Real-time Forecasting of Electrical Power System Loads using Moving Average-Extreme Learning Machine (MA-ELM) Algorithm

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Abstract: - Load Forecasts are the primary factors which considered by electricity utility companies while planning power generation, power infrastructural development and load flows etc. Different forecasting techniques have been proposed from statistical to artificial intelligence-based models and the area of research is still growing. In our research work, considering the real time data of 33KV bus system which is having 34 buses and 54 lines. In this case, forecast the day ahead scheduling of various parameters such as load real power (Pload), voltage magnitude at each bus, apparent power flow between buses and total transmission losses for hourly basis and also forecasted the mentioned parameters for 5 days. The actual real time values are compared with forecasted values using two existing methods namely Extreme Learning Machine (ELM), moving average and proposed Moving Average–Extreme Learning Machine (MA-ELM) algorithm. In addition to this, forecasted the loads and losses for short term and long-term forecasting cases and verified through MATLAB programming.

Key-Words: - Short term load forecasting (STLF), Moving average (MA), Moving Average-Extreme Learning Machine (MA-ELM).

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1 Introduction

categories, which are very short term, Short-term and Long-term forecasts. Particularly in power market these are very significant for the power system safety. To meet the high demand of urban electricity, exact and persistent short-term load forecasting in power systems operation and management plays an important role, especially in expansion of generating power, economic load scheduling and dispatch, and sustainability of electricity supply. For managing the power systems utilities [1] in planning, evaluations of market demand, load switching, reducing cost and finally guaranteed continuous electricity providing [2] short-term load forecasting (STLF) is considered as a key aspect.

Based on different parameters it can predict the future electrical load with the help of electricity load forecasting. The parameters can be atmospheric conditions, geographical conditions, economic conditions, time horizon such as hour, day and month etc. For the development of smart grid, predict loads in advance [3] for hourly, weekly or monthly by the use of Short-term electricity load forecasting (STLF). To deal with generation of energy and consumption, forecasting models' accuracy is very crucible. For the deregulated power system accurate forecasting model is a very important aspect. In the literature many works were done based on forecasting of load. Neural networks, Time series forecasting technique and a Kalman filtering estimator are popularly used techniques for forecasting of load in smart grid applications [4–5].

Auto regressive moving average (ARMA) based models [6], Kalman filter [7], exponential smoothing (ES) [8], linear regression [9], and grey models (GMs) are called as Statistical models and are widely used in urban smart grid systems for short-term load forecasting. Auto regressive integrated moving average (ARIMA) models are also used to manage the time series analysis in Smart grid for short term load forecasting[12].

Based on artificial intelligence/machine learning (ML) or conventional methods Load forecasting can be performed. Based on support vector machines, fuzzy logic, and artificial neural networks (ANNs) [10] methods can give better performance than the conventional methods. Deep learning for STLF [11] can be used for further extensions. Because of good performance and simple implementation ANN based forecasting method can be preferred among the ML forecast models.

The objective of the paper is to enrich the accuracy of forecasting by extreme learning machine algorithm. In this paper, MA-ELM is a novel hybrid algorithm has been proposed for forecasting of load real power, voltage magnitude and transmission line losses. It has a combinational feature of both

Moving Average and Extreme Learning Machine (MA-ELM) algorithm. In the present paper, it has proposed very short term, short term and long-term forecasting and estimate various parameters such as load real power (P_{load}), voltage magnitude at each bus, apparent power flow between buses and total transmission losses. From the obtained results, observed that the MA-ELM algorithm offers good performance in the point of error metrics and convergence time rather than Moving Average and ELM algorithms. In real time, this technique is very much helpful for forecasting of load[13]. The forecasting results are obtained through MATLAB 2016a software.
Paper is organized that Section I gives the electric load forecasting introduction. Section II presents the mathematical modelling of extreme learning machine algorithm and moving average approach. section III describes the proposed methodology and the proposed model performance through MATLAB programming is discussed in Section IV.

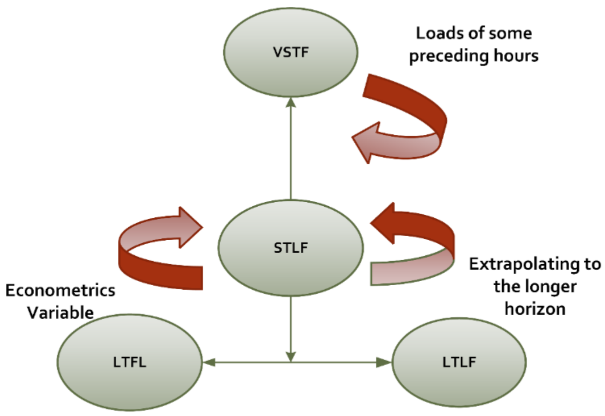

Fig. 1: Process flow of conversion between STLF and LTLF.

STLF is the most popular approach among the various options. Because of its inherent connectedness to other types of projections, it plays a crucial role in the creation of economic and secure operating strategies for the power system. By adding econometric variables to the STLF and projecting the model to a longer horizon, the STLF can be turned into MTLF and LTLF. The VSTLF model, on the other hand, can be created from STLF by include the loads from the previous hours as part of the STLF model's inputs. Short-term load forecasting can incorporate the autocorrelation of the current hour load and the preceding hour load. Additionally, the residuals of previous load can be gathered and used to create a new series based on the STLF. By projecting future residuals and adding them back to the short-term prediction, a very short-term forecast can be obtained. Figure 1 depicts the conversion process between STLF and LTLF, MTLF and VSTLF.

2 Methodology

2.1 Extreme Learning Machine Algorithm

The Extreme Learning Machine model is a Single Layer Feed-forward Network (SLFN) contains input, hidden and output layers. Input layer nodes are interconnected with the hidden layer nodes. This interconnection is known as input layer weights. The hidden layer is the layer between the input and output layers. Each hidden layer nodes are also interconnected with all the output layer nodes. This interconnection is known as the output layer weights. Using different training algorithm weights can be adjusted. The output nodes has been represented the horizon of forecast.
The Extreme Learning Machine (ELM) is a new training algorithm and to reach global minima, it does not require iterative tuning. When compares to gradient descent-based training algorithm, this algorithm has to reduce the training time. The ELM training speed is very faster while comparing with gradient-descent based training algorithm. It can avoid to choose additional parameters like learning rate and stopping criterion. The empirical evidence shows that it has universal approximation capabilities and good generalization.
In ELM, randomly chosen the input weights and hidden biases (linking the input layer with the hidden layer), and by using Moore-Penrose inverse the output weights are determined analytically (linking the hidden layer with the output layer). With a smaller number of iterations, the convergence of ELM is much faster. The ELM can be modelled mathematically as follows:

Given training set Input and Actual Output samples, (x_i,y_i); $i=1,2,\ldots,S$, $x_i \in R^p$, $y_i \in R^q$, where x and y are the input and target matrices of dimensions p and q.

With N hidden layer neurons, the SLFN neural Network is written as

$$\sum_{i=1}^{N} \beta_i . G_i(x_j) = \sum_{i=1}^{N} \beta_i . G(w_i.x_j+b_i)=oj \qquad (1)$$

where w_i is the hidden layer input weight matrix, β_i is the hidden layer output weight matrix, b_i is the threshold of the hidden layer, and G(x) is the activation function. To minimize training error by ELM search:

$$\sum_{i=1}^{N} \beta_i . G(w_i.x_j+b_i) = y_j \qquad (2)$$

The above equations can be re-written as:

$$H\beta = Y \quad (3)$$

H is the hidden layer output matrix;

The output weight matrix can be calculated by:

$$\beta = H^{+}Y \quad (4)$$

Where H^{+} is the Moore–Penrose inverse of H.

2.1.1 Moving Average Approach

In this method, Moving Average formula has been used to average the mentioned number of periods to calculate the next forecasted parameter.

3 Proposed MA-ELM Algorithm

For forecasting of future demand of Chittoor District, APSPDCL, Andhra Pradesh in India, the proposed MA-ELM algorithm is applied.

Moving Average-Extreme Learning Machine algorithm:

MA-ELM is a hybrid approach gives combined features of both Moving average and Extreme Learning Machine algorithm. Simple Moving Average approach for prediction and capability of ELM improves overall efficiency and reduces simulation time with least training. Moving average method is purely statistical method, here we have to possibility to apply error analysis and stability analysis cannot be applied. The mathematical formulation of MA-ELM can be explained as follows:

Let the training set Input and Actual Output sample patterns be (a_i,b_i); $i=1,2,\ldots\ldots,S,S+1$. Where $a_i=[a_{i1},a_{i2},a_{i3}\ldots\ldots,\ a_{is},\ a_{i(S+1)}]^T$ represents input parameters and $b_i=[b_{i1},b_{i2},\ldots\ldots,b_{is}]^T$ represents output parameters.

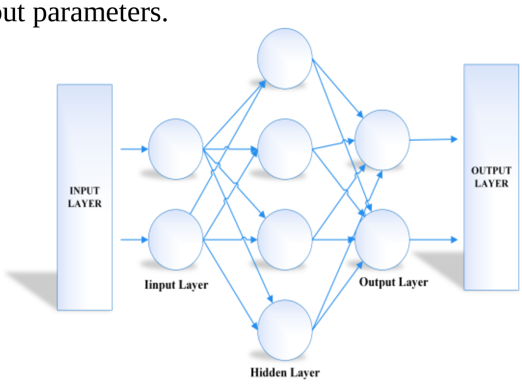

Fig. 2: Single hidden layer MA-ELM structure

Where b_{i1}=average of a_{i1} and a_{i2}, b_{i2}=average of a_{i2} and a_{i3}. Similarly, b_{is}=average of a_{is} and $a_{i(s+1)}$. Mathematical function establishes MA-ELM with activation function $\varphi(.)$ and L number of hidden nodes, it can be expressed as

$$G(a_j)= \sum_{i=1}^{N} \eta_i.\varphi(\lambda_i.a_j+\mu_i);j=1,2,\ldots..(s+1) \quad (5)$$

The above expression written in matrix notation as $\varphi\eta=A^{\square}$ (6)

The activation function is $\varphi(.)$ in matrix form is

$$\phi = \begin{bmatrix} \phi(\lambda_1 a_1+\mu_1) & \phi(\lambda_2 a_1+\mu_2) & \cdots & \phi(\lambda_L a_1+\mu_L) \\ \cdot & \cdot & \cdot\ \cdot\ \cdot & \cdot \\ \cdot & \cdot & \cdot\ \cdot\ \cdot & \cdot \\ \phi(\lambda_1 a_{s+1}+\mu_1) & \cdot & \cdots & \phi(\lambda_L a_{s+1}+\mu_L) \end{bmatrix}$$

$A^{\square}$ is the target matrix,

$$A^{\square}=[b_1,b_2,\ldots\ldots,b_s]^T \quad (7)$$

The parameters λ and μ has been randomly chosen and cost function is minimised based on back propagation learning algorithm. The output weight matrix $\tilde{\eta}$ can be obtained with the help of singular value decomposition (SVD) method using Moore–Penrose inverse approach. It can be calculated as:

$$\tilde{\eta}=\varphi^{-1}A^{\square} \quad (8)$$

In the present work, forecasting of various parameters has been done for Chittoor District, APSPDCL area of the state of Andhra Pradesh, India.

Step 1: Collected the bus data, line data and previous load data for past ten years belongs to Chittoor district from APSPDCL Head Office, Tirupati.

Step 2: Using MA-ELM algorithm forecasting has been done for selected parameters in the given area.

Table 1. P_{load}

Bus No	ELM	MA	MA-ELM	Actual load
1	0	0	0	0
2	3	2.96106	2.944104	2.93832
3	41	41.08519	40.97365	41.00963
4	0	0	0	0
5	13	13.02926	12.94748	12.96294
6	75	74.96796	74.94492	74.94274
7	0	0	0	0
8	150	149.979	149.9498	149.9547
9	121	121.0702	120.9629	120.9917
10	5	5.062028	4.957805	4.98477
11	0	0	0	0
12	377	377.0755	376.9617	376.9963
13	18	18.08279	17.96876	18.00453
14	10.5	10.53167	10.45144	10.4661
15	22	21.9578	21.94083	21.93269
16	43	42.9532	42.94533	42.93931
17	42	42.10348	41.97738	42.01925
18	27.2	27.26037	27.1577	27.18444
19	33	33.05279	32.9548	32.97876
20	23	23.0451	22.95806	22.97677
21	0	0	0	0
22	0	0	0	0
23	63	63.09944	62.97272	63.01789
24	0	0	0	0
25	63	62.98244	62.95338	62.95467
26	0	0	0	0
27	93	92.94735	92.94116	92.93127
28	46	46.09253	45.98746	46.02777
29	17	17.09103	16.97226	17.00927
30	36	36.08836	35.97305	36.00931
31	5.8	5.891067	5.770532	5.809697
32	16	16.07071	15.96261	15.99269
33	38	37.98484	37.95064	37.95561
34	0	0	0	0
Total	1381.5	1382.465	1380.48	1380.991

4 Results and Analysis

In the present work, considered very short-term load forecasting and estimate the day ahead scheduling of various parameters such as load real power (Pload), voltage magnitude at each bus, apparent power flow between buses and total transmission losses for hourly basis and also forecasted the mentioned parameters for 5 days.

In “Table 1” shown the actual load values, forecasted loads using ELM, MA method and proposed MA-ELM method values of load real power (Pload) for 34 buses. From the tabulated results, concludes that the proposed method gives better performance when comparing with the two existing methods. The results of load real power with proposed method is shown in “Figure 3”.

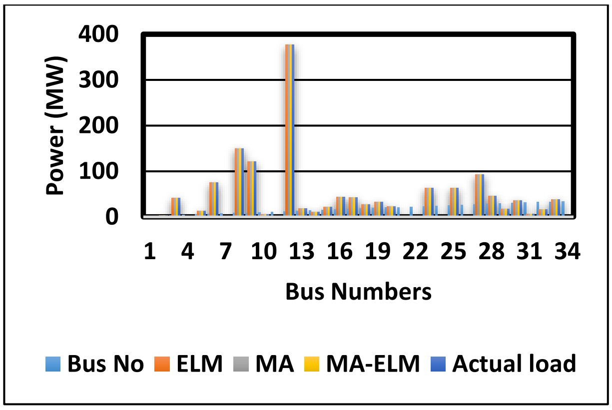

Fig. 3: Load real Power P_{load}

In table.2, shown the actual voltage magnitude values, forecasted values with ELM, MA methods and proposed MA-ELM method for 34 buses. The graphical representation of voltage magnitudes at buses with proposed and existing methods is shown in “Fig. 4”. From this, it has observed that by the proposed method the voltage magnitude is slightly increased

In “Table 3” mentioned the actual values of apparent power flows (Sflow) between buses (for 54 lines), forecasted power flows using existing methods and proposed method values of line flows. The results of apparent power flows with proposed method is shown in “Fig 5”. From the output values understand that the magnitudes of power flows are optimally scheduled with proposed method.

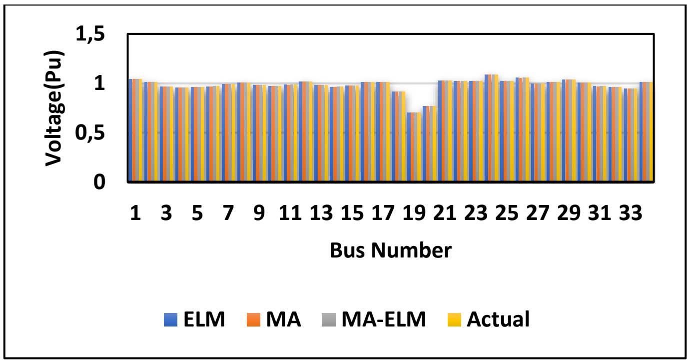

Fig. 4 Bus voltages

Table 2. Voltage magnitudes at buses

Bus No	ELM	MA	MA-ELM	Actual
1	177.8435	178.2019	177.4211	177.6142
2	164.0192	164.3714	163.6927	163.8699
3	109.9472	110.1649	109.7072	109.8195
4	25.96752	26.00539	25.90843	25.93136
5	32.50065	32.54326	32.43836	32.46451
6	20.87292	20.89087	20.84959	20.85895
7	42.20619	42.19622	42.19967	42.19535
8	161.5927	161.5807	161.6705	161.6519
9	13.9734	13.98843	13.97114	13.97632
10	19.80122	19.79508	19.81789	19.81347
11	16.07777	16.15178	16.01028	16.04677
12	6.728811	6.767126	6.689216	6.709259
13	40.91338	40.99192	40.84401	40.8835
14	67.91005	68.05626	67.79406	67.8665
15	248.5747	249.0657	248.0789	248.3331
16	110.8514	111.039	110.6442	110.7455
17	125.104	125.3721	124.8971	125.0273
18	55.10505	55.15557	55.04674	55.07441
19	67.83606	68.01067	67.69476	67.77232
20	19.1667	19.18657	19.14373	19.15567
21	98.03861	98.07942	98.01945	98.0366
22	45.70516	45.87023	45.56174	45.64094
23	36.56608	36.62135	36.5173	36.54608
24	57.25011	57.55941	56.96963	57.12219
25	65.61201	65.84177	65.46171	65.56699
26	80.09802	80.25505	79.91992	80.00454
27	91.9482	92.10797	91.80827	91.88828
28	34.46314	34.54896	34.38838	34.42649
29	8.891935	8.912713	8.874242	8.884053
30	44.06563	44.20001	43.94607	44.00537
31	23.00165	23.01186	22.99684	23.00509
32	11.03039	11.02431	11.01211	11.01165
33	28.16451	28.19558	28.14867	28.16312
34	12.3143	12.3157	12.31517	12.31569
35	34.2143	34.24215	34.20262	34.21513
36	47.70539	47.73062	47.65924	47.67647
37	51.54098	51.46888	51.52435	51.49996
38	67.50628	67.51109	67.51172	67.51449
39	98.86686	98.96312	98.83543	98.87702
40	48.06732	48.2026	48.0149	48.07316
41	6.870753	6.909296	6.850406	6.868304
42	1.691388	1.709101	1.691189	1.697704
43	38.71578	38.70075	38.66417	38.66962
44	13.81919	13.8473	13.79286	13.80765
45	13.81919	13.8473	13.79286	13.80765
46	32.74262	32.75351	32.70465	32.71685
47	5.348144	5.359592	5.339327	5.344595
44	13.81919	13.8473	13.79286	13.80765
45	13.81919	13.8473	13.79286	13.80765
46	32.74262	32.75351	32.70465	32.71685
47	5.348144	5.359592	5.339327	5.344595
48	99.8915	100.0664	99.74588	99.83389
49	76.60924	76.67557	76.54085	76.57724
50	53.68711	53.79858	53.58921	53.64279
51	50.64456	50.7404	50.55892	50.60767
52	48.19963	48.28682	48.11582	48.16222
53	45.02944	45.09858	44.98186	45.01595
54	26.96045	26.96407	26.96151	26.96305

Table 4. Total Power Losses

	ELM	MA	MA-ELM	Actual
Total power losses, MW	67.84491	68.10614	67.59989	67.73047
Iterations	7	8	7	7
Time, Sec	32.443	39.281	30.552	36.284

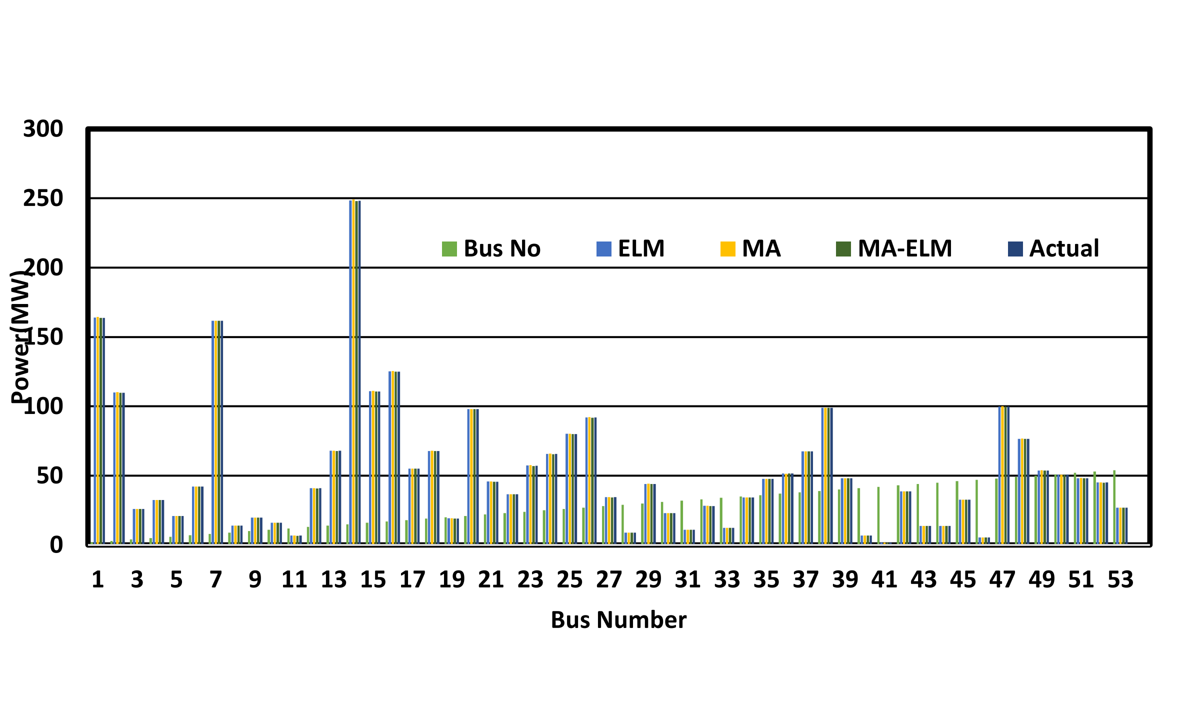

Fig. 5: Apparent Power Flow

In "Table 4" shown the actual total power losses and forecasted losses occurred with existing methods and proposed method. The graphical representation of total power losses with proposed method and existing methods are shown in "Fig. 6". From the obtained data the total power losses are minimized with the proposed method when compares with the existing methods.

In "Table 5" tabulated the actual total power losses and occurrence of forecasted losses with existing methods and proposed method for hour wise upto 24 hours on 01-01-2020. "Figure 8" shows the graphical representation of the power losses on 01-01-2020. Hence, it has observed that the losses are minimized with the efficiency of proposed method.

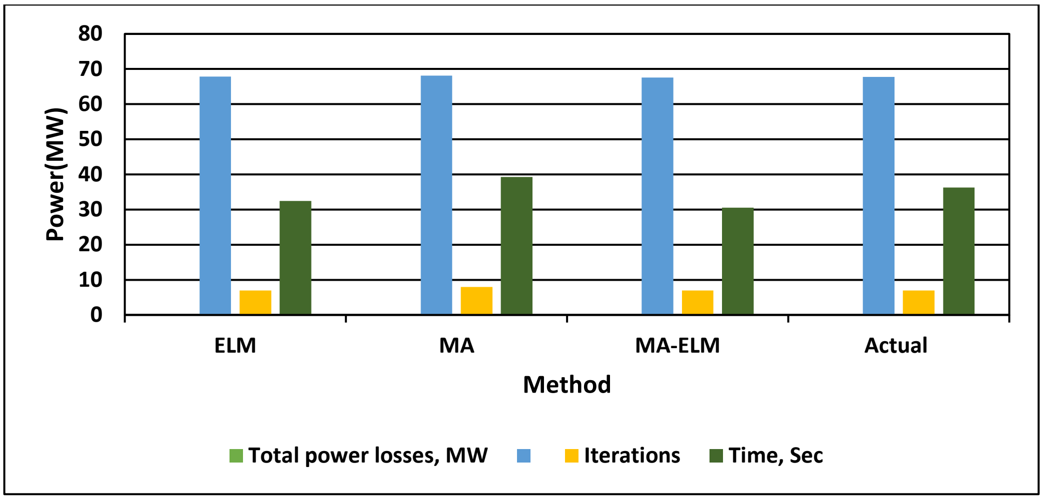

Fig. 6: Total Power losses

Table 5. Total Power losses on 01-01-2020

Time	Total power losses, MW			
	Existing methods		MA-ELM	Actual
	ELM	MA		
00:00	67.8449	68.1061	67.5999	67.7305
01:00	67.6903	67.6646	67.7096	67.7025
02:00	67.6174	67.5795	67.6457	67.6353
03:00	67.6174	67.5796	67.6458	67.6354
04:00	67.7386	67.7209	67.7519	67.7470
05:00	68.0874	68.1280	68.0570	68.0682
06:00	68.6929	68.8358	68.5861	68.6254
07:00	69.0913	69.3024	68.9336	68.9917
08:00	69.1436	69.3635	68.9794	69.0398
09:00	69.0811	69.2902	68.9250	68.9824
10:00	69.0255	69.2250	68.8764	68.9313
11:00	68.9423	69.1275	68.8038	68.8548
12:00	68.8411	69.0090	68.7155	68.7617
13:00	68.8333	68.9999	68.7088	68.7546
14:00	68.8630	69.0346	68.7346	68.7819
15:00	68.9821	69.1742	68.8385	68.8914
16:00	69.3201	69.6017	69.1333	69.2020

17:00	69.8136	70.1986	69.5283	69.6330
18:00	69.8062	70.1902	69.5217	69.6262
19:00	69.6270	69.9785	69.3692	69.4621
20:00	69.3634	69.6637	69.1708	69.2417
21:00	69.0080	69.2049	68.8610	68.9151
22:00	68.5492	68.6677	68.4605	68.4932
23:00	68.1276	68.1750	68.0921	68.1052

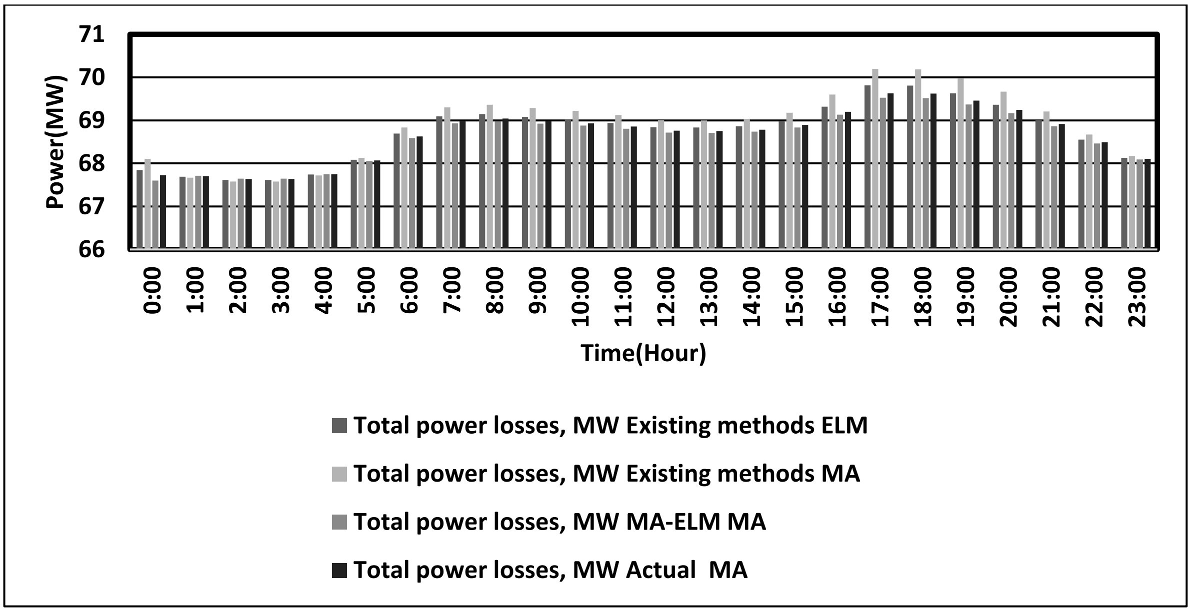

Fig. 7: Total Power losses on 01-01-2020

“Table 6” shows that the comparison of total power losses for actual load and total power losses for the forecasted load using proposed MA-ELM method. “Figure 7” gives the results with comparison of total power losses for actual load and total power losses for the forecasted load with proposed method. From the output results concludes that the losses are reduced with the proposed method when compares with the mentioned two existing methods.In “Table 7” considers the average of daily loads (month) and tabulated total real power load (Pload) and total power losses for monthly basis and upto 1 year with proposed method of forecasting and “Figure 8” shows its graphical representation. “Table 8” shows long term forecasting case, it has considered the annual total load real power (Pload) and total power losses up to 10 years with proposed method of forecasting. So, in “Table 8” tabulated the total real power load and total power losses for yearly basis upto 10 years. “Figure 10” shows the graphical representation of the results shown in Table 8.

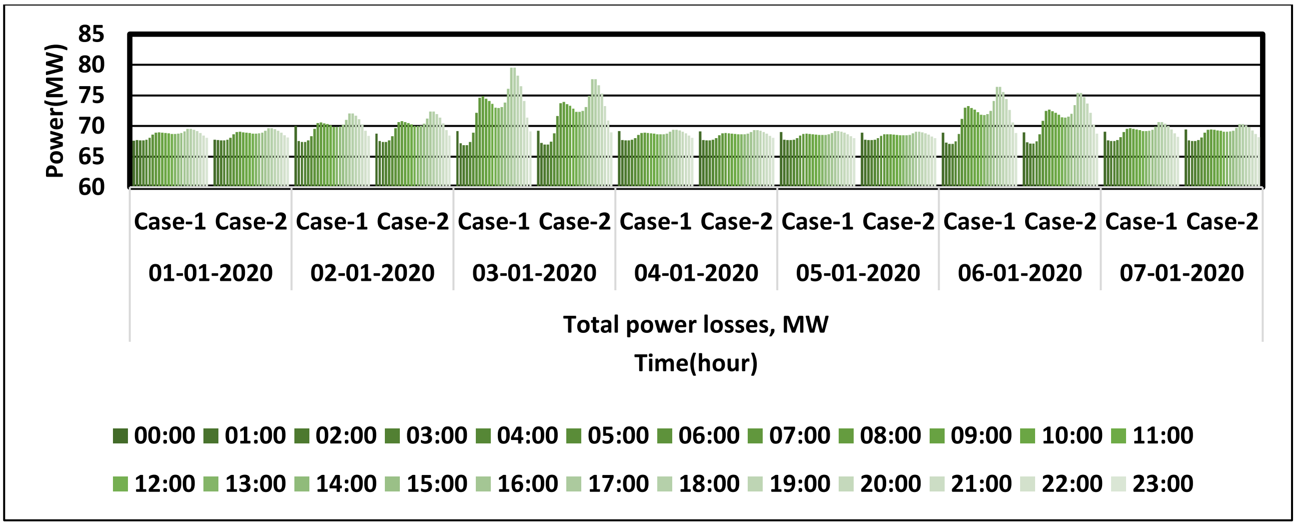

Fig. 8: Total power losses for the forecasted load. case-1: Using proposed MA-ELM method, case-2: Actual load (real time data)

Table 6. Case-1: Total power losses for the forecasted load using proposed Moving Average-ELM method. Case-2: Total power losses for the actual load (real time data).

Time	Total power losses, MW									
	01-01-2020		02-01-2020		03-01-2020		04-01-2020		05-01-2020	
	Case-1	Case-2	Case-1	Case-2	Case-1	Case-2	Case-1	Case-2	Case-1	Case-2
00:00	67.5999	67.7305	69.9906	68.7588	69.1886	69.2450	69.1775	69.1175	69.0277	68.9185
01:00	67.7096	67.7025	67.5448	67.5272	67.1721	67.2464	67.7191	67.7233	67.7367	67.7465
02:00	67.6457	67.6353	67.4034	67.3775	66.8569	66.9657	67.6596	67.6658	67.6855	67.7000
03:00	67.6458	67.6354	67.4036	67.3777	66.8573	66.9661	67.6597	67.6659	67.6856	67.7000
04:00	67.7519	67.7470	67.6385	67.6264	67.3818	67.4330	67.7584	67.7613	67.7705	67.7773
05:00	68.0570	68.0682	68.3177	68.3457	68.9161	68.7958	68.0422	68.0355	68.0145	67.9991
06:00	68.5861	68.6254	69.5302	69.6477	72.1553	71.6067	68.5339	68.5105	68.4368	68.3827
07:00	68.9336	68.9917	70.4680	70.6462	74.5929	73.7000	68.8568	68.8224	68.7138	68.6341
08:00	68.9794	69.0398	70.5879	70.7736	74.8819	73.9529	68.8993	68.8634	68.7503	68.6673
09:00	68.9250	68.9824	70.4356	70.6109	74.4442	73.5866	68.8489	68.8147	68.7071	68.6281
10:00	68.8764	68.9313	70.3038	70.4705	74.1028	73.2932	68.8037	68.7711	68.6684	68.5930
11:00	68.8038	68.8548	70.1088	70.2629	73.5941	72.8566	68.7363	68.7060	68.6106	68.5405
12:00	68.7155	68.7617	69.8702	70.0087	72.9728	72.3227	68.6543	68.6268	68.5402	68.4766
13:00	68.7088	68.7546	69.8529	69.9904	72.9304	72.2857	68.6480	68.6208	68.5348	68.4717
14:00	68.7346	68.7819	69.9235	70.0656	73.1143	72.4438	68.6720	68.6439	68.5554	68.4904
15:00	68.8385	68.8914	70.2052	70.3655	73.8492	73.0747	68.7686	68.7372	68.6382	68.5656
16:00	69.1333	69.2020	71.0133	71.2272	76.0587	74.9437	69.0423	69.0015	68.8729	68.7786
17:00	69.5283	69.6330	72.0736	72.3617	79.5080	77.6662	69.3904	69.3375	69.1710	69.0490
18:00	69.5217	69.6262	72.0616	72.3494	79.5493	77.6731	69.3847	69.3320	69.1661	69.0445
19:00	69.3692	69.4621	71.6852	71.9465	78.2401	76.6793	69.2612	69.2128	69.0603	68.9485
20:00	69.1708	69.2417	71.1290	71.3519	76.4998	75.2839	69.0770	69.0350	68.9025	68.8054
21:00	68.8610	68.9151	70.2758	70.4417	74.0976	73.2738	68.7893	68.7572	68.6559	68.5816
22:00	68.4605	68.4932	69.2255	69.3081	71.3565	70.9091	68.4173	68.3979	68.3367	68.2917
23:00	68.0921	68.1052	68.3969	68.4297	69.1010	68.9589	68.0748	68.0671	68.0425	68.0245

Table 7. Short term(month) Average of daily loads

Month	Total load, MW	Total power losses, MW
January,2020	1382.9	68.1722
February, 2020	1385	68.6508
March, 2020	1388.3	69.4707
April, 2020	1389.9	69.9280
May, 2020	1395.7	71.6703
June, 2020	1397.1	72.0901
July, 2020	1398.7	72.5862
August, 2020	1399.9	72.9680
September, 2020	1401.5	73.4871
October, 2020	1404.5	74.5150
November, 2020	1406.7	75.2814
December, 2020	1413.2	77.7635

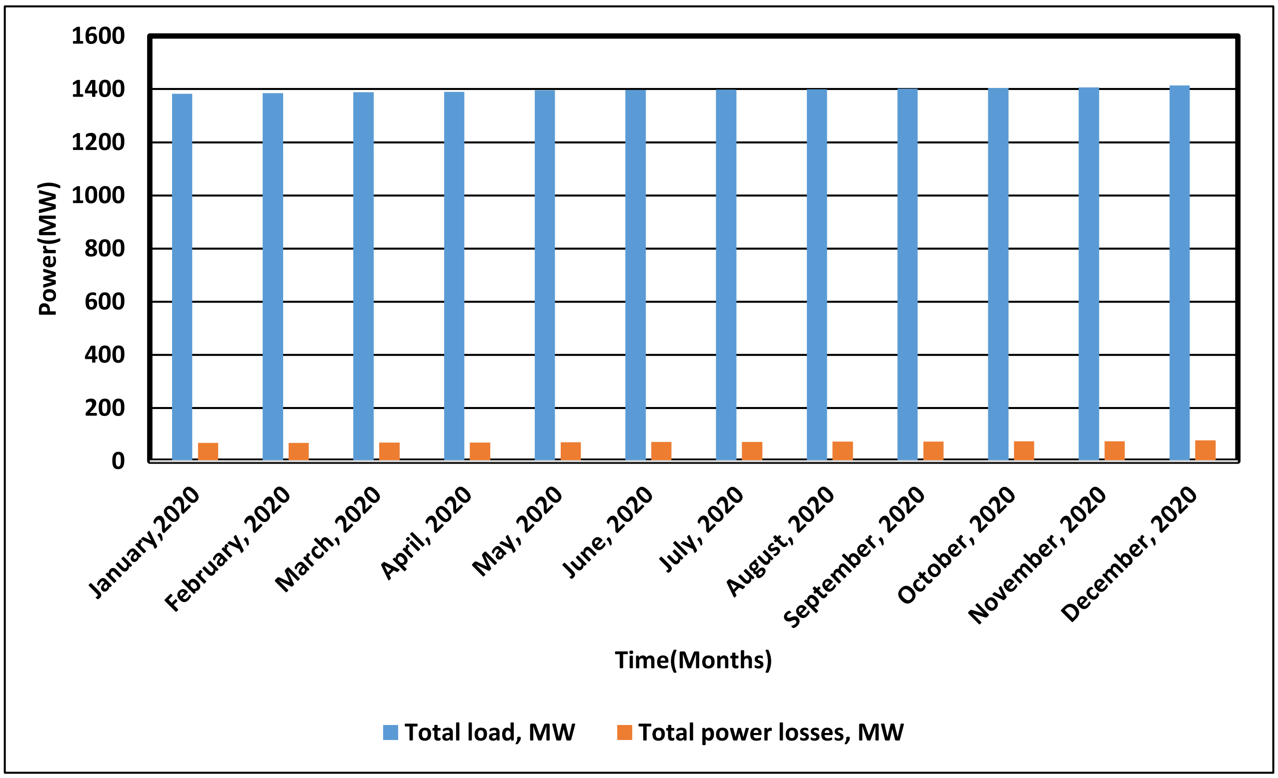

Fig. 9: Short term (monthly) average of daily loads

Table 8. Long term forecasting

Year	Total load, MW	Total power losses, MW
2020	1395.1	71.4698
2021	1401.3	73.4437
2022	1422.6	82.6578
2023	1395.4	71.5511
2024	1405.1	74.7140
2025	1416.6	79.2250
2026	1423.9	83.9394
2027	1421	81.5588
2028	1418.5	80.1559
2029	1424.3	84.6615
2030	1408.2	75.8217

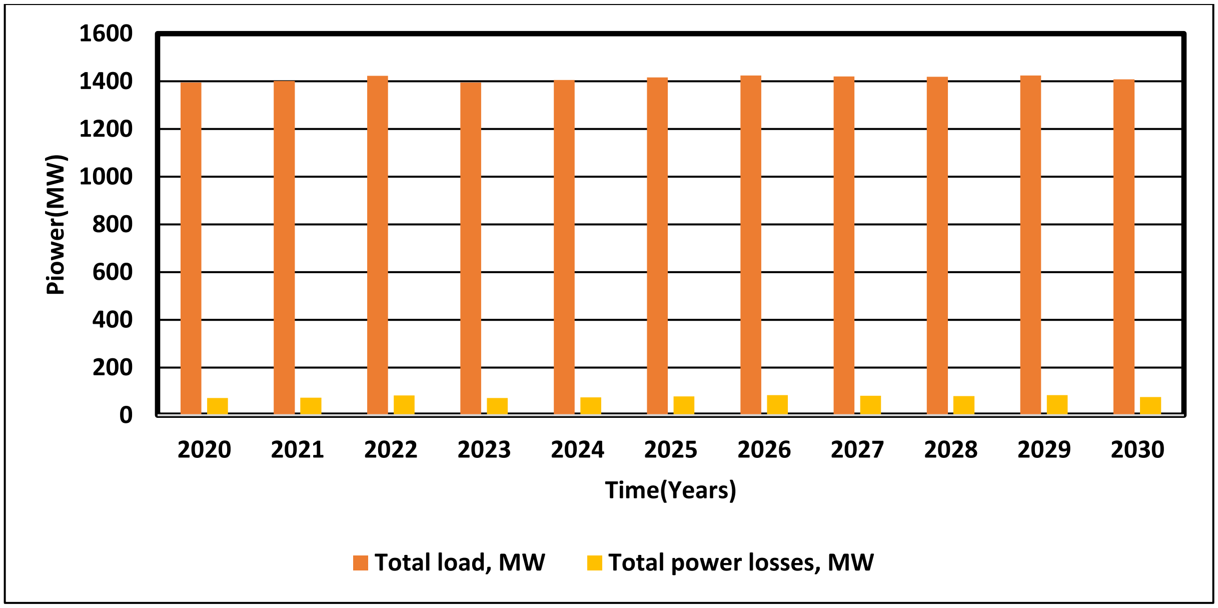

Fig. 10: Long Term Forecasting

5 Conclusions

In this paper, presented the forecasted load values at buses, voltage magnitudes at buses, apparent power flows and total power losses for the real time data of 33KV bus system has been presented by using Moving Average Extreme Learning method. Also presented the short term and long term forecasted values of loads and total power losses. The obtained results are compared with ELM and moving average methods and results are validated through MATLAB.

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