Short-Term Load Forecasting by Knowledge Based Systems on the basis of Priority Index for Selection of Similar Days

Mahnoor Khan*, Nadeem Javaid*, Yuksel Celik†, Asma Rafique†
*Department of Computer Science
COMSATS University Islamabad, Islamabad 44000, Pakistan
{mahnoor.khan2794, nadeemjavaidqau}@gmail.com
†Department of Computer Engineering
Karabuk University, Karabuk, Turkey

***Abstract*—In the modern day world and with growing technology, load forecasting is taken as the significant concerns in the power systems and energy management. The better precision of load forecasting minimizes the operational costs and enhances the scheduling of the power system. The literature has proposed different techniques for demand load forecasting like neural networks, fuzzy methods, Naïve Bayes and regression based techniques. This paper proposes a novel knowledge based system for short-term load forecasting. The proposed system has minimum operational time as compared to other techniques used in the paper. Moreover, the precision of the proposed model is improved by a different priority index to select similar days. The similarity in climate and date proximity are considered all together in this index. Furthermore, the whole system is distributed in sub-systems (regions) to measure the consequences of temperature. Besides, the predicted load of the entire system is evaluated by the combination of all predicted outcomes from all regions. The paper employs the proposed knowledge based system on real time data. The proposed model is compared with Deep Belief Network and Fuzzy Local Linear Model Tree in terms of accuracy and operational cost. In addition, the proposed system outperforms other techniques used in the paper and also decreases the Mean Absolute Percentage Error (MAPE) on yearly basis. Furthermore, the proposed knowledge based system gives more efficient outcomes for demand load forecasting.**

***Keywords*—Short-term load forecasting, knowledge based systems, priority index, similar day, date proximity**

I. Introduction

The systematic and proficient utilization of electrical power is a hot debate topic in today's world [1]. The optimal power management and maintaining balance between demand and supply are considered as challenging tasks for modern power systems [2]. Moreover, the prediction of uncertain production of renewable energy resources [3] and short-term load forecasting [4] are measured as significant components of the power grid for optimal power scheduling. Besides, the short-term load forecasting has wide applications in the energy market like load scheduling, unit commitment and power production [5]. It has been observed in the literature that error maximization in short-term load forecasting can result in substantial growth in the utility operating expenses. Thus, enhancing the accuracy of predicted results is a challenging task and vital issue in the power management.

The literature has proposed many novel methods for short-term load forecasting like fuzzy [6], exponential smoothing [7], regression based [8], neural networks [9] and others. Moreover, every proposed model has incorporated some techniques. For example, regression based processes are usually comprised of Autoregressive Integrated Moving Average (ARIMA) [10], Auto-Regressive Moving Average (ARMA) [11], Support Vector Regression (SVR) [12] and Auto-Regressive Moving Average with Exogenous variable (ARMAX) [13]. Nevertheless, it is essential for aforementioned techniques to learn the process by bulks of preceding data for tuning of various parameters. Furthermore, the complexities of these techniques, minimum time of computation and memory essentials of knowledge based model can initiate a different perspective to knowledge based short-term load forecasting.

In literature, there are some works cited in knowledge based systems that employs a similar day method [14], [15], [16]. Though, there is a lot of room for enhancement in this scenario, which can be studied. The authors in [17] proposed a knowledge based system for short-term load demand forecasting. However, the paper overlooked the consequences of temperature. The change in temperature can cause fluctuations in the load demand. Consequently, the effect of temperature must be included in the short-term load forecasting. The different 8 day categories are enumerated in [18].

Moreover, average stabilized loads of historic data for every day has been evaluated by means of least and maximum load per hour. Furthermore, the least and maximum load for 11 days was forecasted by means of regression techniques. The Mean Absolute Percentage Error (MAPE) of Taiwan electrical power system attained was 2.52%. Moreover, the temperature was also incorporated in this study and was associated with 3.86% by the statistical technique in [19].

The authors in [20] calculated the weighted mean load of every hour for 3 preceding and similar days for short-term load forecasting. Moreover, the impact of temperature on prediction of short-term load is also considered by means of exponential association between power demand and temperature. Likewise, the mean prediction error for a daily peak load of France was attained 2.74% in [20]. Besides, the consequences of temperature, wind pressure and humidity, was scrutinized in [21]. The MAPE calculated in this study was 1.43%. The study in [23] was almost equivalent to the proposed model presented in [22]. Moreover, the MAPE achieved in this study was between 1.23% to 3.35% in 7 different states of America [22].

The mean prediction error for daily peak load in [24] was achieved 4.65% for weekdays and 7.08% for weekends of 3 different states of Turkey [23]. This mean prediction error was achieved after smoothing the temperature discrepancies throughout the day. The precedence of similar days is overlooked in previous studies. It is obvious that there are numerous days, which are advantageous for the knowledge based forecasting of load. Nevertheless, the best suitable preference of these same days has a substantial effect on forecasting results.

This paper divides the entire system in 9 regions. Moreover, the climatic conditions of only 1 city is chosen from every region. The knowledge based short-term load forecasting is employed to every region after the consideration of temperature. In addition, the predicted power load of the entire system is the aggregate of predicted load of particular regions. The impact of temperature is believed to be much more efficient and result improving when the system is divided.

The proposed system model is employed in Pakistan's National Power Network (PNPN), which is taken as a sample system in this paper. The proposed system model shows a significant decrease in MAPE in comparison with other traditional knowledge based methods. This paper uses algorithms of Deep Belief Network (DBN) and Fuzzy Local Linear Model Tree (F-LOLIMOT) for comparison purposes. The experimental results specifies that the proposed model requires minimum time for computation when associated with DBN and F-LOLIMOT.

The major research contributions of this paper include the proposition of the priority index for selection of similar days by means of temperature of specified regions and date proximity. Moreover, the historic power load is separated in 2 different data-sets in the paper. Subsequently, the data-sets predict the short-term load and then the final outcome is supposed to be more precise. The final outcomes are achieved by the summation of predicted results from 2 data-sets.

The remaining paper is organized in following manner: Section II discusses the categorization of knowledge based short-term load forecasting and Section III employs the proposed method on different topographical regions. Moreover, results and their discussion are presented in Section IV and Section V concludes the paper.

II. Knowledge Based Short-Term Load Forecasting

Knowledge based systems and computational intelligence are considered as major tools of artificial intelligence. The knowledge based systems employs categorical representations of knowledge like symbols and words [24]. The knowledge based systems are efficient and simple as the categorical representation makes the knowledge readable and implicit for a human as compared to numerical derived models in computational intelligence. The techniques of knowledge based systems incorporate case based, model based and rule based systems.

The major difference between a traditional program and knowledge based system is in their structure [25]. The knowledge of the domain is closely associated with software for monitoring the performance of that particular knowledge in a traditional program. However, the roles are clearly divided in knowledge based systems. Moreover, there are 2 basic components of knowledge based systems, which are knowledge base and inference engine. Nonetheless, some interface proficiencies are also compulsory for a real-world system, as presented in Fig. 1.

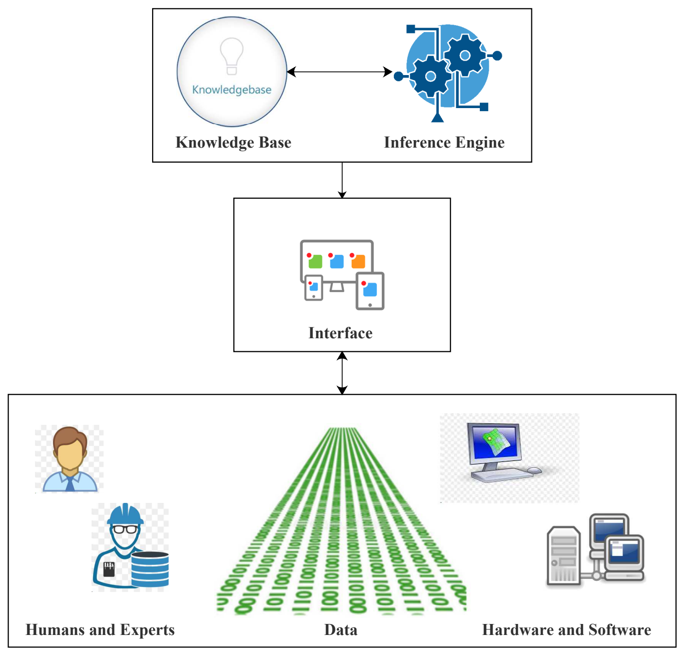

Fig. 1. Principle components of knowledge based system

A. Proposed Knowledge Based Short-Term Load Forecasting

The proposed knowledge based short-term load forecasting is categorized in following parts, which are explained as follows:

1) Distribution of Historic Load Data: The selection of similar days from historic days is considered as crucial for knowledge based forecasting. Moreover, the selection of similar months and days also have a significant impact on the results of short-term load forecasting. Therefore, this paper presents 2 historic data-sets, which are well-defined for every type of days. The first data-set is comprised of similar days from preceding month along with the selected date. Furthermore, the second data-set incorporates same days from 7 days earlier and subsequent to the target day of the week. The target year and similar days are also chosen from all preceding years in both data-sets. Besides, the data-sets are specified by scrutiny of annual load demand and meteorological conditions of Pakistan.

It is a well-known fact that temperature and load demand have a direct relationship with each other. For example, usage of air conditioners and other cooling devices increases in summers especially. This phenomenon shows variations in load curve and peak hour of the entire system. Moreover, the impact of climatic conditions on the load demand in summers is usually more than other time of year [26].

The Fig. 2 illustrates the load curves for Thursday as an example. Moreover, this load curve is for Pakistan and depicts all 4 seasons. It is obvious from the Fig. 2 that the load level and hourly peaks by day and nights shows a significant fluctuation in different spells. Therefore, it can be determined that by maximization of the measured time, the range of both data-sets may affect the selection of similar days with similar temperature. However, this phenomenon is not suitable for load curves because changes in climate also affect load consumption behavior.

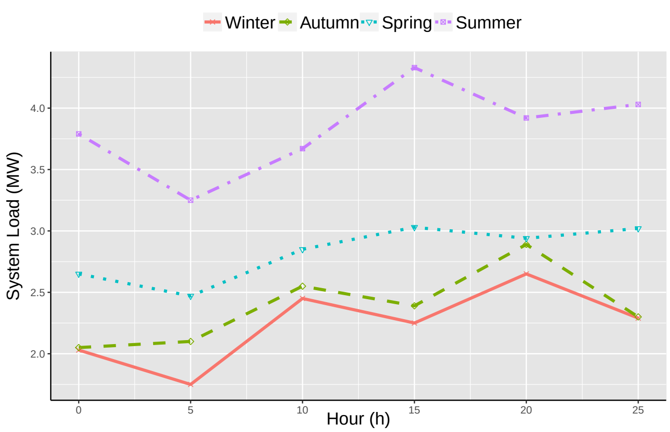

Fig. 2. Variations in load behavior of sample Thursday during 2015 of PNPN

In first data-set, the same days are chosen from days that have equivalent month along with the target day. Moreover, this paper has assumed that the selected day can also be similar to its month or preceding month. Contrary to this, load curves from 7 days earlier and subsequent to the target day is more comparable to the target day when associated to load bends of the preceding month. Consequently, the other data-set specifies the consideration of these days in a data-set.

2) Priority Index for Same Day: In knowledge based short-term load forecasting, temperature has a significant role. The fluctuating behavior of climate and weather throughout a week or month shows a significant effect on load curves. Therefore, it is a vital part in choosing similar days for target year. Conversely, there can be different motives that are the cause of divergence for load curves. For instance, the power evaluating strategies and variations in utilization behaviors of Pakistan alter the levels of load demand. Thus, the selection of similar days along with date proximity is effective to choose for knowledge based forecasting.

3) Distribution of PNPN: The selection of exclusive temperature for huge topographical states usually affects the results in short-term load forecasting. Therefore, an exclusive temperature could not be given to a huge topographical state or zone in order to attain satisfactory forecasted outcomes. However, it is practical to give an exclusive temperature to every region when the entire region is distributed. The distribution of vast topographical zones has been observed in [27], [28]. Nevertheless, these studies overlooked priority index for similar day selection.

The paper distributes the region separately and then predicts the short-term load by consideration of the proposed priority index for similar selection. Furthermore, the forecasting of short-term load for the entire system can be achieved by summation of predicted results from all regions. Besides, this technique takes the temperature for similar selection knowledge based load forecasting in an efficient way.

III. Application of Proposed Method on Vast Topographical Zone

This paper employs the knowledge based short-term load forecasting model on a vast topographical region. Moreover, this paper has selected regions of Pakistan for implementation of the proposed model. Pakistan has 4 seasons and different climates with significant discrepancies throughout the year. A city is selected from every region that is supposed to be the representative of the region. Moreover, a city also specifies the temperature of that particular region. There is no restriction on any system to distribute into specified number of regions. However, the system can be divided according to the requirement of the system and fluctuating behavior of weather.

The paper scrutinizes hourly load for 9 regions of PNPN. In this regard, the data form the duration of June 2014 to May 2016 is used as historic data for short-term load forecasting. Besides, the paper predicts the load demand for the duration of June 2016 to May 2017. A city is chosen from every region as a representative of that particular region. It is observed in the literature that there is no concept of splitting the data-set into training and test data in knowledge based systems. Moreover, the knowledge based systems use the entire historic data for choosing the best optimum results and similar days as discussed in Section II. However, the data-sets are divided into training and test data in DBN and F-LOLIMOT. This paper labels the 77% of the data as training data and the remaining 23% of the data as test data.

A. Deep Belief Network

In [29], the basis of DBN is presented briefly. Moreover, the auto-correlation of load demand data has been depicted in Fig. 3 for the previous data. It is obvious from the auto-correlation plots that the preceding data is more auto-correlated to experimental data, to some extent.

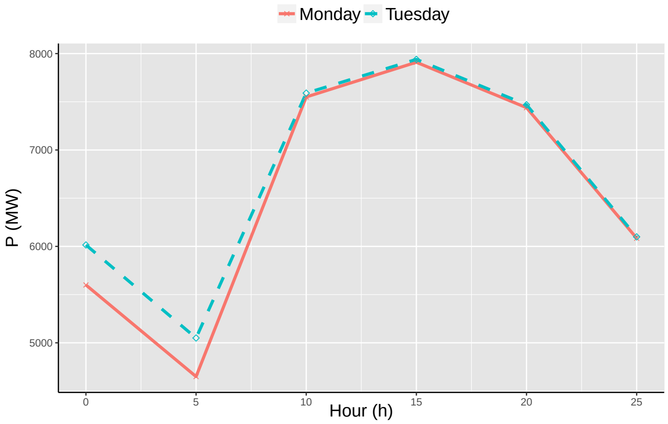

Fig. 3. Fluctuating Behavior of Load Curve in Pakistan and Difference of Monday and a Sample Week-day

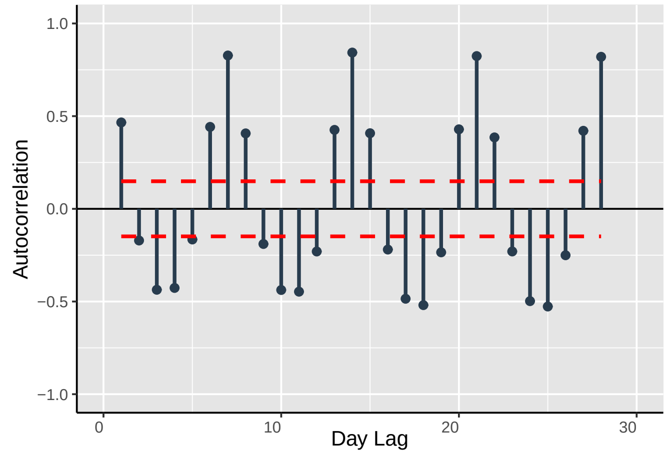

Fig. 4. Autocorrelation of preceding load demand data for day lag

The autocorrelations tests are performed whose outcomes are shown in Table I. The outcomes show that the preceding data is much more auto-correlated as compared to the experimental data.

TABLE I
ρ VALUES OF THE LJUNG BOX AUTOCORRELATION TEST WITH DIFFERENT REGION VALUES

	Original Data	Experimental Data	Region size
(0, 1)	1.00e-07	0.5510981	8175
(0, 1)	6.75e-04	0.6528330	14798
(1, 1)	0.00e+00	0.4384530	16856
(1, 2)	0.00e+00	0.7561250	15087

The paper also performs sensitivity analysis and the structure of DBN used for this paper includes 1 hidden layer with 5 neurons. Moreover, there are 25 neurons are in input layer and 20 neurons in the output layer in the proposed architecture. These neurons generate the prediction of load demand for the target day (24 hours). On the topic of architecture of this network, the input layer is comprised of 2 constraints for mean and maximum temperature for selected day.

B. Fuzzy Local Linear Model Tree Algorithm

The paper employs F-LOLIMOT algorithm for training of the linear fuzzy model. The explanatory analysis of F-LOLIMOT algorithm has been discussed in detail in [30]. Moreover, the F-LOLIMOT algorithm is capable enough to predict the hourly demand load of, which is ahead than the current time by means of climatic and load data. The Fig. 4 depicts that there are different inputs and outputs of demand load and climatic data. This is done after sensitivity analysis on the system. Furthermore, the lags of climate are the climatic condition of the preceding week and target day. Likewise, the time lags of each hour load demand (inputs) are actually demand load data of similar hour at preceding, 9 and 10 days earlier than selected hour

IV. RESULTS AND DISCUSSION

This paper implements the proposed method on PNPN. In this regard, following cases are observed to discuss the consequences, which are associated with distribution of the forecasting results and taking temperature in priority index.

1) Case 1: Short-term load forecasting of PNPN without taking temperature and distribution of data
2) Case 2: Short-term load forecasting of PNPN including consequences of data distribution without taking the temperature

The data distribution is overlooked in Case 1. Therefore, a distinctive temperature is not suitable for the system. Moreover, the priority index is the center of attention in this case along with the date proximity. Besides, the whole system is distributed in different sections in Case 2. Subsequently, the prediction is performed for every respective section. The prediction of the entire system is a combination of predicting outcomes in all sections. The Case 2 differs from Case 1 as the data distribution is carried out in this scenario.

The paper compares the results achieved from proposed knowledge based system with DBN and F-LOLIMOT. The results are evaluated in terms of precision and operational time. The short-term load predicting techniques is applied on PNPN to forecast the load demand for the duration of June 2016 to May 2017. Moreover, these predictions are based on temperature and load demand data, which lies in the range of June 2014 to exactly one day before the target day. The results are presented in Table II, which shows that proposed knowledge based system has enhanced MAPE to 1.01. The DBN and F-LOLIMOT techniques show MAPE is approximately higher than 3% for a month and approximately 5% greater in 47-50 days (maximum error). Nonetheless, the proposed method has MAPE, which is greater than 3% in 15-18 days and 5% with 23 days (maximum error). The variances discussed are notable enhancements in forecasting.

On the topic of operational cost, the proposed knowledge based method takes minimum time in training and executing

TABLE II
COMPARISON OF F-LOLIMOT, DBN AND PROPOSED METHOD

Technique	MDME	MAPE	Operational Time (s)
Proposed	2.83	1.10	15
DBN	2.89	1.21	29
F-LOLIMOT	3.43	1.50	215

in comparison with DBN and F-LOLIMOT. The proposed knowledge based system, DBN and F-LOLIMOT are executed to predict the days on a yearly basis. Besides, the operational time is distributed to total number of predicted days in order to get the usual operational time of prediction for a specified day. Moreover, the proposed system, DBN and F-LOLIMOT are executed with the same conditions. Besides, the parameters were tuned for every specified day and forecasted demand load has been achieved for every technique. The paper distributes the day, according to training and operational time in every technique. The proposed knowledge base systems have less operational time as it does not require as much training as compared to DBN and F-LOLIMOT. The proposed method lays emphasis on the selection of similar day and then predicts the load demand as discussed above.

The forecasting of sample day is presented in Fig. 5 by means of DBN, F-LOLIMOT and proposed knowledge based system. It is obvious that MAPE of the proposed method is 0.69 for a sample day. This MAPE is lesser than MAPEs of DBN and F-LOLIMOT, which is 0.91 and 0.97 respectively. Moreover, the DME is minimized in the presented knowledge based system as compared to others.

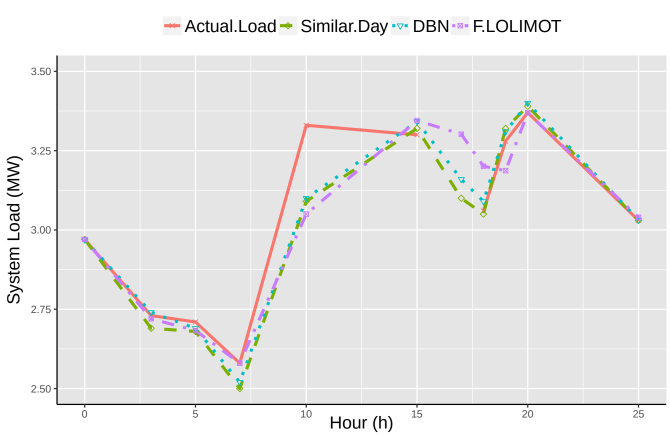

Fig. 5. Load forecasting for August 22, 2015 and comparative analysis of similar Day, DBN and F-LOLIMOT

V. CONCLUSION

This paper presents a novel knowledge based short-term load forecasting method. The entire system (region) is distributed in 9 sub-systems (zones) by consideration of temperature to predict the demand load more efficiently. The outcomes depict that distribution of huge topographical power network improves the forecasting results. Moreover, this paper presents a novel priority index in which climatic conditions and the date proximity of every particular region is observed. The proposed knowledge based system is verified on PNPN. The achieved outcomes depict that proposed method minimizes the MAPE and other errors of forecasting in comparison with traditional forecasting techniques. Furthermore, the obtained results from proposed system are 15-20% improved as compared to DBN and F-LOLIMOT techniques. Furthermore, this paper defines 2 standard measures for error distribution. The outcomes verify that the total amount of exceeded days is reduced through proposing knowledge based systems from acceptable criteria. This phenomenon specifies more efficient forecasting results as compared to DBN, F-LOLIMOT and traditional knowledge based systems.

REFERENCES

[1] R. Azizipanah-Abarghooee, V. Terzija, F. Golestaneh, and A. Roosta, "Multiobjective Dynamic Optimal Power Flow Considering Fuzzy-Based Smart Utilization of Mobile Electric Vehicles," *IEEE Transactions on Industrial Informatics*, vol. 12, no. 2, pp. 503–514, apr 2016. [Online]. Available: http://ieeexplore.ieee.org/document/7384482/

[2] M. Khan, N. Javaid, M. N. Iqbal, M. Bilal, S. F. A. Zaidi, and R. A. Raza, "Load Prediction Based on Multivariate Time Series Forecasting for Energy Consumption and Behavioral Analytics," in *Conference on Complex, Intelligent, and Software Intensive Systems*. Springer, Cham, jul 2019, pp. 305–316. [Online]. Available: http://link.springer.com/10.1007/978-3-319-93659-8_27

[3] S. Rahim, N. Javaid, A. Ahmad, S. A. Khan, Z. A. Khan, N. Alrajeh, and U. Qasim, "Exploiting heuristic algorithms to efficiently utilize energy management controllers with renewable energy sources," *Energy and Buildings*, vol. 129, pp. 452–470, oct 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378778816306867

[4] G. Zhu, T.-T. Chow, and N. Tse, "Short-term load forecasting coupled with weather profile generation methodology," *Building Services Engineering Research and Technology*, vol. 39, no. 3, pp. 310–327, may 2018. [Online]. Available: http://journals.sagepub.com/doi/10.1177/0143624417740858

[5] A. Ahmad, N. Javaid, M. Guizani, N. Alrajeh, and Z. A. Khan, "An Accurate and Fast Converging Short-Term Load Forecasting Model for Industrial Applications in a Smart Grid," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 5, pp. 2587–2596, 2017.

[6] G. C. Silva, J. L. R. Silva, A. C. Lisboa, D. A. G. Vieira, and R. R. Saldanha, "Advanced fuzzy time series applied to short term load forecasting," in *2017 IEEE Latin American Conference on Computational Intelligence (LA-CCI)*. IEEE, nov 2017, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/document/8285726/

[7] V. Mayrink and H. S. Hippert, "A hybrid method using Exponential Smoothing and Gradient Boosting for electrical short-term load forecasting," in *2016 IEEE Latin American Conference on Computational Intelligence (LA-CCI)*. IEEE, nov 2016, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/document/7885697/

[8] Y. He, Q. Xu, J. Wan, and S. Yang, "Short-term power load probability density forecasting based on quantile regression neural network and triangle kernel function," *Energy*, vol. 114, pp. 498–512, nov 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544216311264

[9] S. Li, P. Wang, and L. Goel, "A novel wavelet-based ensemble method for short-term load forecasting with hybrid neural networks and feature selection," *IEEE Transactions on Power Systems*, vol. 31, no. 3, pp. 1788–1798, 2016.

[10] J. Wang and J. Hu, "A robust combination approach for short-term wind speed forecasting and analysis Combination of the ARIMA (Autoregressive Integrated Moving Average), ELM (Extreme Learning Machine), SVM (Support Vector Machine) and LSSVM (Least Square SVM) forecasts usi," *Energy*, vol. 93, pp. 41–56, dec 2015. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544215011202

[11] E. A. Jackson, “Comparison between Static and Dynamic Forecast in Autoregressive Integrated Moving Average for Seasonally Adjusted Headline Consumer Price Index,” *SSRN Electronic Journal*, jan 2018. [Online]. Available: https://www.ssrn.com/abstract=3162606

[12] G. Mitchell, S. Bahadoorsingh, N. Ramsamooj, and C. Sharma, “A comparison of artificial neural networks and support vector machines for short-term load forecasting using various load types,” in *2017 IEEE Manchester PowerTech*. IEEE, jun 2017, pp. 1–4. [Online]. Available: http://ieeexplore.ieee.org/document/7980814/

[13] L. Di Persio, A. Cecchin, and F. Cordoni, “Novel approaches to the energy load unbalance forecasting in the Italian electricity market,” *Journal of Mathematics in Industry*, vol. 7, no. 1, p. 5, dec 2017. [Online]. Available: http://mathematicsinindustry.springeropen.com/articles/10.1186/s13362-017-0035-y

[14] M. Barman, N. Dev Choudhury, and S. Sutradhar, “A regional hybrid GOA-SVM model based on similar day approach for short-term load forecasting in Assam, India,” *Energy*, vol. 145, pp. 710–720, feb 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544217321990

[15] S. Sepasi, E. Reihani, A. M. Howlader, L. R. Roose, and M. M. Matsuura, “Very short term load forecasting of a distribution system with high PV penetration,” *Renewable Energy*, vol. 106, pp. 142–148, jun 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148117300198

[16] R. R. Eapen and S. P. Simon, “Performance Analysis of Combined Similar Day and Day Ahead Short Term Electrical Load Forecasting using Sequential Hybrid Neural Networks,” *IETE Journal of Research*, pp. 1–11, may 2018. [Online]. Available: https://www.tandfonline.com/doi/full/10.1080/03772063.2017.1417749

[17] A. Ahmad, T. N. Anderson, and S. U. Rehman, “Prediction of Electricity Consumption for Residential Houses in New Zealand.” Springer, Cham, apr 2018, pp. 165–172. [Online]. Available: http://link.springer.com/10.1007/978-3-319-94965-9_17

[18] B. A. Hoverstad, A. Tidemann, H. Langseth, and P. Ozturk, “Short-Term Load Forecasting With Seasonal Decomposition Using Evolution for Parameter Tuning,” *IEEE Transactions on Smart Grid*, vol. 6, no. 4, pp. 1904–1913, jul 2015. [Online]. Available: http://ieeexplore.ieee.org/document/7042772/

[19] K. Kavanagh, M. Barrett, and M. Conlon, “Short-term electricity load forecasting for the integrated single electricity market (I-SEM),” in *2017 52nd International Universities Power Engineering Conference (UPEC)*. IEEE, aug 2017, pp. 1–7. [Online]. Available: http://ieeexplore.ieee.org/document/8231994/

[20] M. H. Alobaidi, F. Chebana, and M. A. Meguid, “Robust ensemble learning framework for day-ahead forecasting of household based energy consumption,” *Applied Energy*, vol. 212, pp. 997–1012, feb 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261917317695

[21] M. Lydia, S. Suresh Kumar, A. Immanuel Selvakumar, and G. Edwin Prem Kumar, “Linear and non-linear autoregressive models for short-term wind speed forecasting,” *Energy Conversion and Management*, vol. 112, pp. 115–124, mar 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0196890416000236

[22] L. Bramer, J. Rounds, C. Burleyson, D. Fortin, J. Hathaway, J. Rice, and I. Kraucunas, “Evaluating penalized logistic regression models to predict Heat-Related Electric grid stress days,” *Applied Energy*, vol. 205, pp. 1408–1418, nov 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261917313697

[23] E. Yukseltan, A. Yucekaya, and A. H. Bilge, “Forecasting electricity demand for Turkey: Modeling periodic variations and demand segregation,” *Applied Energy*, vol. 193, pp. 287–296, may 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261917301848

[24] N. Emami and A. Pakzad, “A New Knowledge-Based System for Diagnosis of Breast Cancer by a combination of the Affinity Propagation and Firefly Algorithms,” *Shahrood University of Technology*, vol. 0, no. 0, jul 2018. [Online]. Available: http://jad.shahroodut.ac.ir/article_1264.html

[25] A. GhaffarianHoseini, T. Zhang, O. Nwadigo, A. GhaffarianHoseini, N. Naismith, J. Tookey, and K. Raahemifar, “Application of nD BIM Integrated Knowledge-based Building Management System (BIM-IKBMS) for inspecting post-construction energy efficiency,” *Renewable and Sustainable Energy Reviews*, vol. 72, pp. 935–949, may 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032116311170

[26] M. Q. Raza, M. Nadarajah, D. Q. Hung, and Z. Baharudin, “An intelligent hybrid short-term load forecasting model for smart power grids,” *Sustainable Cities and Society*, vol. 31, pp. 264–275, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.scs.2016.12.006

[27] F. Golestaneh, P. Pinson, and H. B. Gooi, “Very Short-Term Nonparametric Probabilistic Forecasting of Renewable Energy Generation; With Application to Solar Energy,” *Power Systems, IEEE Transactions on*, vol. PP, no. 99, pp. 1–14, 2016.

[28] G. Cerne, D. Dovzan, and I. Skrjanc, “Short-term load forecasting by separating daily profile and using a single fuzzy model across the entire domain,” *IEEE Transactions on Industrial Electronics*, vol. 65, no. 9, pp. 1–1, 2018. [Online]. Available: http://ieeexplore.ieee.org/document/8264813/

[29] A. Dedinec, S. Filiposka, A. Dedinec, and L. Kocarev, “Deep belief network based electricity load forecasting: An analysis of Macedonian case,” *Energy*, vol. 115, pp. 1688–1700, nov 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544216310076

[30] Q. Dong, Y. Sun, and P. Li, “A novel forecasting model based on a hybrid processing strategy and an optimized local linear fuzzy neural network to make wind power forecasting: A case study of wind farms in China,” *Renewable Energy*, vol. 102, pp. 241–257, mar 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148116308965