Artificial Intelligence Based Approach for Short Term Load Forecasting for Selected Feeders at Madina, Saudi Arabia

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***Abstract*—Short term load forecasting is one of the most important tools for smart energy management particularly in the planning and operation of large buildings. It assists in minimizing the energy losses as well as in maintenance scheduling for critical times. One of the widespread methods for load predicting is implemented by artificial intelligence techniques. In this research, fuzzy logic and artificial neural networks are utilized for short term load forecasting of selected feeders in one of the biggest buildings, Madina, Saudi Arabia. A high-quality measured data is collected from the selected locations and used here in training, testing and validation purposes. The performance of the models is evaluated on the basis of statistical indices such as an absolute relative error. Obtained results are compared with the high-quality measured data and it is found that the performance of the fuzzy logic model is found better as compared to artificial neural network model for the selected feeders.**

***Index Terms*—Artificial intelligence, short term load forecasting, smart energy management, fuzzy logic, artificial neural network**

I. Introduction

Load forecasting is a critical component in power system operation and planning. This is required to achieve an equilibrium between the load demand and production of electricity. Depending on the purpose and applications of load forecasting, it can be varying from seconds to years. The categories of load forecasting based on time period are: short term load forecasting, midterm load forecasting and long-term load forecasting. Each one of these categories helps in solving and enhancing the operation of load scheduling leading to an appropriate use of electrical energy. The common factor between all of load forecasting categories is to reach to the best optimization of resources [1].

A. Categories of Load Forecasting

Depending upon the time horizon, the load forecasting can be broadly classified into three types.

Short term load forecasting: (hour to week) Used to manage the generation and transmission of electricity.

Midterm load forecasting: (week to a year) Used for the managing fuel supplies and unit maintenance.

Long term load forecasting: (more than one year) Used to supply electric utility company management with prediction of future needs for expansion, equipment purchases, or employing.

B. Methods of Load Forecasting

According to the latest research mentioned in reference [1] there are two main methods for load forecasting.

Malty factor forecasting method: Malty factor or cross-sectional forecasting method depends on causes that affecting forecasting values.

Time series forecasting method: Time series method depends on a series of historical data. Accordingly, a lot of research papers used this method because of simplicity and accurate results.

Time series forecasting can be termed as the act of predicting the future by understanding the past. It can be divided into three subcategories:

Statistical model: The statistical model is usually specified as a mathematical relationship between one or more random variables and other non-random variables. Several statistical modeled developed to implement forecasting, some of these models are: Box-Jenkins basic models, Kalman filtering algorithms in the State space, Grey models, etc.

Artificial intelligence or machine learning model: Artificial intelligence methods consist of Artificial Neural Networks (ANN), fuzzy logic, Expert Systems (ES).

Hybrid model: Hybrid or combination model can be obtained with better performance of forecasting by summing the advantages of different single models. Hybrid used widely in load forecasting many methods such as optimization algorithms, and data processing techniques. According to [1] many researchers focus on developing hybrid models with a hope of improving prediction performance.

A study on load forecasting was conducted by Hamad *et al.* [1]. In the work, over 15 models used for load forecasting distributed into 45 most relevant scientific papers were discussed. The study concludes that the most of the models used for load forecasting in order are ANN, regression model, fuzzy logic, and support vector machine.

Markou *et al.* [2] used several MLPs (multilayer perceptron) to implement short term load forecasting

Manuscript received April 4, 2021; revised April 23, 2021; accepted April 24, 2021.
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doi: 10.18178/ijeetc.10.5.300-306

(STLF) of minimum 24 hours ahead in each period of load prediction. Also, a classification of week days was done according to specific criteria. The data used were load generation, temperature and humidity for each hour. The forecasting error for stable weather conditions was 1 to 2 % it rises as a sudden change in the temperature.

According to Mi *et al.* [3] traditional grey prediction models have been applied in load forecasting because of its simplicity and it doesn't require a higher sample data. On the other hand, the model suffers from its inner defective results and leads to inaccurate load prediction. To overcome this problem the author implemented an improved model to reduce the randomness of the data and smoothing it to reach the desired accuracy.

Peng *et al*. [4] applied the various techniques of machine learning to forecast the hour ahead load of residential buildings. The study concluded that the errors of load predicting increase as the aggregation level decreases for all algorithms. For a small residential load, research recommends implementing a data processing before applying forecasting techniques and the selection of data processing technique should be based on the characteristics of the data.

Regarding to forecasting at low aggregation level, Ruiz-Abellon *et al.* [5] developed a model of forecasting load demand and renewable energy generation. The real time data was used in level of some megawatts in Spanish town. The model can balance errors through a closed control loop that was taken from net demand and results in error reduction by 50%.

For a residential load forecasting, Acharya *et al.* [6] proposed a paper and discussed the types of loads. Using conventional neural network which was structured from using convolution and pooling layers allowing model to learn. Using many filters, convolution neural network (CNN) can learn the inherent of series load data for a single household. The generated data is converted to another residential load to reduce lack of data and more identity.

Fallah *et al*. [7] explained the main framework of methodologies that applied for computational intelligence. These methods are: similar pattern approach, variable selection method, hierarchal method and weather station selection method.

A comparison between artificial neural network and multiple linear regression was performed by Govender and Folly [8]. The study used input data that had a strong correlation. Simulation results shows that ANN gives better result for daily forecast whereas MLR more accurate in seasonal forecasting.

A study of using Deep Neural Network (DNN) model for STLF was proposed by Cai *et al*. [9]. To improve the accuracy of load forecasting, an STLF method based on deep neural network with sample weights is proposed. To improve the accuracy of the DNN approach, the filtering samples and corresponding weights to different training samples are used. By implementing DNN technique for the actual load data of Guangdong Power Grid for a period of 31 days, the suggested model can improve the accuracy of load prediction.

A hybrid model based on Empirical Mode Decomposition (EMD), minimal Redundancy Maximal Relevance (mRMR), General Regression Neural Network (GRNN) with fruit Fly Optimization Algorithm (FOA), namely EMD-mRMR-FOA-GRNN was developed [10]. Here, in this paper, the actual load series is initially decomposed into a quantity of intrinsic mode functions (IMFs) and a residue with different frequency so as to weaken the volatility of the series influenced by complicated factors. To obtain the best feature set, mRMR is employed. The correlation analysis is performed between each IMF and the features including day types, temperature, meteorology conditions, and so on. At the end, FOA is utilized to optimize the smoothing factor in GRNN. Finally, the load is forecasted from the summation of the predicted results for all IMFs. The obtained results were validated with the help of load data from Langfang, China. From this research, it is revealed that the EMD-mRMR-FOA-GRNN is a better option for short term load forecasting.

An attempt has been made for short term load forecasting [11] which could cater load management at the selected feeder. A high-quality measured data was utilized to develop the fuzzy logic-based model for the selected feeders in Rajasthan, India. The results obtained from the fuzzy logic model was validated with the actual data and found accurate. The Mean Absolute Percentage Error (MAPE) in the forecasted demand is 1.39% in comparison with the desired demand.

In one of the latest researches done by Lee [12] related to short-term load forecasting. The outcome of the proposed research is utilized for efficient energy management in small and middle-sized buildings in Korea. In this work, few simple forecasting equations were derived based on regression analyses using linear, seasonal linear, and quadratic models. Based on the obtained results the quadratic model was found most appropriate for Korea's climate with four distinct seasons. Here, in this work, the load forecasting is performed without installing the sensors in all the target buildings. The sensors were installed at some places which has the same features like the target building by using the least possible data.

Park *et al*. [13] has developed an algorithm for short term load forecasting using a similar day selection method based on reinforcement learning. Here, in this work selection of similar days was carried out using a reinforcement algorithm based on Deep Q-Network technique. The obtained results based on the same day selection model was validated with the actual data for selected locations of Korea. The proposed algorithm is expected to improve the predictive accuracy of short-term load forecasting because it can be applied in a complementary manner along with other load forecasting algorithms.

This study conducted by Zheng *et al*. [14] presented a hybrid algorithm which is a combination of similar days (SD) selection, Empirical Mode Decomposition (EMD), and Long Short-Term Memory (LSTM) neural networks to construct a prediction model (i.e., SD-EMD-LSTM) for short-term load forecasting. Here, in this work, the extreme gradient boosting-based weighted k-means algorithm is utilized to validate the forecasted data with the historical data. The decomposition process is performed using EMD approach. Further, to forecast each IMF and residual separated LSTM neural networks were utilized. Finally, the forecasting values from each LSTM model were reconstructed. Form the obtained result, the SD-EMD-LSTM method is found more accurate to forecast the electric load. Gandoman *et al.* [15] has implemented a PV output based on cloud coverage and temperature changes. The model illustrates the output of PV with oktas variation depending on cloud movement and the temperature of PV in a specific longitude and latitude. The results obtained from the proposed work based on statistical indices were found accurate. In one of the recent studies conducted by Refaat *et al.* [16] an adaptive neuro fuzzy interference system is developed for long term load forecasting up to 2040. The input of this system is historical year data and the output is the peak load data. The results illustrate the benefit of dynamic planning in rising the accuracy of the network.

As mentioned, many researches implemented load forecasting for generation plants or utilities but none of these researches are for the geographical area like Madina, Saudi Arabia. In this research artificial intelligence-based approach is utilized to forecast electrical power consumption in selected feeders of Madina by using fuzzy logic and ANN models. This is one of the biggest building in Madina and a significant amount of electrical energy is consumed throughout the year. Therefore, it is utmost important to perform the load forecasting and try to implement smart energy management system and the concept of demand response. The obtained results are compared with the high-quality measured data for validation purpose. This will aid to a better maintenance scheduling in such buildings for efficient operations.

C. Short Term Load Forecasting (STLF)

According to [2] STLF is an integral part of the energy planning sector. Designing a time-ahead power market requires demand-scheduling for various energy divisions, generation, transmission, and distribution.

STLF helps power system operators in decision-making of the power system, including supply planning, generation reserve, system security, dispatching scheduling, demand-side management, financial planning, and so forth. Further, the STLF is essential for the time-ahead power market operation and inaccurate demand forecasting.

II. Artificial Intelligence Based Approach for STLF

Here, a brief about the fuzzy logic and artificial neural networks approaches are described for load forecasting application.

A. Fuzzy Logic Model

This model is used to forecast the load of the identified building. It contains a set of rules which are implemented by the linguistic variables and qualitative descriptions of the measured value sets. Depending on the degree of membership, some of these rules are activated with the help of fuzzy inference. Some statistical tools are used to measure the performance and the accuracy of model forecasting such as absolute relative error (ARE) and mean absolute percentage error (MAPE). The linguistic descriptions of fuzzy variables for example, very low, low, low medium, medium high and very high are defined and represented by membership functions. Depending on the range of these parameters a fuzzy logic-based model would be controlled and implemented. In this model, the data of load for 1-hour period would be used as input parameters and the output is the next time horizon according to the inputs.

B. Artificial Neural Network Based Model

The definition of ANN is defined as a huge group of connected simple units that operate in parallel to implement a common general objective. Sample units will learn in a process called the learning process in such a way that network parameters are updated automatically according to a possibly evolving input environment [17]. Here, an ANN based model would be designed to perform load forecasting at a given location using the high-quality measured data. To perform this task the weights are modified using network training until reaching the desired output or very close to it. This is the important step of ANN; if modifying weights are not good then the required output will not be good. Error is calculated between output of the model and desired values after the output of the network is determined.

Thereafter the errors would be reduced by adjusting the weights. This step will be repeated until the error is reduced or becomes equal or close to zero.

III. Methodology

The methodology adopted in this paper is shown in Fig. 1. First, the data has been collected from the selected feeders and then scaled to the range from 0.1 to 0.9 to avoid the convergence problem. After that, a generation of rule base for fuzzy logic and weights for ANN is implemented. Next, hourly load forecasting is done using these two models. Then, the error is calculated and the rules and weight for each model separately were adjusted until reaching accurate results. Finally, the result of the models is stored.

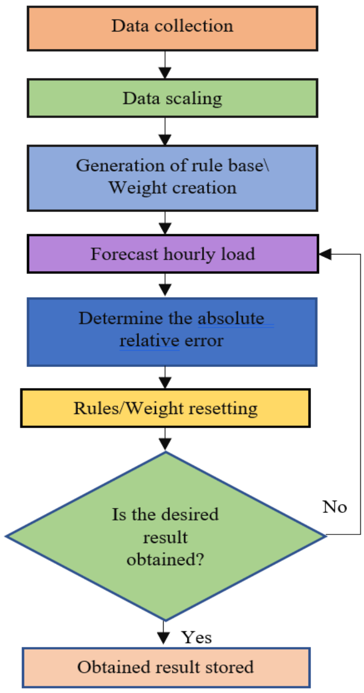

Fig. 1. Flowchart for the proposed methodology.

TABLE I: HOURLY POWER CONSUMPTION FOR THE SELECTED BUILDING

Time	Input 1	Input 2	Input 3	Input 4	Input 5	Output
	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6
6:00	2318.4	2318.4	2346	2359.8	2304.6	2304.6
7:00	2359.8	2304.6	2304.6	2332.2	2014.8	2373.6
8:00	2001	1959.6	2083.8	2056.2	1959.6	2056.2
9:00	1987.2	1890.6	1918.2	2001	2001	2056.2
10:00	1987.2	1807.8	2014.8	2028.6	2001	2070
11:00	1973.4	1987.2	2070	2028.6	2070	2042.4
12:00	2070	2014.8	2070	2001	2014.8	2139
13:00	2070	2014.8	2056.2	2070	2014.8	2139
14:00	2070	2014.8	2070	2070	2001	2152.8
15:00	2070	2014.8	2070	2001	2042.4	2152.8
16:00	2097.6	2001	2056.2	2001	2139	2180.4
17:00	2083.8	1987.2	2056.2	2014.8	2083.8	2166.6
18:00	2332.2	2277	2332.2	2263.2	2359.8	2484
19:00	2332.2	2290.8	2346	2304.6	2359.8	2484
20:00	2332.2	2332.2	2359.8	2318.4	2373.6	2456.4
21:00	2332.2	2332.2	2359.8	2332.2	2373.6	2442.6
22:00	2346	2346	2442.6	2332.2	2373.6	2346
23:00	2346	2318.4	2442.6	2318.4	2290.8	2359.8
0:00	2359.8	2318.4	2442.6	2318.4	2290.8	2359.8
1:00	2332.2	2318.4	2442.6	2318.4	2304.6	2359.8
2:00	2318.4	2497.8	2346	2318.4	2304.6	2359.8
3:00	2277	2359.8	2346	2290.8	2304.6	2401.2
4:00	2277	2346	2346	2304.6	2318.4	2401.2
5:00	2277	2346	2359.8	2304.6	2318.4	2359.8

IV. DATA COLLECTION AND NORMALIZATION

Table I shows the average hourly power consumption of the selected feeder during 23rd to 28th of January. This data is the average data for a period of more than 10 years.

In order to resolve convergence issue, the above data has been transferred to values that ranges from 0.1 to 0.9 by using the following rule:

$$S_d = \left[\left(\frac{X_{\max} - X_{\min}}{C_{\max} - C_{\min}}\right)(C - C_{\min})\right] + X_{\min} \qquad (1)$$

where C is the data to be scaled, S_d is the scaled data, $C_{\max}$ and $C_{\min}$ are the highest and the lowest values, respectively, in the column to be scaled, and $X_{\max}$ and $X_{\min}$ are the maximum and minimum limits.

TABLE II: POWER CONSUMPTION AFTER NORMALIZATION

Time	Input 1	Input 2	Input 3	Input 4	Input 5	Output
	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6
6:00	0.814286	0.692	0.752632	0.9	0.766667	
7:00	0.9	0.676	0.689474	0.838462	0.206667	
8:00	0.157143	0.276	0.352632	0.223077	0.1	0.575
9:00	0.128571	0.196	0.1	0.1	0.18	0.7
10:00	0.128571	0.1	0.247368	0.161538	0.18	0.125
11:00	0.1	0.308	0.331579	0.161538	0.313333	0.125
12:00	0.3	0.34	0.331579	0.1	0.206667	0.15
13:00	0.3	0.34	0.310526	0.253846	0.206667	0.1
14:00	0.3	0.34	0.331579	0.253846	0.18	0.275
15:00	0.3	0.34	0.331579	0.1	0.26	0.275
16:00	0.357143	0.324	0.310526	0.1	0.446667	0.3
17:00	0.328571	0.308	0.310526	0.130769	0.34	0.3
18:00	0.842857	0.644	0.731579	0.684615	0.873333	0.35
19:00	0.842857	0.66	0.752632	0.776923	0.873333	0.325
20:00	0.842857	0.708	0.773684	0.807692	0.9	0.9
21:00	0.842857	0.708	0.773684	0.838462	0.9	0.9
22:00	0.871429	0.724	0.9	0.838462	0.9	0.85
23:00	0.871429	0.692	0.9	0.807692	0.74	0.825
0:00	0.9	0.692	0.9	0.807692	0.74	0.65
1:00	0.842857	0.692	0.9	0.807692	0.766667	0.675
2:00	0.814286	0.9	0.752632	0.807692	0.766667	0.675
3:00	0.728571	0.74	0.752632	0.746154	0.766667	0.675
4:00	0.728571	0.724	0.752632	0.776923	0.793333	0.675
5:00	0.728571	0.724	0.773684	0.776923	0.793333	0.75

The result of normalized data is shown in Table II. The hourly electrical loads for the selected feeders at Madina for 23, 24, 25, 26, 27 and 28 January are represented in Fig. 2 to Fig. 7, respectively.

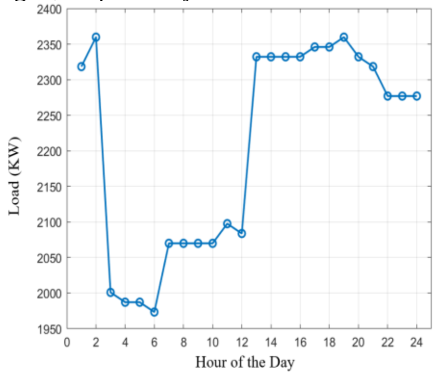

Fig. 2. Hourly electrical load for January 23.

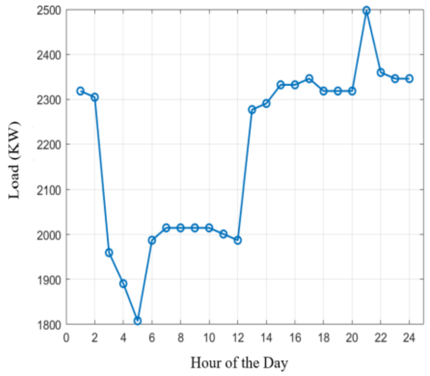

Fig. 3. Hourly electrical load for January 24.

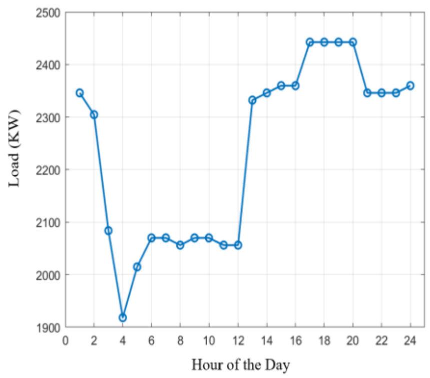

Fig. 4. Hourly electrical load for January 25.

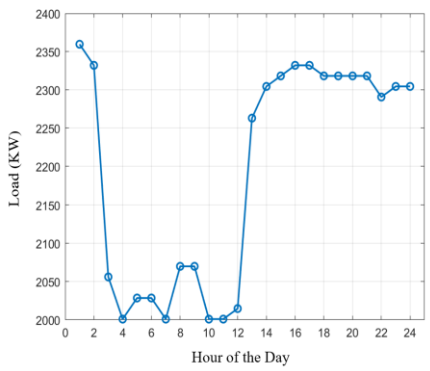

Fig. 5. Hourly electrical load for January 26.

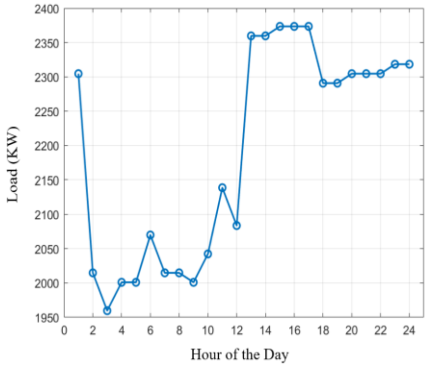

Fig. 6. Hourly electrical load for January 27.

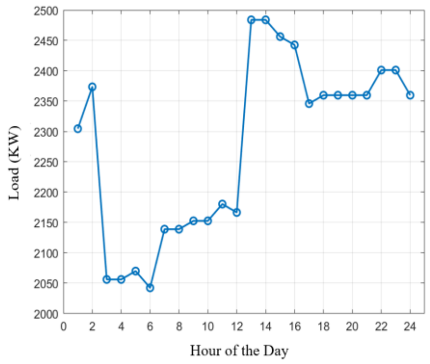

Fig. 7. Hourly electrical load for January 28.

V. Development of AI Based Models

In order to get accurate results, two models are used which are fuzzy logic and artificial neural network-based models.

A. *Fuzzy Logic Model*

In a fuzzy logic model, the hourly load for five days is considered as inputs and the sixth day represents the forecasted value which is the output of the model as shown in Fig. 8.

To implement fuzzification process, the membership function in Fig. 9 is used for the input of the model. For defuzzification process, the membership function in Fig. 10 is used for the output.

The set of fuzzy rule base for STLF that are used in this model is shown in Table III.

TABLE III: Fuzzy Rule Base for STLF

Time	Input 1	Input 2	Input 3	Input 4	Input 5	Output
	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6
6:00	H	MM	H	VH	H	H
7:00	VH	MM	MM	H	L	MM
8:00	VL	L	LM	L	VL	VL
9:00	VL	L	VL	VL	L	VL
10:00	VL	VL	L	L	L	VL
11:00	VL	L	L	L	L	VL
12:00	L	L	L	VL	L	L
13:00	L	L	L	L	L	L
14:00	L	L	L	L	L	L
15:00	L	L	L	VL	L	L
16:00	LM	L	L	VL	LM	LM
17:00	L	L	L	VL	L	LM
18:00	H	MM	H	M	VH	VH
19:00	H	MM	H	H	VH	VH
20:00	H	H	H	H	VH	VH
21:00	H	H	H	H	VH	H
22:00	VH	H	VH	H	VH	VH
23:00	VH	MM	VH	H	H	MM
0:00	VH	MM	VH	H	H	MM
1:00	H	MM	VH	H	H	MM
2:00	H	VH	H	H	H	MM
3:00	H	H	H	H	H	H
4:00	H	H	H	H	H	H
5:00	H	H	H	H	H	MM

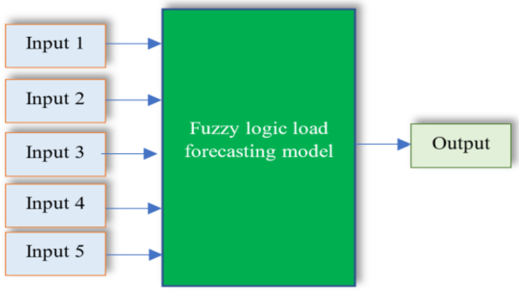

Fig. 8. Block diagram of fuzzy logic model.

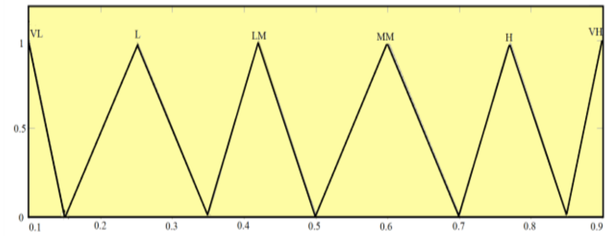

Fig. 9. Membership function of the inputs.

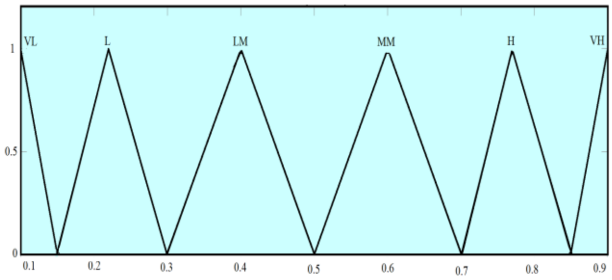

Fig. 10. Membership function of the output.

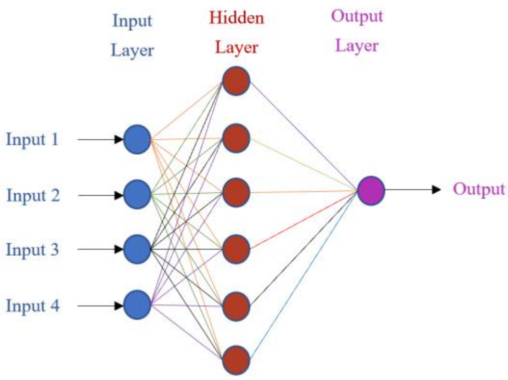

Fig. 11. Block diagram of ANN based model for load forecasting.

B. *ANN Model*

ANN model is implemented by using 16 neurons and one hidden layer in MATLAB toolbox. The general block diagram of the proposed research is provided in Fig. 11. The input matrix is of size 24 rows and 5 columns and the output matrix is of size 24 rows and one column. The layout of the developed ANN based model is provided in Fig. 12.

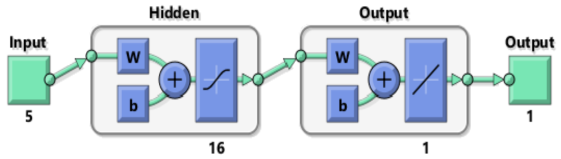

Fig. 12. Layout of ANN model.

VI. Results and Discussion

After implementing short term load forecasting, the result of both fuzzy logic and ANN model is shown in Table IV.

TABLE IV: DESIRED AND FORECASTED VALUES FOR STLF FOR FL AND ANN MODELS

Time	Desired output	Fuzzy logic		ANN	
		Forecasted output	ARE%	Forecasted output	ARE %
6:00	2304.6	2415	-4.79042	2406.72	-4.43114
7:00	2373.6	2318.4	2.325581	2472.96	-4.18605
8:00	2056.2	2263.2	-10.0671	2024.736	1.530201
9:00	2056.2	2052.888	0.161074	2092.08	-1.74497
10:00	2070	2053.44	0.8	2053.44	0.8
11:00	2042.4	2053.44	-0.54054	2566.8	-25.6757
12:00	2139	2163.84	-1.16129	2075.52	2.967742
13:00	2139	2108.64	1.419355	2067.24	3.354839
14:00	2152.8	2111.4	1.923077	2070.552	3.820513
15:00	2152.8	2166.048	-0.61538	2157.768	-0.23077
16:00	2180.4	2263.2	-3.79747	2340.48	-7.34177
17:00	2166.6	2166.048	0.025478	2226.216	-2.75159
18:00	2484	2472.408	0.466667	2472.96	0.444444
19:00	2484	2472.408	0.466667	2425.488	2.355556
20:00	2456.4	2429.904	1.078652	2447.016	0.382022
21:00	2442.6	2472.408	-1.22034	2379.12	2.59887
22:00	2346	2467.44	-5.17647	2296.32	2.117647
23:00	2359.8	2318.4	1.754386	2317.296	1.80117
0:00	2359.8	2318.4	1.754386	2313.984	1.94152
1:00	2359.8	2318.4	1.754386	2316.744	1.824561
2:00	2359.8	2318.4	1.754386	2413.896	-2.2924
3:00	2401.2	2359.8	1.724138	2403.408	-0.09195
4:00	2401.2	2359.8	1.724138	2398.44	0.114943
5:00	2359.8	2359.8	0	2403.408	-1.84795
Avg. ARE %			-0.34319		-1.02251

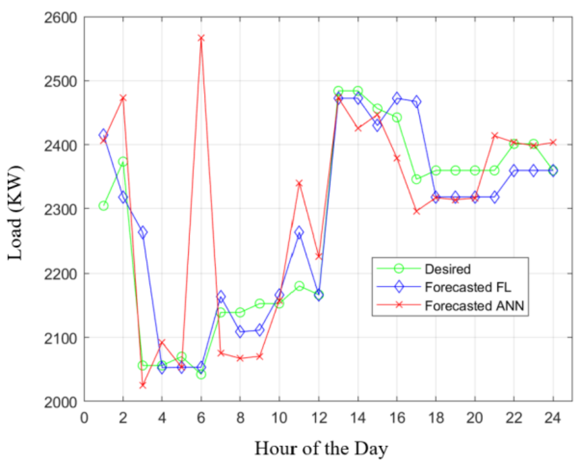

Fig. 13. Comparison of forecasted load using fuzzy logic and artificial neural network model with desired data.

The absolute relative error (ARE) is calculated for both systems using the following relationship:

$$\text{The absolute relative error}\,(\text{ARE\%}) = \frac{P_{\text{desired}} - P_{\text{forecasted}}}{P_{\text{desired}}} 100$$

The average value of ARE is very small which are 0.34% and 1.02% for fuzzy logic and ANN respectively. Fig. 13 display a plot for measured load and forecasted load using fuzzy logic and artificial neural network-based models.

From previous graph and the calculation of the value of ARE it is clear the performance of fuzzy logic system is higher and very close to measured values and error is zero in more than one point.

VII. Conclusion

In this research, an hourly load has been measured for the month of January in order to implement hourly load forecasting by using two artificial intelligence-based techniques. From the result, both fuzzy logic and ANN models are appropriate tools for short term load forecasting. The percentage of ARE calculated is 0.13% for fuzzy logic model whereas 0.56% for ANN. For further research, it is recommended to enhance these models by a different input such as temperature and population. From this study it is revealed that the proposed model may be implemented for other feeders as well. The proposed work may be utilized in dynamic pricing-based techniques for effective demand side management in the built environment. Moreover, the study related to real time pricing, time of use and critical peak pricing (CPP) may be conducted in the future research work.

Conflict of Interest

Authors declare no conflict of interest.

Author Contributions

Mohammad Rizwan who conceptualized the topic, analyzed the data, validated the result and written/edited this manuscript. Yousef R. Alharbi have collected the data for selected location, perform the case study and prepared the manuscript. All authors had approved the final version.

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