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A Network of Neural Model for Small Term Load Prediction Using Novel Feedforward (FITNET)

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ABSTRACT: Load forecasting is a challenging task in the setting of modern power systems, which have risen in complexity as conventional and non-conventional energy sources have been integrated into an increasingly varied energy environment. Utility companies are under growing pressure to not just provide cost-effective and adequate power generation, but also to maintain system dependability for today's discriminating customers. While there are several load forecasting systems, neural network-based techniques appear as a potential alternative due to their ability to reveal hidden subtleties within the input/output load data connection, resulting in fewer predicting mistakes. Artificial neural networks (ANNs)-based short-term load prediction methods have become more widely used, successfully overcoming issues related to weather, temperature, humidity, precipitation, air pressure, and the shifting patterns of human and industrial activity. This has made accurate load forecasting easier. We present FITNET, a novel feedforward neural network model designed for short-term load prediction (STLF), as our contribution to this effort. FITNET is Zunique in that it can adjust to events occurring in real time and allows training with a wide range of input kinds and sequences. We collected data from the ISO New England NE-Pool region over a period of four and a half years and combined it into a single, coherent dataset. Important inputs include time-related components and meteorological characteristics, such as day and night, dew point, and dry bulb temperature, with weekdays having a substantial impact on the output data. To improve the performance of the ANN model, we carefully examined alternate neuron configurations, using the Levenberg-Marquardt backpropagation approach for training. Extensive testing of our suggested model across both weekly and daily load forecasting methodologies continually shows outstanding efficiency, with the ANN model constantly having a forecasting MAPE of less than 1%. This finding emphasizes the model's stability and its potential to considerably improve the dependability and cost-effectiveness of power generation in today's complex and ever-changing energy landscape.

Keywords: ANN, FITNET, STLF, Electricity Load Forecasting, Feedforward Neural Network, Weather Parameters, Load Dataset

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Introduction:

In the intricate network of our global existence, energy stands out as one of the most important resources required to support life on Earth. The growing effect of modern lives emphasizes the critical need for a consistent and adequate energy supply, which is a vital pillar of daily living [1]. Electricity is widely recognised as a cornerstone for societal growth, playing a critical role in raising the standard of living in a variety of places [2]. This global need on steady energy flow transcends geographical boundaries, serving as an essential stimulus for both developing and industrialized countries in their quest of long-term economic growth [3]. The symbiotic link between energy consumption and a country's socioeconomic success becomes clearer, revealing a close-knit association that reflects the intertwined tapestry of global development. Unlike traditional commodities, electricity's distinguishing feature of 'production on demand' emphasises its unique significance by emphasising that its distribution to end users is dependent on dynamic changes in demand [4, 5]. Addressing this requirement requires the creation of precisely constructed strategic initiatives aimed at providing an uninterrupted, secure, and adequate supply of energy, while dynamically responding to the ever-changing contours of consumer demand [6]. The strategic application of economic load dispatch is crucial in the development of power-generation systems that are not only dependable and adequate, but also economically feasible. Given the recurring and inherent fluctuations in energy demand that deviate from expected figures, load forecasting methods become inextricably linked to various aspects of power system operations, including unit commitment, stability margins, estimated available transfer capacity, load-shedding schedules, and a slew of other influential factors [7]. This complicated interaction of variables emphasises the diverse character of the energy landscape, necessitating a comprehensive and adaptive strategy to addressing the dynamic problems offered by changing consumer wants and system challenges as well.

Literature Review

As electricity businesses develop and evolve fundamentally, load forecasting technologies are becoming increasingly vital. In the 1960s, Heinemann et al. developed short-term load forecasting algorithms that were primarily focused on the temperature-load connection [8]. Following that, Lijesen et al. [9] study statistical techniques for electrical demand forecasting. Numerous approaches based on linear and nonlinear algorithms have been studied for reliable forecasting of electricity consumption. Several hybrid models that combine linear and nonlinear approaches, such as multi-layer perception and self-organizing map methods, have also aroused academics' interest throughout the years [10, 11].

Researchers began to focus on developing non-linear approaches related to Artificial Intelligence (AI) technologies in the early 1990s [12, 13]. Data modeling flexibility was useful for ANN-based load prediction experiments. Park et al. were among the first academic groups to employ ANN in short-term load forecasting research [14]. Back Propagation (BP) Algorithm inclusion into ANN-based load forecasting was examined by researchers He et al. and Hamid et al. [15, 16]. Yang et al. devised a more precise fuzzy logic-based forecasting technique [17]. Chaturvedi et al. examined the implementation of [18].

Using New data, [19] employed deep learning. The temporal and frequency domain parameters of the model were evaluated [20].

STLF is a tactical technique that combines Artificial Neural Network (ANN) with Particle Swarm Optimisation (PSO) algorithms. According to studies [22], the foundation of this technique is a three-tiered feedforward neural network trained using the Backpropagation (BP) algorithm [23]. Notably, with a lower prediction error, the Error-Correcting Neural Network (ENN) model beats the BPNN model [23]. Another novel STLF-based time series model, described in [24], employs a K-Means clustering strategy within the ANN framework, resulting in improved prediction capabilities and much lower errors. In addition, a neural network wavelet transformation approach described in [25] is used to estimate future load levels by utilising input factors collected from comparable days' load data.

Artificial Neural Network (ANN) Model

Artificial Neural Networks (ANNs) are mathematical algorithms inspired by organic neural systems. ANN's basic base is an immense array of linked processing units known as neurons, with communication channels permitting data flow between these nodes. Numerous input nodes provide numerical data to the network, and the information is attenuated or amplified based on weights assigned. These weights are obtained by the use of various training patterns and adaption approaches. A neuron is activated when the synapses have the necessary weightings, and the neuron's activity is dependent on the cumulative total of weighted inputs above a predefined threshold [21]. Figure 1 depicts the core structural model of an ANN.

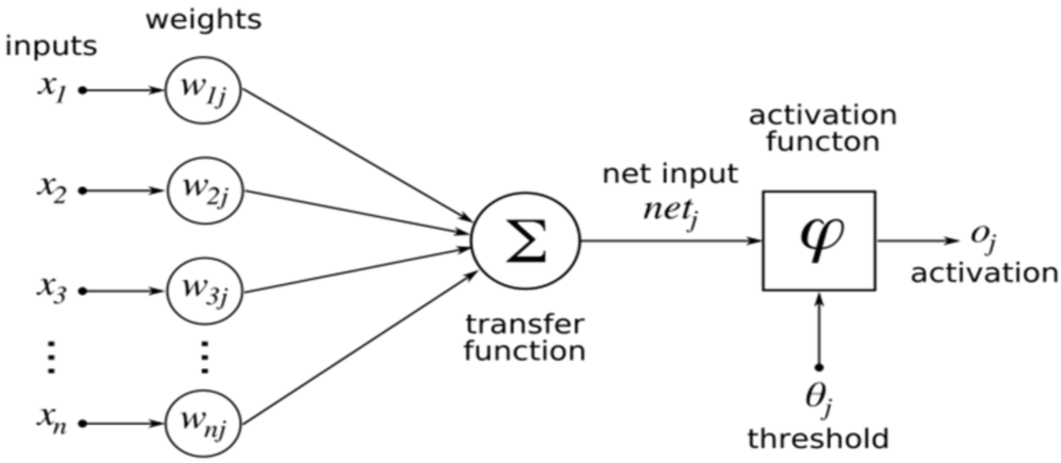

Fig. I: ANNBS (Artificial Neural Network Basic Structure)

There are three layers in a neural network. The weights between the hidden and input layers decide which neurons in the hidden unit are activated.

Leveberg – LM (Marquardt Algorithm)

Back-propagation using Levenberg-Marquardt (LM) optimum solutions is used as a network training technique to change biases and weights. The LM technique, also known as the damped least-square approach, is particularly good at tackling nonlinear least-square issues. Unlike the traditional Hessian matrix, the LM approach computes corrections using a gradient vector and a Jacobian matrix. The following is the loss function associated with this training process:

$$F = \sum \frac{a}{i} = 1\ Ui^2 \qquad (1)$$

Here "a" is the dataset instances number &

u = all error-term vectors

Jacobian-Matrix (JM) is:

$$A_i, j = \partial y / \partial x_i \qquad (2)$$

Here i vary from 1 …, a, and j varies from 1…, b,

"a" is data-set instances numbers

A is Jacobian Matrix & the Jacobian Matrix size is [a, b].

Loss function gradient vector is expressed as:

$$\text{“}\Delta f = 2A^{T} u\text{”} \qquad (3)$$

Here, Hessian matrix is approximately:

$$\text{“}Bf \approx 2A^{T}.A + \beta.I\text{”} \qquad (4)$$

In the first step, B = Hessian-Matrix, = Damping Factor that keeps Hessian positive, and I = Identity Matrix are chosen. If an error occurs at any iteration, the value will be increased. when loss decreases, Algorithm LM is bringing closer to the Newton approach [26].

The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are used to evaluate predicting effectiveness. However, the authors chose to exclude MAE and RMSE due to RMSE's sensitivity to outliers and both measures' scale dependency. Instead, the authors argue that Mean Absolute Percentage Error (MAPE) is a more robust evaluation measure, especially in the context of load forecasting. As a result, MAPE is chosen as the statistic for measuring the model's expected accuracy. The MAPE formula is defined in reference [20].

$$MAPE = 100/n\ \Sigma^{T}{}_{i}\hat{}(=1)\ |\ ((Ai - Fi))/Ai| \qquad (5)$$

Here Ai = Value of actual Load

&

Fi = Value of Forecasted Load

Methodology

It is evaluated one output variable (actual load data) to eight input factors (daily hours. To improve the model's efficacy, the available information was preprocessed, which included the elimination of outliers and irregular data, since ANNs are particularly sensitive to such abnormalities, negatively influencing their performance [27]

It is common practice to perform a normalization procedure before feeding inputs into the network.

We used MATLAB R2019b to train and test our suggested ANN model. Many neuron counts were investigated during the training phase, and 35 neurons yielded the best results. The output layer only has one neuron for load prediction output [27].

The learning rate is defined as the proportion of the error gradient that controls the weights. Fast convergence happens at higher levels, although oscillations become more intense. The momentum defines the proportion of earlier weight changes that are taken into account when computing new weights [27].

DATA

The authors obtained data region from January 1st, 2017 to June 30, 2021. After that, the yearly load data is put into a single data set of 39,408 data points. The data collection includes the date, hour, dry-bulb (°F), dew-point (°F), and system electrical load (MW).

Analysis

A key step forward in developing ANN for momentary load prediction, the necessary framework attributes should be investigated. The initial step in building any load predictor is to examine historical load records to extract load features such as periodicity and trends.

Following preprocessing, data was examined for the. The table under shows real numbers from 2017 through June 2021.

Table I: Month basis Load

Year/ Month	**Jan.**	**Feb.**	**Mar.**	**Apr.**	**May**	**Jun.**	**Jul.**	**Aug.**	**Sep.**	**Oct.**	**Nov.**	**Dec.**
Day/ Hour 2017	9/18	9/19	15/20	6/18	18/8	13/17	19/18	22/17	27/17	9/19	28/18	28/18
2017 Load (MW)	19592	18165	17502	15843	20250	23968	23579	22769	20999	17255	17079	20524
Day/ Hour 2018	5/18	7/18	7/19	3/20	29/18	18/17	5/18	29/17	6/16	10/19	15/18	18/18
2018 Load (MW)	20662	18308	16943	15778	17518	21076	24512	26024	24475	17479	17590	18466
Day/ Hour 2019	21/18	1/19	6/19	9/20	20/18	28/18	30/18	19/16	23/17	2/15	13/18	19/18
2019 Load (MW)	20773	18585	17876	15034	15748	19913	24361	23365	19162	16138	17548	19065
Day/ Hour 2020	20/18	14/19	1/19	27/18	29/18	23/18	27/18	11/18	10/18	30/19	18/18	17/18
2020 Load (MW)	18097	16991	15888	14254	16593	21519	25121	24335	19260	15616	17157	18922
Day/ Hour 2021	29/18	1/18	2/19	16/12	26/18	29/16	---------	--------	--------	--------	--------	--------

2021 Load (MW)	18839	18185	17738	14649	18846	25726	---------	--------	--------	--------	--------	--------

According to the statistics, the greatest load value is 26024 MW for all the years, which happened in the seventeenth hour on 29th August 2018. Seventeenth, Eighteenth, and Nineteenth hours of the day have the highest peak load. Load increases throughout the summer months (June-September), whereas it decreases during the winter months (October-May). The MATLAB annual load graphs shown below will assist you in interpreting lines in the preceding:

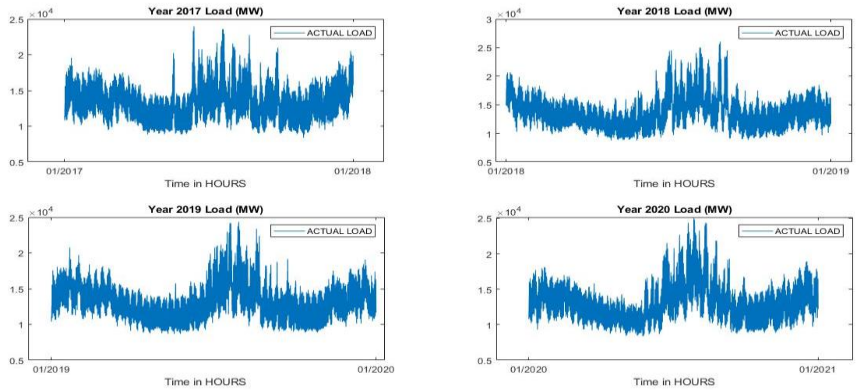

Fig. II: Yearly Actual load data

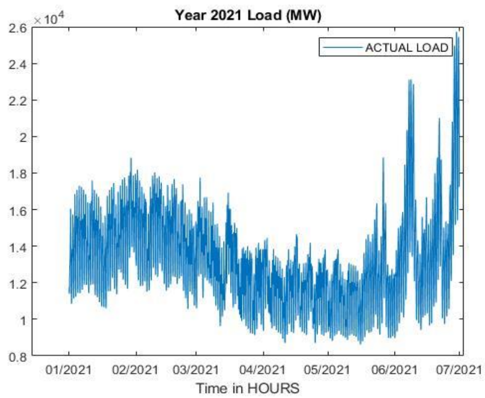

Fig. III: 2021 forecast actual load data.

In the Figure 3, demonstrates intermittent power surges and unexpected load drops throughout the year, particularly in the summer. However, overall load changes are essentially the same over time.

Data Analysis

When examining load trends over the course of a year, it is critical to account for critical factors such as weather conditions and public holidays. Previous study has shown that temperature and humidity have a significant impact on the dynamic variations in electrical load behaviour. While wind speed, air pressure, weather patterns, geographical location, public interruptions, and lockdowns can all have an effect on load behaviour, they were not particularly explored in this study. Table 2 depicts the actual load fluctuations for each hour on June 30, 2021, illuminating the link with dew point and dry bulb readings.

Table II: Dew-Point, Dry-Bulb, & Actual Load Data

Hour / Weather Information June 30, 2021	Dry Bulb (°F)	Dew Point (°F)	Actual Load (MW)
1	78	71	17,517
2	77	71	16,549
3	77	70	15,881
4	77	71	15,459
5	76	70	15,416
6	75	70	15,830
7	75	69	17,095
8	78	70	18,756
9	80	70	20,143
10	83	70	21,233
11	86	70	22,299
12	89	70	23,246
13	91	70	24,087
14	92	70	24,879
15	93	69	25,333
16	94	68	25,420
17	94	69	25,436
18	91	69	25,153
19	86	69	24,020
20	78	70	22,980
21	75	70	21,888
22	75	70	20,481
23	74	70	18,854
24	73	70	17,249

As shown in Table 2, on the load there is a little dew point effect, with the dry bulb temperature (oF) appearing as an important component trendy load variation. There is a direct association seen; as the dry bulb value increases, so does the load, and vice versa, as the dry bulb value decreases, so does the load. Figure 4 depicts graphs covering the whole dataset of dew point, dry bulb, and real load demand to present a holistic perspective, encouraging deeper examination for more insights into their interplay.

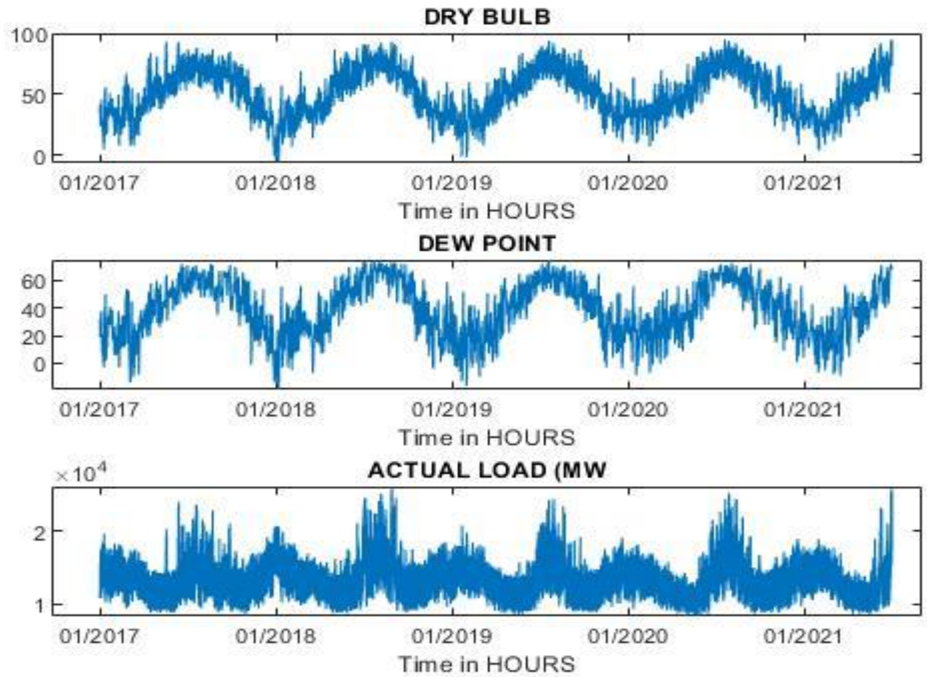

Fig. IV: Load Analysis, Dew-point, and Dry-bulb

Datasets Distribution

Datasets were divided into two broad categories: Testing Data and Training Data. In 80% of situations, data was picked for training and 20% for testing. To get the necessary weights for the ANN model, the Levenberg-Marquardt back-propagation technique was utilised. Finally, the dataset was put through its paces. After multiple trial-and-error tries with varied numbers of neurons, the precise timely network stayed chosen based on the least MAPE criteria. Hidden-layer sigmoid-transfer functions were used to evaluate the models on 20-40 neurons. 1-5 hidden layers were utilised in a trial-and-error fashion, with 35 neurons, one hidden layer, and one output layer producing the best results.

For testing purposes the month of June 2021 was picked in the second stage of the STLF forecasting procedure, then the outstanding whole previous dataset data was estimated during model exercise. During the last week of June 2021, the expected load values were tested in the third phase. The 30th of June 2021 was chosen as the last day of the fourth phase of power load forecasting. In the last stage, we forecasted the last hour of June 30th, 2021.
In this study, we concentrated on weekly and daily load data as the inputs and goal data were same throughout all stages, resulting in nearly identical outcomes.

Simulation Results

Before developing Artificial Neural Networks (ANN), a preliminary analysis was carried out with the Multiple Linear Regression (MLR) approach to determine the predicted load values for all 39,408 data points in the dataset. A comparison of the actual electrical demands (MW) and the corresponding projections produced by the MLR technique is shown in Figure 5. Notably, other inputs were not included in the study when the MLR technique was evaluated; only regular load data was taken into account.

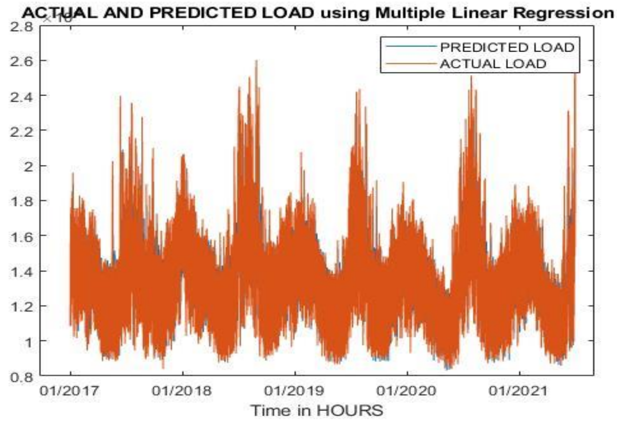

Fig. V: Predicted & actual load

When it is zoomed its results are shown more clearly as:

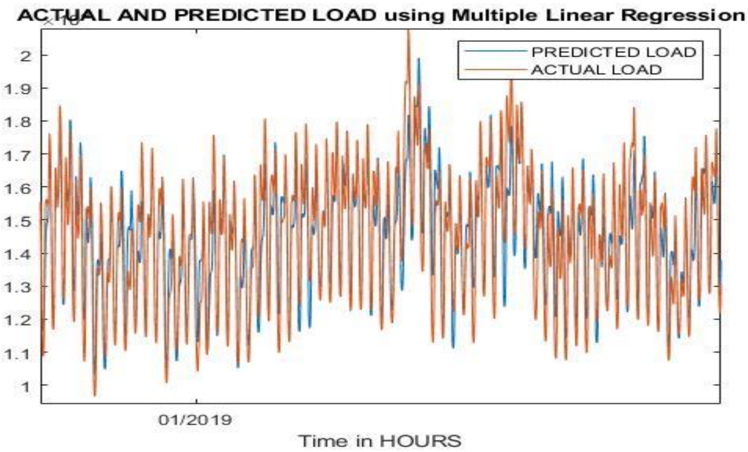

Fig.VI: Clear Plot of MLR

Findings indicates the real and expected load statistics differ significantly. Only a few deviations occur along the linear variable line, with the majority occurring under peak loads. As an outcome, the approach is ineffective for adjustable loads then effective for linearly changing loads.

In addition to applying the Levenberg-Marquardt (L-M) training procedure, the networks were also examined for Bayesian Regularisation (BR). Nevertheless, the BR approach performed noticeably worse than L-M, which resulted in its removal from the report and the conclusions drawn from it not being taken into account in the end.

Arithmetical features of the hourly, weekly, and monthly load data are shown in Figure 7, which also shows the load changes that may be observed, such as weekend decreases, month-to-month variations, and hourly variations. Since these unique load behaviour patterns are determined by network parameters, they must be examined in order to be considered when creating an appropriate Artificial Neural Network (ANN) model [28].

The results of this variation—which concentrate on the hourly load projections—are shown in the table. A detailed visual comparison of the actual load and the accompanying forecasts throughout a 24-hour period is shown in Figure 7. It is noteworthy that the trough occurred between 3 and 4 hours, while the highest load was recorded between 17 and 18 hours. This research provides insights into the temporal dynamics of load forecasts and illuminates how sensitive the model is to variations in the number of neurons.

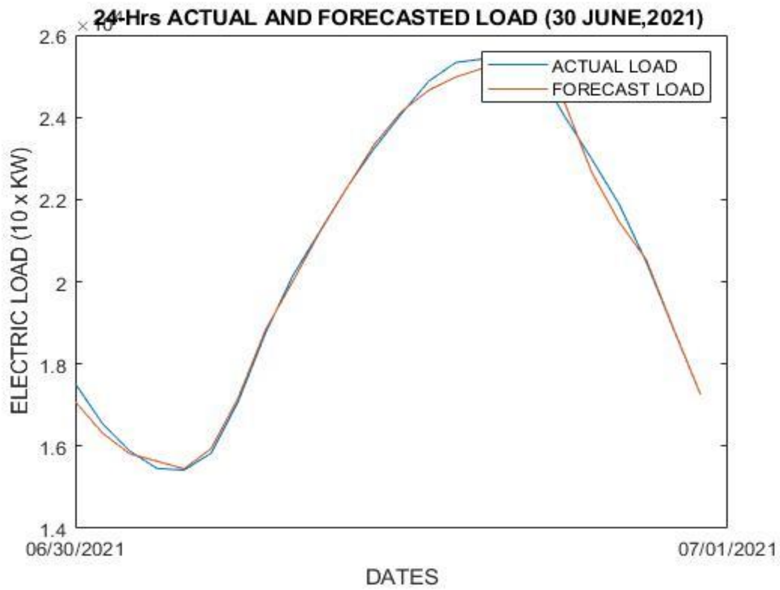

Fig. VII: 24 hours forecast & actual load

The graph showing the real and expected load shows that there are very little fluctuations throughout peak and midday hours. The graph's stability highlights how well our Artificial Neural Network (ANN) model design predicts similar load data. The model's aptitude for precise load forecasts is confirmed by the consistency in performance across peak and noon situations, which demonstrate the model's resilience and dependability in capturing the underlying patterns and trends in the load data.

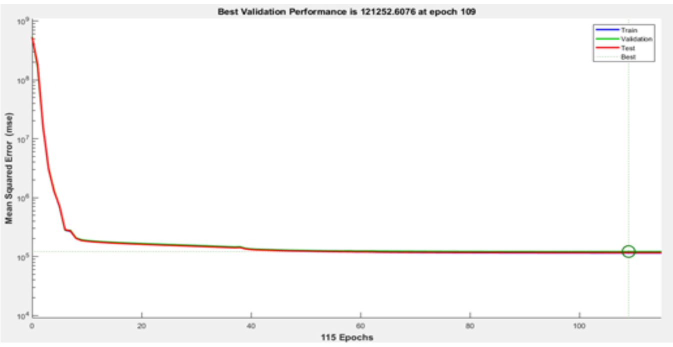

Fig. VIII: Number of EPPCH's Against Mean Squared Error

Using the Levenberg-Marquardt back-propagation technique produced convergence after 115 iterations and 109 epochs. The results show stability post-convergence, with no appreciable increase, as seen in Figure 8. Refinement is evident in the output, which is characterised by a decrease in data loss and an increase in accuracy. There isn't any divergence in mistakes when looking at the convergence charts for the training set.

In Figures 10 and 11, the regression plot depicting the target values against the predicted load data, and the comprehensive regression plots encompassing training, validation, testing, and overall datasets. The assessment of targeted and projected errors employs a regression measure, with Figure 12 illustrating the histogram of fit-set errors. Figure 13 provides a visual representation of both the distribution of absolute errors and the distribution of absolute percent errors, allowing for a thorough comparison of performance.

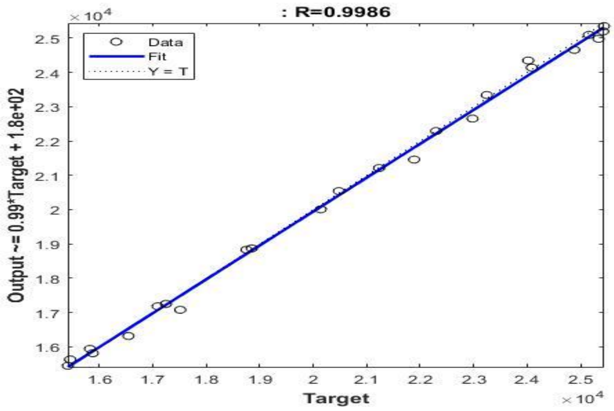

Fig. IX: Neural Network Training Curve of Performance

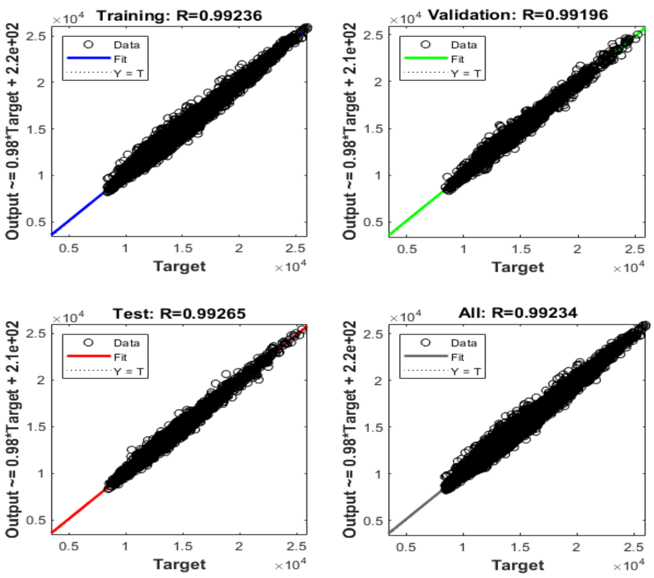

Fig. X: ANN Complete Regression Plot

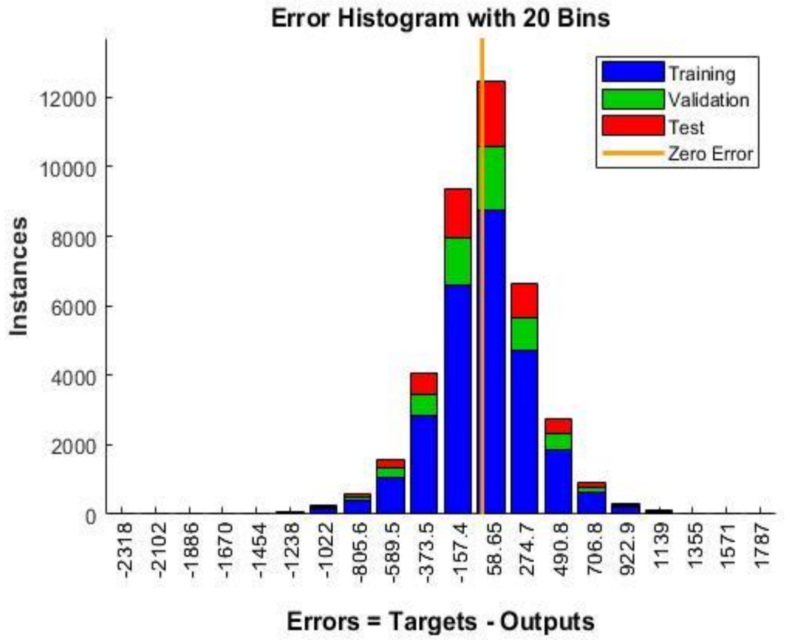

Fig. XI: Histogram Error

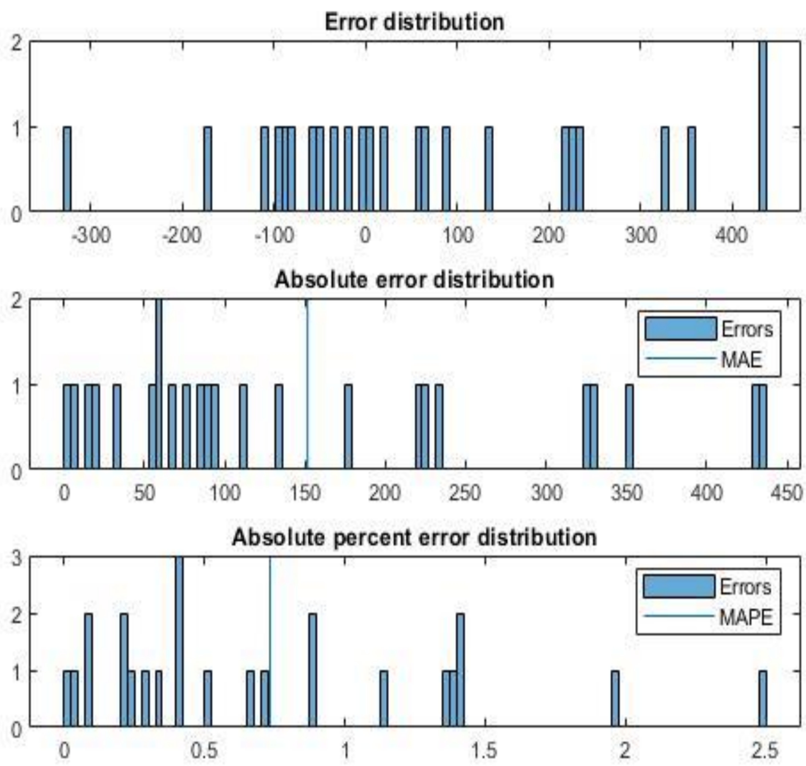

Fig. XII: Distribution Error

Table 3 depicts the projected 24-hour load data for June 30th, 2021 for each example used to estimate effectiveness by varying the number of neurons.

Table III: Actual and Predicted Loads of 24-Hours

Hr's	PL For n = 40	PL For n = 35	PL For n = 30	PL For n = 25	PL For n = 20	AL (MW)
1st Hr.	17226	17108	16853	17000	17014.5	17,517
2nd Hr.	16393	16407	16054	16379	16301	16,549
3rd Hr.	15970	15935	15591	16026	15892.75	15,881
4th Hr.	15915	15764	15448	15902	15821	15,459
5th Hr.	15772	15525	15316	15678	15573	15,416
6th Hr.	16041	15822	15705	15950	15765.5	15,830
7th Hr.	16883	16787	16908	16977	16780.6	17,095
8th Hr.	18640	18730	18942	18534	18765.5	18,756
9th Hr.	19779	20071	20108	19793	19848	20,143
10th Hr.	20865	21182	21129	20994	20916.7	21,233
11th Hr.	22011	22207	22108	22261	22013	22,299
12th Hr.	23305	23328	23180	23481	23095	23,246
13th Hr.	24468	24322	24168	24294	23938.6	24,087
14th Hr.	25342	24964	24948	24741	24580	24,879
15th Hr.	25986	25261	25417	25028	25113	25,333
16th Hr.	26505	25442	25623	25365	25547.9	25,420
17th Hr.	26808	25626	25759	25825	25871	25,436
18th Hr.	26089	25368	25393	25460	25576	25,153
19th Hr.	24669	24623	24579	24166	24791	24,020
20th Hr.	22464	22837	22993	22026	22881	22,980
21st Hr.	21121	21483	21850	20841	21465	21,888
22nd Hr.	20213	20581	20893	20069	20551.8	20,481
23rd Hr.	18752	18972	19280	18879	18891	18,854
24th Hr.	16808	17104	17418	17291	16924.6	17,249

Table IV: Predicted Load Performance

	n = 40	n = 35	n = 30	n = 25	n = 20
Number of Iterations	53	115	164	425	281
Regression	0.99222	0.9986	0.99788	0.99458	0.99510
EPOCH	47	109	158	419	274
Performance	**1.1826e+05**	**1.1005e+05**	**1.1219e+05**	**1.2761e+05**	**1.1814e+05**

In Table 4, the findings of a huge dataset including 39,385 training data points compared to a simple 24 data points during a 24-hour testing period, using hourly data received from June 30, 2021. The neural network model was rigorously tested under a variety of scenarios, each corresponding to a different number of neurons chosen, with the ultimate objective of determining the best data aggregation. When 35 neurons are used, the MAPE error is 0.73 percent, and it rises to 0.93 percent when 40 neurons are used. During the neural network training with 35 neurons, the peak performance curve reached 0.9986. As a consequence, when confronted with 24-hour test data, the best load forecasting outcomes were obtained by deploying 35 neurons within a single hidden layer, as demonstrated by the acquired findings.

The use of 30 neurons resulted in optimal weekly load analysis findings with notable accuracy. Notably, the training regression value is 0.99213, R=0.99215 summarises the total response, whereas the testing regression score is 0.99211 and the validation regression score is 0.99229. The best fit peaks at 220 epochs and 226 iterations with a strong regression value of R=0.99856, excellent performance shown by P=1.1171e+05, and a low MAPE of 1.40 percent. Figure 13 depicts the graphical display of error statistics for both weekly and hourly load data, emphasising the rigorous comparison between actual and expected loads during the final week of June 2021.

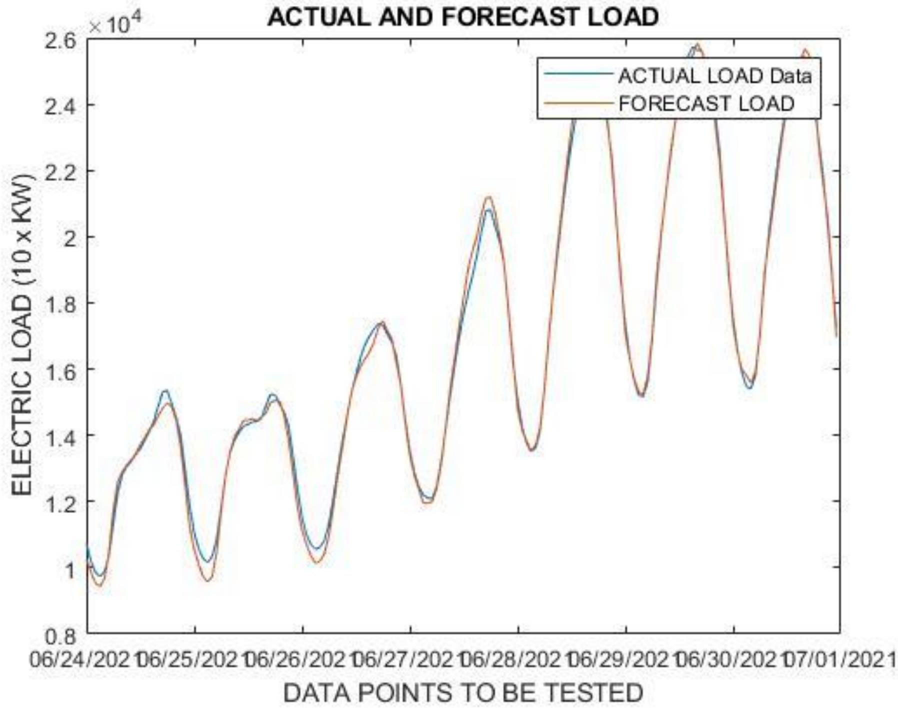

Fig. XIII: Actual and Forecast Load & Actual Data (June2021)

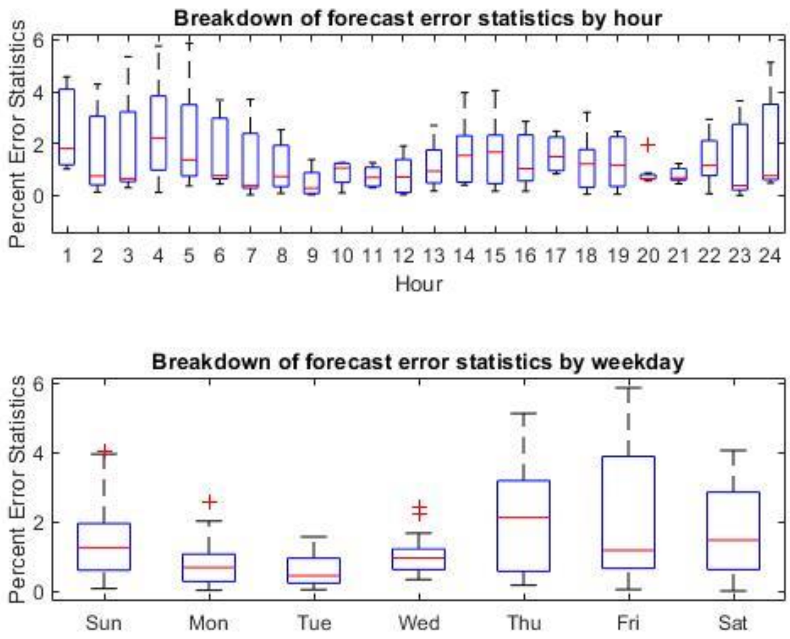

Fig. XIV: Time & Electric Load Correlation

Figure 14 highlights diverse load ranges by illustrating load distribution over various hours and days of the week. Notably, Sundays have the lowest load levels during the week, indicating a trough in the load pattern. Fridays, on the other hand, have the greatest load levels, forming the apex of the weekly load distribution. This graphic depiction captures the variations in load intensity across different days and hours, providing insights into the load profile's dynamic character throughout the week.The expected hourly load curves follow the same pattern as the weekly load curves. There are tiny oscillations at the load peaks, and no aberrations in the load lines change linearly. To decrease these slight changes, the model will need to be fine-tuned by modifying the weights/biases and other parameters that were kept constant during our network training.

Conclusions

The method shows that ANN models may be trained using a variety of types and sequences of real-time inputs, and it was tested in MATLAB software using a Novel Feedforward (FITNET) Neural Network implementation for short-term load prediction (STLF). This data set is the result of a four-and-a-half year effort by researchers in the ISO New-England NE-Pool region. The main inputs (output data) used were time and weather variables (time, dew point, dry bulb), in addition to weekdays. The Levenberg-Marquardt backpropagation method was used to train the ANN model for various orders of neurons. We ran the model through its paces for both weekly and daily load forecast approaches to see what worked best. The network efficiency of the ANN model was improved, and it achieved two very respectable MAPE errors: 0.73% for hourly load prediction and 1.40% for weekly load forecasting.

Author's Contribution: K. R, Conceived the idea; K. R, M. A, J. S. K, and J. M, Designed the simulated work, K. Rehman, M. Altamash, Jan Sher Khan, J. Miraj, and Z. Farooq did the acquisition of data; K. Rehman, M. Altamash, Z. Farooq, and J. Miraj, Executed the simulated work, data analysis or analysis and interpretation of data and wrote the basic draft; K. Rehman, Did the language and grammatical edits or Critical revision.

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