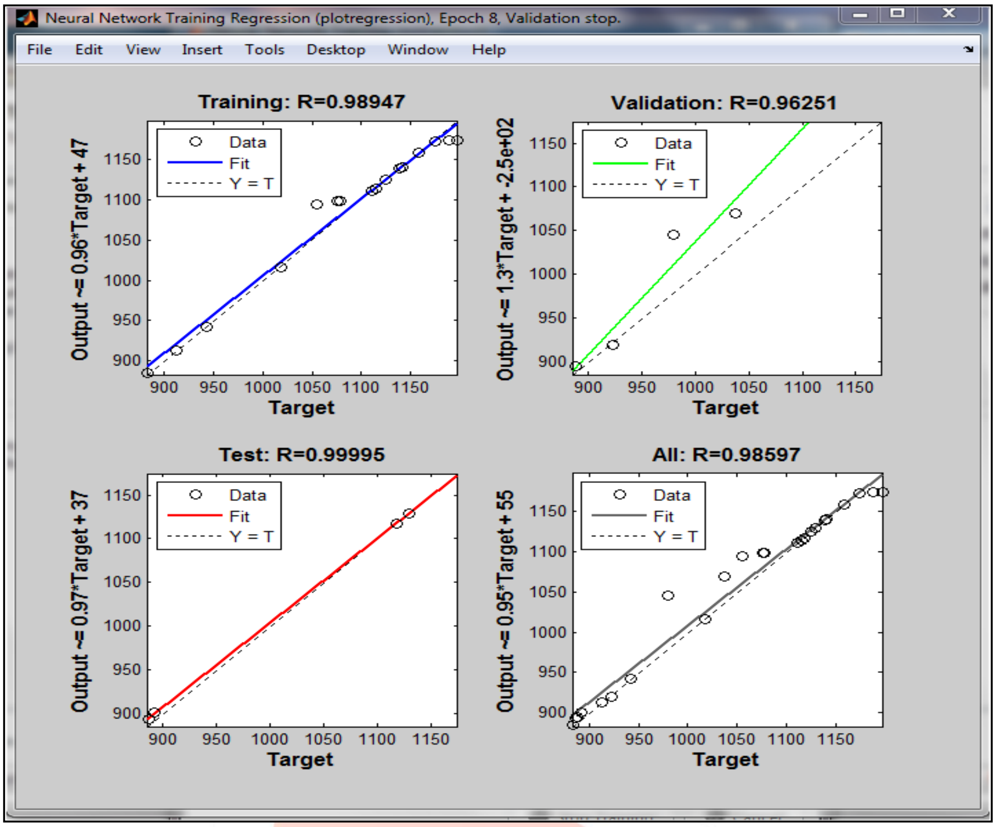


Fig 6. Neural Network regression plot

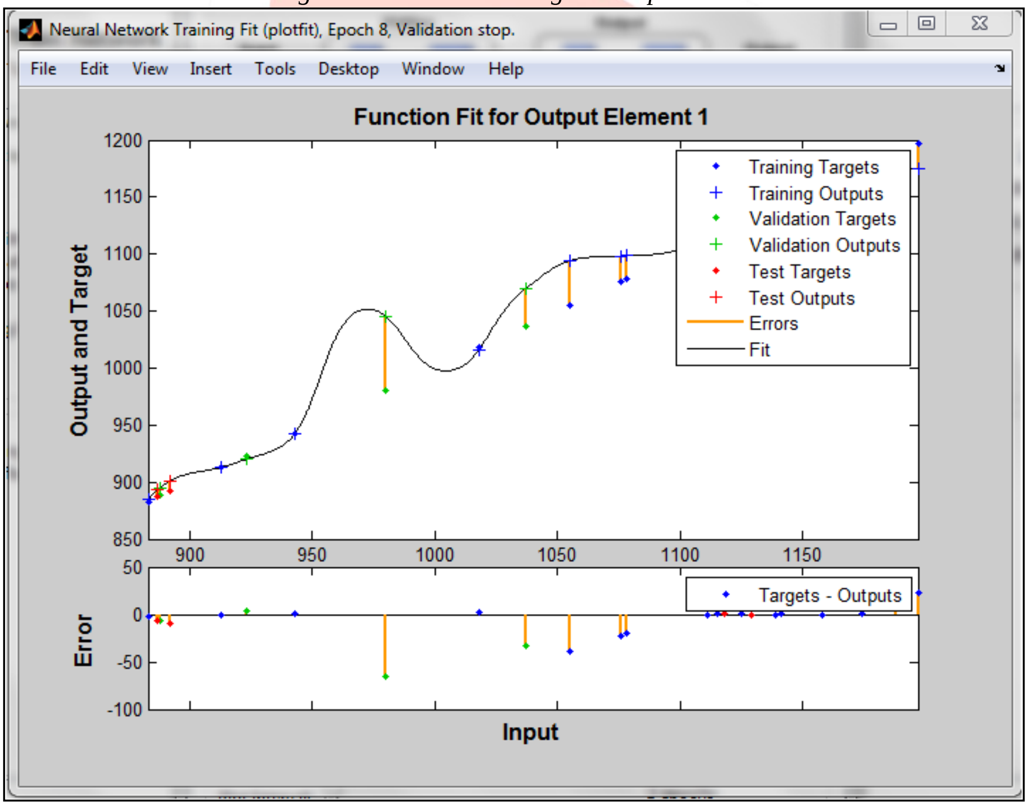


Fig 7. Neural Network fit plot

The best performance achieved for validation is at epoch 2. The R (correlation coefficient value) values for training, validation and testing are 0.98947, 0.96261 & 0.99995 respectively. The overall R value is 0.98597 resulting and very closes prediction.

III. RESULTS

The training process is based on the error produced by ANN. To determine the error, the absolute percentage error (APE) and mean absolute percentage error (MAPE) are used. Based on test Result, APE and MAPE can calculated. If calculated MAPE is higher than 3%, training must be done. This process continues until all MAPE from test results are below 3%. Includes comparison of actual load and forecast load as shown in figure. Mean percentage absolute error is before training is 3.9231% and after training error is 0.9592% which good overall forecast.

Hour	Forecasted load	Actual load	New Forecast	APE Error	New APE Error
1	965	913	913	5.6955	0
2	949	892	901	6.3901	1.0089
3	930	887	893.2	4.85	0.6989
4	931	883	885.3	5.436	0.2604
5	929	888	895	4.6171	0.7882
6	969	923	920	4.9837	0.325
7	1053	1018	1016	3.4381	0.1964
8	1113	1076	1098	3.4386	2.0446
9	1132	1078	1098	5.0092	1.8552
10	1184	1141	1141	3.7686	0
11	1212	1188	1174	2.0202	1.1784
12	1208	1174	1173	2.896	0.0851
13	1187	1158	1159	2.5043	0.0863
14	1168	1139	1139	2.546	0
15	1179	1129	1129	4.4286	0
16	1147	1111	1111	3.2403	0
17	1143	1115	1114	2.5112	0.0896
18	1167	1118	1117	4.3828	0.0894
19	1231	1197	1197	2.8404	0
20	1192	1125	1125	5.9555	0
21	1104	1055	1094	4.6445	3.6966
22	1049	1037	1070	1.1571	3.1822
23	1011	980	1045	3.1632	6.6326
24	983	943	943	4.2417	0

TABLE-II New Analysis forecast 2-1-2014

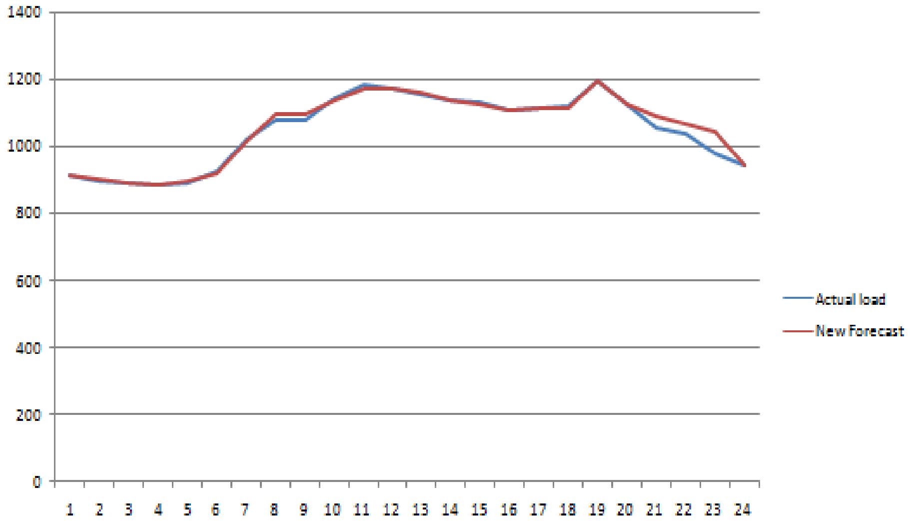


Fig 8. New forecast 2-1-2014

Result Analysis

- The training process is based on the error produced by ANN. To determine the error, the absolute percentage error(APE) and the mean absolute percentage error(MAPE) are used,
- Based on test results, APE and MAPE can calculated.
- If calculated MAPE is higher than 3%, training must be done.
- This process continues until all MAPE from test results are below 3%.
- Before training 2-1-2014 the MAPE error is 3.9231%.
- After training 2-1-2014 the MAPE error is0.9592%.

One Week Analysis

Date	Before training MAPE error	After training MAPE error
2/1/2014	1.9232	0.9257
3/1/2014	4.1455	0.5707
4/1/2014	3.151	0.3606
5/1/2014	4.8457	0.7071
6/1/2014	2.7542	0.5557
7/1/2014	2.5471	1.7432
8/1/2014	3.1181	0.8703
9/1/2014	2.8966	0.189

IV. CONCLUSION

In present work short team load forecasting is done using artificial neural network. Neural network is trained using past data of system load and humidity. The data set is divided into two sets, testing set and training set. Test set with data from 2014 onwards.

Artificial intelligence tools using to improve the forecasting result. It is very difficult to predict the load accurately using analytical methods. A neural network is the advanced approach for accurate short-team load forecasting. Short-team load forecasting is using Artificial intelligence method and error minimized.

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