Qubahan Academic Journal
گوڤارا قبهان یا ئەکادیمی
مجلة قبهان الأكاديمية
Doi: 10.58429/Issn.2709-8206

Fuzzy Models for Short Term Power Forecasting in Palestine

Raed Y. Basbous
Al-Quds Open University, Palestine
https://doi.org/10.58429/qaj.v3n4a268

Abstract

Short-Term Load Forecasting (STLF) is needed to efficiently manage the power systems. In this paper, two kinds of models that depend on the Fuzzy based techniques are developed to represent the STLF models in Palestine. Different types of these models have been developed using the available data sets that include the past electric load values and the climatic variables as inputs. It is shown that the climatic variables have a major effect on the predicted load. Various optimization techniques are used to develop the proposed models including hybrid and Backpropagation optimization techniques, Subtractive Clustering, and combining the Subtractive Clustering and Hybrid optimization techniques. The obtained results indicate the efficiency of the proposed models using the time and weather data.

Keywords: *Subtractive Clustering, Fuzzy Logic, Sugeno, ANFIS, Neural Networks, Hybrid Optimization.*

1. INTRODUCTION

Load Forecasts (LF) are needed for the efficient management of power systems (Khan et al., 2001)[10]. LF can be categorized to three different categories (Desouky & Elkateb, 2000)[5]. They are Long-Term Load Forecasting (LTLF), Medium-Term Load Forecasting (MTLF), and Short-Term Load Forecasting (STLF). STLF can cover an interval ranging from one hour to a week. For the STLF several factors must be considered, such as time factor, and weather data.

The aim of this paper is to explore and build different neuro fuzzy models for the STLF problem in Palestine using the available historical electric power load and climate readings. The adequacy of the developed models is tested using different measures including; the Correlation Coefficient (CC), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE).

Two different kinds of the proposed models have been developed depending on the Fuzzy based techniques including integrated and adaptive Neuro-Fuzzy approaches.

In developing and testing these models, real historical data profiles for Beir Nabala village in Palestine as a case study. These datasets are obtained from Jerusalem District Electric Company (JDECO), and the Palestinian Meteorology Office (PMO).

A pre-processing technique are applied for the available dataset including detecting and removing the bad data and the outliers. For the SISO models; the time was considered as an input, while in MISO models; the time, high and low temperatures of each day were considered as the system inputs. The output for the two kinds of models is fixed to be the power load that consumed.

Different optimization methods are used to build the models including hybrid, back-propagation, Subtractive Clustering, and cascaded model using Subtractive Clustering and hybrid optimization technique to improve the models efficiency.

Finally, the proposed models were tested using real unseen historical datasets to predict the load for one day and one week ahead.

The organization of this paper is as follows. Section 2 describes the data provided, the analysis of the available data, the pre-processing process, and the currently available fuzzy-based modeling techniques. Section 3 shows the development and implementation steps followed to build the proposed models. The results obtained from the developed models are presented in section 4. Section 5 concludes the paper.

2. Materials and Methods

A. *Data Sources*

To develop any supervised soft computing system, pairs of data (inputs and output) are needed, and in order to have a reliable STLF models that best represents the trends of these input and output data, we have to collect reasonable actual sets of data composed of the electric power load as an output for a certain time during a day with known weather measures as an inputs for a specific line that serves a chosen area.

As mentioned in the previous section, our sources of the datasets profiles are the Jerusalem District Electric Company (JDECO) and the Palestinian Meteorology Office (PMO) for two years (2006 and 2007). The Beir Nabala village is used as a case study. The provided power historical data profile includes the time and the corresponding power load at that time, while the weather historical data profile includes humidity, highest temperature, and lowest temperature for each day.

B. *Data Sources*

The selection of the training datasets from the available data significantly affects the forecasting results, and to achieve a reliable and a more comprehensive approach to load forecasting, the days which have similar load and historical temperature values should be chosen to train (develop) the models (Peng et al., 1992)[16].

The success of model training for a given task may affected by many factors. The quality and representation of the instance data is an important factor (Pyle, 1992)[17]. If there is much unneeded and redundant data present or outliers, then this make extraction the knowledge during the training phase more difficult.

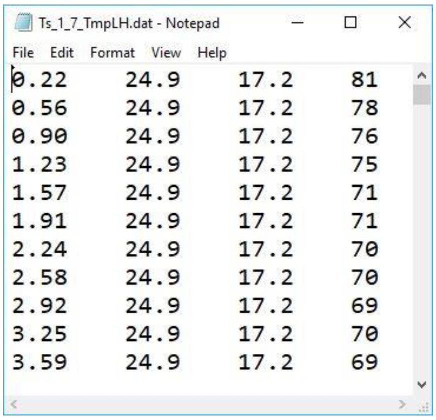
In this research, pre-processing stages have been accomplished for the collected data. These stages are as shown in Fig. 1. They are, obtaining historical profiles, input variables selection, bad data and outliers detecting and removing, time formatting, and cross validation.

Fig. 1: Collected data pre-processing stages.

In the second stage, the time, power load, and temperature elements (low and high temperatures) have been selected to train the models.

Rosner algorithm (Rosner, 1983)[18] is used to detect and remove the outliers from the historical profiles, and a manual procedure has been followed for detect and remove the zero loads. Time formatting in the fourth stage is necessary since the input to the models should be a real number format and not in a time format (hour: minutes) as provided. Finally, a cross validation technique has been applied to divide the datasets into training and testing datasets.

Fig.2 shows a sample of the used pre-processed testing dataset.


Ts_1_7_TmpLH.dat - Notepad

File Edit Format View Help

0.22	24.9	17.2	81
0.56	24.9	17.2	78
0.90	24.9	17.2	76
1.23	24.9	17.2	75
1.57	24.9	17.2	71
1.91	24.9	17.2	71
2.24	24.9	17.2	70
2.58	24.9	17.2	70
2.92	24.9	17.2	69
3.25	24.9	17.2	70
3.59	24.9	17.2	69

Fig. 2: A pre-processed training data set sample

In order to test the developed models using new unseen datasets, new profiles for the year 2008 are obtained from JDECO and PMO. Two small samples are selected to test the developed models. The first one is for one week from July (1st -7th of July) to test the general July and Summer MISO models. The second datasets are for one week from May (1st -7th of May) to test the general May and Spring MISO models.

C. Fuzzy Inference Systems

Fuzzy Inference Systems (FISs) are playing a major role in decision making systems (Arafeh et al., 1999)[1]. It formulates the rules that help in making the decision.

For these systems, the inputs can be either fuzzy or crisp, while the outputs are usually fuzzy sets. In case that the output needed to be a crisp, a defuzzification is used to best represent the fuzzy set.

Fig. 3 below shows the FIS model elements (Jang, 1993)[8].

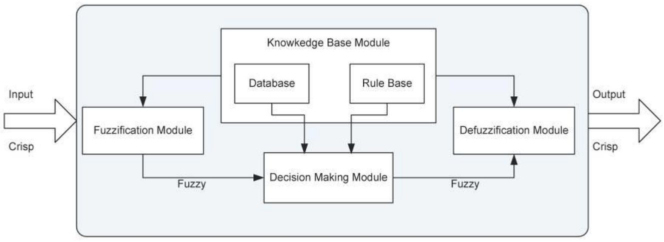


Fig. 3: The FIS model elements

The most common methods of fuzzy inference are; Mamdani's fuzzy inference method (Houimli et al., 2020)[6], and Takagi-Sugeno method of fuzzy inference process (Salkuti, 2018)[19].

D. Adaptive Neuro Fuzzy Inference Systems

In fuzzy modeling, the selection of the membership functions, the rule based, the best fitting boundaries of membership functions, and number of rules determined generally by trial-and-error approaches which are very difficult.

In Adaptive Neuro Fuzzy Inference Systems (ANFIS) it is possible to celebrate the constructed FIS membership function parameters using either a Backpropagation algorithm, or by combining it with another method such as the least squares method. These methods can be applied to the fuzzy systems to let them learn from the available data used for modeling. Many algorithms can be used to adjust the system parameters including; the Least-Squares, the Hybrid, and the Back-propagation. The Least-Squares optimization algorithm (Dennis, 1977)[4], (Levenberg, 1944)[13], and (Mrquardt, 1963)[14] is a technique that minimizes the sum of the squares of the ordinate differences between points generated by the system and the actual points in the dataset. The Hybrid Learning algorithm (Jang, 1993)[8], and (Jang et al., 1997)[9], combines the Gradient Descent and the LSQ algorithms and used to identify the parameters of the ANFIS. The Backpropagation learning algorithm is a method to teach the artificial neural networks how to perform a given task and used to adjust the weights of the neural network.

E. Data Clustering

Data Clustering is considered for grouping similar data together in clusters by finding similarities in data (Jang et al., 1997)[9]. It divided the data set into a number of groups such that the similarity within a group is larger than that among other groups. Four of the most Clustering techniques frequently used in (Jang, 1993)[8] including K-means Clustering, Fuzzy C-means Clustering, Mountain Clustering, and Subtractive Clustering.

Readers not familiar to fuzzy inference systems are referred to (Arafeh et al., 1999)[1], (Hwan & Kim, 2001)[7], (Jang, 1993)[8], (Jang et al., 1997)[9] , and (Sugeno & Takagi)[21], or similar materials.

3. IMPLEMENTATION

In system modeling and identification, it is important to identify the structure and the parameters of the system based on the available data. The identification consists of two parts; the identification of the input variables of the model and the input–output relation.

Two kinds of models have been developed, SISO and MISO models to study the effect of the temperature in STLF. Fig. 4 shows the architecture of the proposed SISO model. The time has been used as the input for the model and the power load at that time has been considered as the output.

Fig. 4: SISO architecture

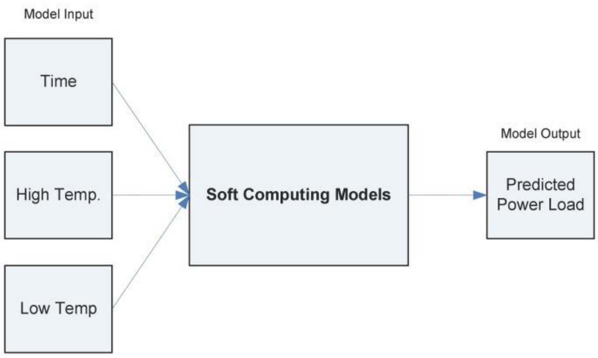


Fig. 5: MISO architecture

Fig. 5 represents the proposed MISO model. In this model three variables (Time High Temperature, and the Low Temperature for that day) are considered as an input for the developed models, and the power load at that time is considered as the model output.

To check the adequacy of obtained results, three measures are used (Arafeh et al., 1999)[1], and (Arikat, 2012)[2]. These measures include the Correlation Coefficient CC, Mean Absolute Percentage Error MAPE, and Root Mean Square Error RMSE:

1. *The CC measure*, that indicates the strength and direction of a linear relationship between the forecasted and actual loads and calculated by (Arafeh et al., 1999)[1]:

$$CC_{xy} = \sqrt{1 - \frac{\sum_{i=1}^{N} (y_i - x_i))^2}{\sum_{i=1}^{N} (y_i - y)^2}} \qquad (1)$$

2. *The MAPE,* which is traditionally used to capture the proportionality between the forecast and the actual load. The MAPE is calculated by (McSharry, 2006)[15]:

$$\text{MAPE}= \sum_{i=1}^{N}\left|\frac{y_i - x_i}{y_i}\right| * \frac{100}{N}\% \qquad (2)$$

3. *The RMSE,* which is used to evaluate the error between the forecasted and actual loads. The general form of the RMSE equation for the actual power loads (Y) and the forecasted ones (X) is given by (Arikat, 2012)[2]*:*

$$\text{RMSE}= \frac{\sqrt{\sum_{i=1}^{N}(y_i - x_i)^2}}{(N-1)} \qquad (3)$$

Where:

y_i : is the i^{th} actual data,

y : is the average of actual data,

x_i : is the i^{th} predicted data,

N : is the number of data points.

To study the effect of the temperature input variables on the predicted power load, the proposed models (MISO and SISO) with hybrid optimization are tested using sample dataset. The results show that the temperature input variables have a considerable effect on load forecasting. This effect reflected as an enhancement in the error measures. The CC enhanced from 0.91 in SISO model to 0.98 in MISO model while the MAPE is reduced from 0.06 in SISO model to 0.02 in MISO model.

The obtained historical data profiles from JDECO and PMO have to be used to develop/train the proposed models. Several models have been developed including, Sugeno with different optimization techniques, Subtractive Clustering, and finally Subtractive Clustering cascaded with Hybrid optimization technique to improve the proposed models.

Fig. 6 shows a general diagram of the models developing process for the proposed models that consists of three main steps mentioned below:

1. The first stage is to pre-process the selected input and output datasets for the system (three of them are inputs; namely, the time, the high temperature, and the low temperature of the day and one output (the actual loads)).
2. The second stage is to select the proposed soft computing models that to be developed. In our paper, SISO/MISO models will be developed using different techniques (Hybrid and Backpropagation optimization techniques, Subtractive Clustering and finally by cascading two models). The same training and testing datasets are used in developing all these models.
3. The last stage is to check the adequacy of the developed models to show their performance.

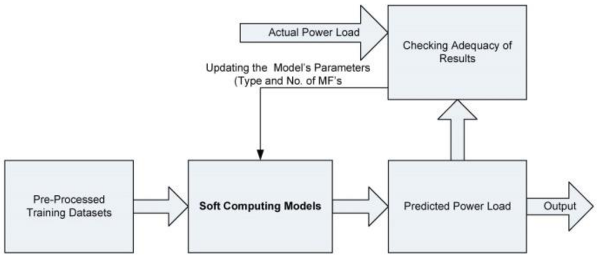


Fig. 6: The developing/training block diagram

The model parameters such as the type and the number of membership functions have been determined and fixed manually for the proposed models. The Matlab fuzzy toolbox is used to test the effect of selecting the type and number of MFs. Several MFs are implemented including: Gaussian Curve, Generalized Bell, Trapezoidal and Triangular. It is noticed that the best results have been obtained when using the Generalized Bell (GBell) type with 12 MFs for the time input, and 7 MFs for the temperature inputs (High and Low).

Finally, to study the effect of removing the outliers from the available dataset, two MISO Sugeno model with hybrid optimization have been developed using a sample from the available dataset. The results showed that the CC between the actual and predicted loads is increased from 0.94 (before removing the outliers from the dataset) to 0.98 (after removing the outlier from the dataset)

Using the fixed parameters that mentioned above (the inputs, and the type and number MFs) and after removing the outliers from the datasets, two types of models have been developed (SISO and MISO) using datasets from the month of July and May, spring season (month of April and May), and summer season (month of July and August). Different optimization techniques are used to develop these types of models.

Fig.7 and Fig.8 show the effect of the temperature elements on training the models to predict the required power load using a selected dataset. In Fig.7 the load predicted using a SISO model where the input to the model is only the time, while in Fig.8; the predicted load is retrieved from a proposed MISO model where the input to the model include the time, and the lowest and the highest temperatures.

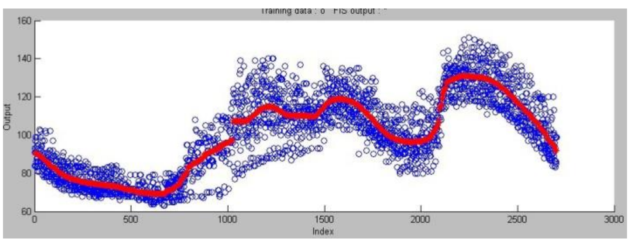


Fig. 7: Predicting the power load using the time as input.

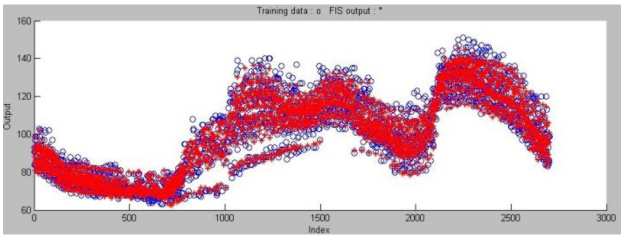


Fig. 8: Predicting the power load using the time and temperature as inputs.

4. RESULTS AND COMPARISONS

Eight Sugeno models with different optimizing techniques (including hybrid, back-propagation, Subtractive Clustering, and a cascaded model by combining Subtractive Clustering and hybrid) were developed. Four of these proposed models are SISO models and the other four are MISO models. These models have been used to predict the power load in specific months (May, July) or general model to be used.

As mentioned in the previous sections, the models have been fixed and used to develop the proposed models. For the models that have been constructed using the Subtractive Clustering, a cluster radius equal to the value 0.1 are fixed and used to construct these models.

A. *Results Of The Developed Models*

As mentioned in the previous sections, three error measures are used the CC, MAPE, and RMSE. These measures indicate how are the performance of the developed models.

Table 1 and Table 2 below list the average error measures (CC, MAPE, and RMSE) for all the SISO and MISO developed models using Hybrid, Back-propagation, Subtractive Clustering and Subtractive Clustering with Hybrid optimization.

Table 1: The Average Error Measures for all the SISO Models

Optimization Algorithm	**CC**		**MAPE**		**RMSE**	
	Trn	***Tst***	***Trn***	***Tst***	***Trn***	***Tst***
Hybrid	0.88	0.87	0.09	0.09	0.18	0.31
Backpropagation	0.82	0.82	0.10	0.10	0.21	0.37
Subtractive	0.88	0.87	0.09	0.09	0.17	0.31
Subtractive with Hybrid	0.88	0.87	0.09	0.09	0.17	0.31

Table 2: The Average Error Measures for all the MISO Models

Optimization Algorithm	**CC**		**MAPE**		**RMSE**	
	Trn	***Tst***	***Trn***	***Tst***	***Trn***	***Tst***
Hybrid	0.95	0.95	0.05	0.05	0.11	0.20
Backpropagation	0.91	0.90	0.08	0.08	0.15	0.28
Subtractive	0.96	0.95	0.05	0.05	0.10	0.19
Subtractive. with Hybrid	0.97	0.96	0.04	0.05	0.08	0.16

Table 2 shows that the cascaded model has produced the best CC results with an average equal to (0.97) for the MISO models, while Table 1 shows that the lowest CC results is obtained from the model that has been developed using the Backpropagation with an average equal to (0.82).

Furthermore, Table 2 shows that the lowest MAPE values are obtained from the cascaded MISO model with an average value equal to (0.04). This low value reflects the highest CC that achieved from these models as shown in the same table. You can notice that the MISO models have the lowest MAPE values over the SISO models because of the temperature parameters effect on the power load. The same thing has been noticed in the CC measures since the MISO models produced the best results and have the highest CC values.

In addition, the above tables (1 and 2) show the average RMSE results for all the models. The same thing for the RMSE results as in the MAPE; the best results model (the lowest RMSE values) achieved when using the cascaded model. The developed MISO models with the temperature parameters produce the lowest RMSE values over the SISO models. It is clear from the tables that the lowest value is obtained from the MISO models developed using the cascaded models with an average of the RMSE equal to (0.08), while the highest value is obtained from the SISO model with Backpropagation optimization.

As described above, a relation can be concluded from the tables which is: an increasing in the CC measure leads to a decrease in RMSE and MAPE measures. One example that shows this, is when the average CC for the MISO cascaded models are equal to (0.97) the corresponding average MAPE and RMSE values for the cascaded model are equal to (0.04 and 0.08) respectively.

It is clear that the cascaded models have the highest CC results while the models with Backpropagation optimization have the lowest CC compared to the other models and similarly for the two error measures. Furthermore, it is shown that the results from the models that developed with Subtractive Clustering enhanced when subjected to the Hybrid optimization technique.

B. *One Day And One Week Ahead Prediction Using Unseen Datasets*

It is mentioned in the previous sections that a new unseen historical profiles obtained from JDECO and PMO for the year 2008. The selected datasets (one day and one week from July and May) are used to test the developed models. These datasets have not been considered in the cross validation process that applied in developing the proposed models. One day from the months May and July (1st of May and 1st of July) is selected in order to use the models to predict the load for one day ahead. To test the models in predicting the load for one week ahead, the first week of the months May and July (1st to 7th of May, and 1st to 7th of July) are considered.

Table 3 shows the average correlation and error measures for one day and one week forecasting using the developed models. The table shows that the best results have been obtained from the model the developed using the datasets from May month in case of one day and one week ahead forecasting. The lowest CC average is obtained from the spring model. This is because of the wide range of the input parameters (low and high temperatures) in this season. The obtained results show the adequacy of the proposed models to forecast the power loads for the new unseen datasets one day and one week ahead.

Table 3: The Unseen Data Measures for One Day and One Week Prediction

Model	**One Day**			**One Week**		
	CC	***MAPE***	***RMSE***	***CC***	***MAPE***	***RMSE***
July	0.97	0.04	0.22	0.94	0.05	0.29
Summer	0.94	0.05	0.32	0.93	0.06	0.35
May	0.98	0.03	0.20	0.96	0.05	0.28
Spring	0.87	0.11	0.49	0.90	0.08	0.43
Average	**0.94**	**0.06**	**0.31**	**0.93**	**0.06**	**0.34**

5. COMPARISON WITH OTHER STUDIES

Several studies have shown the accuracy of using the artificial intelligence techniques in the field of STLF.

In (Rosner, 1983)[18], the author implemented artificial neural networks to forecast the half-hourly electric load demand in Tunisia. They used the past electric load values, the climatic and calendar variables as inputs. The MAPE values range between 1.1 and 3.4%.

Taheri et al. (2020)[22] analyzed a distributed DC power patterns with their weather parameters to forecast the power consumption of each collaborating DC in a cloud. The obtained results show that the proposed prediction model reaches the accuracy of 87.2%.

In (Salkuti, 2018)[19] the author proposed a hybrid ANN and wavelet transforms based model to forecast the power load demand data. The obtained MAPE from this model for winter and spring weeks are 0.028 and 0.029, respectively.

Lei et al. (2019)[12] represent a load forecasting approach based on Spark platform and Clustering–regression model. The results obtained from the proposed model show that the it has a high efficiency in and can be effectively applied to the electric load forecasting.

Different models are proposed by Shu & Hyndman (2012)[20] to estimate the relationships between demand and the driver variables. The overall MAPE value of the proposed models is 0.0188.

In (Khawaja et al., 2015)[11], the authors presented an improved STLF technique based on bagged ANNs. The overall MAPE obtained using the proposed system is 0.015.

From the results obtained in the researches mentioned above, it is clearly noticed that the soft computing methods provide a promising solution to the STLF problem. In addition, combining or integrating more than one method together can improve the proposed models. For example Tamimi & Egbert (2000)[23] combined the NN with FL, and Hwan & Kim (2001)[6] developed a forecasting system and include it with different forecasting models to increase the forecasting accuracy. Furthermore, it is shown in the lowest results obtained from the models developed using the Backpropagation optimization as it is proposed by Bhattacharyya & Thanh(2004)[3]. This agrees with the results obtained from the developed Sugeno FIS models with Backpropagation optimization in this paper.

Comparing the results from the mentioned above systems we can see that the results on this paper are satisfactory using the temperature parameters only (average high and low temperatures) to predict the load without taking into account the other conditions including the type of the day.

6. SUMMERY AND CONCLUSION

In this paper a real historical data sets that provided by JDECO and PMO are used to develop different models based on neuro fuzzy inference systems. Two kinds of models have been developed. In building these models; time, high temperature, and low temperature are considered as inputs and the power load at certain time as an output. From the results it is shown that the temperature plays a major effect on STLF.

The performance of the proposed models has improved by the cascaded models.

The developed models were tested using unseen real historical data sets for the year 2008 to predict the load for one day and one week ahead. The overall results indicates the suitability and adequacy of the developed models to solve the short term load forecasting problem using the time and weather variables. Further work can be done in this field to enhance the models by taking into account additional input variables such as humidity; hourly temperature measures instead of average high and low ones; or the type of the day such as the weekends and holidays.

REFERENCES

[1] Arafeh L, Singh S, Putatunda, S (1999). A Neuro Fuzzy Logic Approach to Material Processing. IEEE Transactions on Systems, Man, and Cybernetics, Part C, 29:3:362-370.

[2] Arikat Y, (2012). Subtractive Neuro-Fuzzy modeling techniques applied to short essay auto-grading problem. Sciences of Electronics, Technologies of Information and Telecommunications. https://doi.org/10.1109/SETIT.2012.6482032

[3] Bhattacharyya S, Thanh L (2004). Short-Term Electric Load Forecasting Using an Artificial Neural Network: Case of Northen Vietnam. International Journal of Energy Research 28:463-472.

[4] Dennis J (1977). Nonlinear Least-Squares, State of the Art in Numerical Analysis, Academic Press, Orlando, FL.

[5] Desouky A, Elkateb M (2000). Hybrid adaptive techniques for electric-load forecast using ANN and ARIMA. IEE Proceedings of Generation, Transmission and Distribution, 147:4:213–217.

[6] Houimli R, Zmami M, Ben-Salha O (2020). Short-term electric load forecasting in Tunisia using artificial neural networks. Energy Systems,11:357–375. https://doi.org/10.1007/s12667-019-00324-4.

[7] Hwan K, Kim G (2001). A Short-Term Load Forecasting Expert System. Proceedings of The Fifth Russian-Korean International Symposium on Science and Technology, pp 112– 116.

[8] Jang J (1993). ANFIS: Adaptive-Network-Based Fuzzy Inference System. IEEE Transactions on Systems and Machine Cybernetics 23:3:665–685.

[9] Jang J, Sun C, Mizutani E (1997). Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. Prentice-Hall, Englewood Cliffs, NJ, pp. 7-9, 219-336.

[10] Khan M, Abraham A, Ondrusek C (2001). Soft Computing for Developing Short Term Load Forecasting Models in Czech Republic. Hybrid Information Systems, pp. 207-222.

[11] Khwaja A, Naeem M, Anpalagan A, Venetsanopoulos A, Venkatesh B (2015). Improved Short-Term Load Forecasting Using Bagged Neural Networks. Electric Power Systems Research 125:109-115.

[12] Lei J, Jin T, Hao J, Li F (2019). Short-Term Load Forecasting With Clustering–Regression Model in Distributed Cluster. Cluster Computing, 22:7: 10163–10173. https://doi.org/10.1007/s10586-017-1198-4

[13] Levenberg K (1944). A Method for the Solution of Certain Nonlinear Problems in Least Squares. Quart Appl Math 2:164–168.

[14] Marquardt D (1963). An Algorithm for Least-Squares Estimation of Nonlinear Parameters. Journal of the Society for Industrial and Applied Mathematics 11:431–441.

[15] McSharry P (2006). Evaluation of Short-Term Forecasting Methods for Electricity Demand in France, RTE-VT workshop, Paris.

[16] Peng M, Hubele N, Karady G (1992). Advancement in the Application of Neural Networks for Short-Term Load Forecasting. IEEE Transactions on Power Systems 7:250 – 257.

[17] Pyle D (1992). Data Preparation for Data Mining. Morgan Kaufmann Publishers, Los Altos, CA.

[18] Rosner B (1983). Percentage Points for a Generalized ESD Many-Outlier Procedure. Technometrics, 25(2):165-172. https://doi.org /10.2307/1268549.

[19] Salkuti S (2018). Short-Term Electrical Load Forecasting Using Hybrid ANN–DE and Wavelet Transforms Approach. Electrical Engineering 100:2755-2766. https://doi.org/10.1007/s00202-018-0743-3

[20] Shu F, Hyndman R (2012). Short-Term Load Forecasting Based on a Semi-Parametric Additive Model. IEEE Transactions On Power Systems 23:1:134-141.

[21] Sugeno M, Takagi T (1985). Fuzzy Identification of Systems and its Application to Modeling and Control. IEEE Transactions on Systems and Machine Cybernetics 15:116–132.

[22] Taheri S, Goudarz M, Yoshie O (2020). Learning-Based Power Prediction Or Geo-Distributed Data Centers: Weather Parameter Analysis. Big Data. https://doi.org/10.1186/s40537-020-0284-2

[23] Tamimi M, Egbert R (2000). Short Term Electric Load Forecasting via Fuzzy Neural Collaboration. Electric Power Systems Research 56:243–248.

\