

Electrical and Computer Engineering

Deep Learning Techniques in Load Forecasting

A proposal in partial fulfillment of the MScE

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Table of Contents

[1 Load Forecasting Overview 2](#_Toc73969378)

[2 Investigation 2](#_Toc73969379)

[2.1 The Benchmark Algorithms 2](#_Toc73969380)

[2.1-a Seasonal Naïve Forecaster 2](#_Toc73969381)

[2.1-b Multiple Linear Regression Forecaster 2](#_Toc73969382)

[2.1-c Auto-Regressive Integrated Moving Average with Exogenous Variables 2](#_Toc73969383)

[2.1-d Artificial Neural Network Short Term Load Forecaster – Generation Three 2](#_Toc73969384)

[2.2 Deep Learning Algorithms 2](#_Toc73969385)

[2.3 Metrics for Evaluation 2](#_Toc73969386)

[3 Contributions 2](#_Toc73969387)

[4 References 2](#_Toc73969388)

Table of Figures

[Figure 1:- The Block Diagram of the third generation ANNSTLF [25] 2](#_Toc70354493)

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# Load Forecasting Overview

Load forecasting is an integral part of the planning and operation of electric utilities; it has played a vital role in the power industry for over a century. For example, to have a stable supply of electricity, reserve power must be prepared beforehand to serve consumers in the future (e.g., in case of high demand or failure in the current grid supply). However, load forecasting can also be helpful to organizations other than electric utilities, such as load aggregators, power marketers, independent system operators, regulatory commissions, and even industrial/commercial companies, banks, trading firms, and insurance companies [1], [2]. These organizations use load forecasting in power systems planning/operations, revenue projection, rate design, energy trading, and other activities [3]–[5].

Electric load forecasting is well studied [1], [6]–[8], and most current research focuses on developing more accurate forecasts. Load forecasting is particularly relevant in today's context, with the advent of new smart grid technologies. The demand patterns used to drive these technologies are complex due to the deregulation of energy markets and the number of different random variables, often governed by human behavior, which needs to be considered to predict future electricity demand. Developing a forecasting model that is appropriate for a particular power network is not a simple task [4], [5], [9]. Different factors can affect load forecasts, such as the location of the area, the type of customers in the region, weather factors (e.g., temperature), the time of the day, day of the week, and other unpredictable factors (i.e., coronavirus outbreak). Also, electricity demand can be assessed by tracking it periodically - hourly, daily, weekly, monthly, or yearly and forecasting processes can be applied to various horizons: very short-term load forecasting (VSTLF, <1-day), short-term load forecasting (STLF, <2-weeks), medium-term load forecasting (MTLF <3-years), and long-term load forecasting (LTLF >3years) [10]. Shorter-term forecasting has been the focus in most current research, concentrating on horizons of less than two weeks [1], [10], [11].

Both statistical techniques and machine learning (ML) have been applied to provide load forecasts, and with the advent of the widespread application of data science, the boundary between these two approaches is becoming more equivocal [1]. Examples of statistical techniques applied to electrical load forecasting include multiple linear regression analysis [12], [13] exponential smoothing [14], [15], and auto-regressive integrated moving average (ARIMA) modeling [16], [17]. On the other hand, ML algorithms are more intelligent and can be better, as they provide the capacity to learn and adapt to the non-linear and complex relationships between load and other influencing factors (e.g., weather, time of day) automatically [10]. Artificial Neural Networks (ANNs) [18][19], Fuzzy Regression Models [20], [21], Support Vector Machines [22], Gradient Boosting Machines [23] have all been applied to electrical load forecasting. In recent years, deep learning approaches like the recurrent neural network (RNN) [24], long-short-term-memory network (LSTM) [25], and the 1-D convolution neural network (CNN) [3], [6] have also become enticing to researchers in this field, primarily because of their ability to learn about temporal dependencies in data inputs, and their ability to quickly adapt to abrupt changes in load patterns, as they occur.

Tao Hong spoke about the myth of finding the best technique [1]. He concluded that it is essential that researchers and users know that a universally best technique does not exist. The approach applied to load forecast should be based on forecasting needs and the dataset being analyzed. It is not likely that one approach will be helpful in all load forecasting scenarios. Different algorithms perform better or worse with different datasets. Furthermore, forecast errors differ significantly for different utilities, utility zones, different horizons, etc. The purpose of this work is to compare deep learning forecasting against some conventional forecasters in use by specific utilities to determine if deep learning can better suit their needs.

# Investigation

This work aims to determine whether deep learning approaches can improve forecasting accuracy for data sets by comparing the accuracy of deep learning forecasters to some of the current forecasters used by utilities. This work will focus on STLF horizons. Three data sets will be investigated. Two sets come from an Independent Electrical System Operator in Ontario and have been included because the data is publicly available, which helps with the reproducibility of this work. One set is from Ottawa [26], and the other is from Toronto [26], and they both consist of city-wide load aggregation measurements taken hourly, spanning ten years from 2010-2019. The third set comes from Saint john Energy, a municipally-owned utility reseller. This data is included because the work proposed here supports efforts in a larger Smart Grid Technologies project underway at UNB, which partners with that utility reseller. The Saint John Energy data set is smaller than the others, spanning about 3.5 years, from 2018 to the present, but otherwise matches with the hourly measurements of city-wide Saint John load aggregates. In some parts of this work, weather data (temperature) obtained from Environment Canada [27] will augment the time-series data. Four benchmark forecasters will be used for comparison: a Seasonal Naïve forecaster, a Multiple Linear Regression (MLR) forecaster, an Auto-Regressive Integrated Moving Average (ARIMA) forecaster, and a forecaster based on a shallow Artificial Neural Network (ANN). These benchmark algorithms have been available for many years and have been implemented and used by researchers and utilities [1], [4], [5], [9], [28]–[30].

Three phases of this work are planned. First, each of the benchmark algorithms will be implemented. Then, one or more deep learning algorithms will be implemented, starting with a CNN. Finally, the performance of the deep learning forecasters will be assessed by comparing them against the performance of the benchmark algorithms, using the data sets available. Overall accuracy and accuracy in peak detection will be compared. Details of each of these phases are delineated below. For an overview of work completed, and pending, see the Gantt chart in the appendix.

## The Benchmark Algorithms

Many publications lack detailed information about their experimental set-ups, making it challenging to conduct direct comparisons with reported results. The benchmark algorithms proposed for this work have been selected because they are relevant and because they are sufficiently well documented to reproduce [1], [4], [5], [9], [28]–[30].

### Seasonal Naïve Forecaster

The naïve forecaster is a simple forecaster based on a random walk model [31]; it has often been implemented as a ground-level benchmark for developing more sophisticated forecasters [28], [32]–[34]. It is used to demonstrate how much value is added by forecasters under comparison – when a naïve forecaster outperforms a more complex forecasting model, we know that the complex model offers little value. Bracale [33] et al. point out that; "The simplest method to anticipate the next value in a time series is to assume it will have the same values as the current value." which forms the basis of the naive forecaster. The Seasonal Naïve Forecaster (SNF) improves this by considering seasonal trends [35]. The SNF can be expressed by the simple mathematical relationship shown in (1):

where  is the time series, and is the seasonal period (for hourly data, m=24 if we take the hourly sample from the day before). The naive formula takes the last observed value as the future value, while the seasonal naive formula takes the value from the previous season. This forecaster is excellent for making short-term forecasts of variables that are generally stable or vary consistently. However, it is highly ineffective at forecasting time series data that fluctuate significantly or are susceptible to irregular elements such as temperature [32].

### Multiple Linear Regression Forecaster

Multiple linear regression (MLR) is one of the most commonly used statistical techniques for load forecasting [11], [13], [20], [28], [36]–[41]. MLR forecasters model the relationships between a continuous dependent variable and one or more independent variables. The equation below shows an MLR with two independent variables:

In the case of load forecasting,  is the load, and  are independent variables such as temperature and time-of-day, s are coefficients estimated, and is an error term. The error term  has a mean of zero and a constant variance [13]. MLR models are fitted such that the sum-of-squares of differences of actual and forecasted values are minimized.

MLRs' accuracy is largely determined by the relationships between the data and the independent variables included. Increasing the number of relevant independent variables generally improves predictive accuracy, but it eventually reaches a point where the improvement is negligible. Additionally, while MLRs can simulate non-linear relationships, they cannot do so without explicit user specifications [42]. Additionally, MLRs are incapable of intelligently learning and adapting to data changes caused by newer factors.

### Auto-Regressive Integrated Moving Average (ARIMA)

A lag feature is a fancy phrase for a variable that holds data from earlier time steps. Lags are essential in time series research because of a phenomenon known as autocorrelation. Autocorrelation is the tendency for values within a time series to relate to prior copies of itself. For example, if we want to anticipate the demand for today t, we can use the demand from yesterday t-1 as a feature.

Auto-regressive (AR) modeling is like linear regression modeling but uses past values (lagged values) as predictors. ARIMA does this and includes past forecast error terms (lagged errors) as predictors by combining AR with a moving average (MA) model [43]. The result is an estimate based on a linear combination of weighted lagged values and lagged errors as delineated in (3) [44]–[46]:

Here  is estimated to account for the average change between consecutive observations, the lag operator is the nth lag value of the time series, is the nth lag error of the time series. Generally, the error terms are assumed to be independent, uniformly distributed variables taken from a normal distribution with a mean of zero. and respectively are the parameters of the autoregressive and moving average parts; they represent the nth coefficients of that lag term estimated by the model to minimize the error. Other parameters in the model include the AR order, *p*, the MA order, *q*, and the differencing order, *d.*  Differencing is required since linear regression models work better when applied to stationary signals [41], [47].

In [48], Fernandez et al. forecasted energy load for non-residential buildings using an ARIMA model, a polynomial model, a neural network model, and a support vector machine model. The study analyzed energy consumption data from the Spain's University of Deusto in Donostia-San Sebastian. The goal was to forecast six days in advance at hourly intervals. The results when compared to the other models, the ARIMA model had the lowest MAPE value. Additionally, the authors noted that the ARIMA model runs 200 times quicker than the Support Vector Machine model because of the lower number of parameters.

### Artificial Neural Network Short Term Load Forecaster – Generation Three

One of the most popular ML-based load forecasters is the ANNSTLF [1], [29], [41]. The configuration of this load forecaster has undergone a few revisions since it was first proposed [49], [50], and we will implement the third-generation design (G3) [51], which uses two shallow multi-layer feed-forward ANNs together with a recursive least squares (RLS) combiner to predict short-term load. The figure below shows the block diagram of the system:

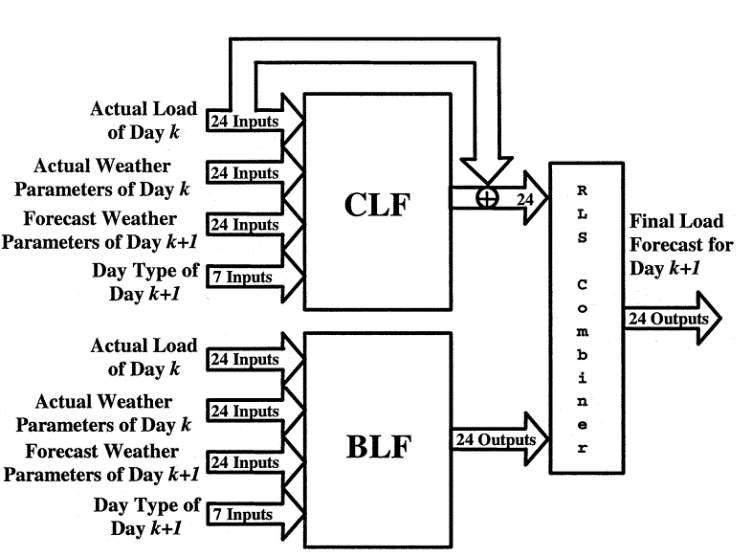


Figure :- The Block Diagram of the third generation ANNSTLF [51]

Both ANN blocks are multi-layer perceptron trained with the error back-propagation algorithm. The base-load forecaster (BLF) is trained to forecast regular next-day load, while the change-load forecaster (CLF) is trained to forecast changes in the load demand from one day to the next. It is argued that the CLF forecaster allows the model to rapidly adapt to abrupt changes in temperature [41], [52], [53]. Both blocks are presented with the same 79 inputs (see Figure 1) and output a 24x1 vector representing hourly forecasts. The CLF sums predicted changes with actual last-day values to produce its output. The final forecast is based on a weighted average of each block's outputs, with the weights adaptively determined using an RLS algorithm.

A neural network-based approach [54] was developed compared to a regression-based approach [55] developed earlier in the same utility. Both models were validated using training data from 1986 to 1990 on peak and hourly loads for 1991. It was shown that the ANN model enhanced forecasting accuracy for both peak load and hourly forecasts. The ANNSTLF-G3 has improved prediction accuracy and generated economic benefits for over a dozen utilities [42], [56]. Some publications have named ANNSTLF-G3 as the best forecaster for short-term load forecasting [1], [41].

## Deep Learning Algorithms

The Recurrent Neural Network (RNN) introduced memory into neural networks, which helps to model sequential data. However, RNNs have a weakness in that they are susceptible to the effects of either a vanishing or exploding gradient [6], [57]. This weakness led to the development of the Long Short-Term Memory (LSTM) network. The LSTM provides a model capable of storing information for an extended period and better control of gradients. Munem[58] et al. argue that LSTM is better than other deep neural networks because of its memory cell configuration. One of our graduate students at UNB has already used the LSTM algorithm as part of a similar project involving load forecasting. We will take his present implementation and alter it to meet our datasets and input feature sets.

Convolutional Neural Networks (CNNs) have also gained the attention of researchers studying load forecasting [3], [59]–[62]. The CNN is a feed-forward network designed to process data with a grid topology; its primary application has been for image classification [3], [63]. However, CNNs can also be applied to time-series data using a 1D topology [3], [64]–[66]. For electrical load forecasting, CNNs are known to boost the power of the ANN because they have deeper layers and have model parameters such as a receptive field length and dilation, which can help interpret load data better [6], [67]. Amaradinghe[3] et al. compared the CNN with the LSTM, SVM, ANN, and other algorithms for individual building level load forecasting. They concluded that CNN is a viable technique that produces accurate load forecasts.

Because the ANNSTLF structure was recognized as the best forecaster for short-term load forecasting [1], [41], our approach for CNN use mimics the ANNSTLF structure by creating a Base Load Forecaster, a Change in the Load Forecaster, and RLS combiner. The architecture will have the same inputs and structure as the ANNSTLF, but the BLF and CLF components will be trained using CNNs.

## Metrics for Evaluation

Mean Absolute Percent Error (MAPE), Mean Bias Error (MBE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Standard Deviation (SD) are all commonly used performance metrics for load forecasting. The MAPE value indicates the magnitude of the forecasted values' error in percentage terms; it is also the most frequently used load forecasting metric [1]. However, MAPE returns undefined values when the actuals are zero, as is the case with demand forecasting. It produces extreme values when the actuals are close to zero and penalizes negative errors (when forecasts exceed actuals) more severely than positive errors. This is because the percentage error for forecasts that are too low cannot surpass 100%, while there is no maximum limit to overly high forecasts. MBE denotes the mean error of all forecasts across the entire forecast horizon; it quantifies the model's overall bias and determines if the model produces over-or under-estimation (MBE > 0 or MBE < 0). Since a positive error on one pair can compensate for a negative error on another, a forecast model can attain a very low bias while remaining imprecise. However, evaluating our forecast precision solely based on the MBE value will be insufficient; but a forecast that is significantly biased already indicates that something is amiss with the model.

MAE is a measure of the average magnitude of forecast errors without regard for their direction. The root mean square error (RMSE) indicates the model's absolute fit, or how closely the observed values match the expected values. One disadvantage of the MAE is that the amount of the error is not always noticeable. It might be difficult to tell the difference between a big and a minor error at times. This issue was addressed by including the mean absolute error in percentage terms (MAPE). Both the MAE and MAPE risk underestimating the effect of significant but infrequent errors. By focusing exclusively on the mean, we run the danger of being blindsided by a colossal error. To accommodate for severe, unusual errors, we incorporated the Root Mean Square Error (RMSE). By squaring the errors before computing their mean and then taking the square root of the mean, we arrive at an error size measure that favors significant but rare errors above the mean.

Finally, standard deviation indicates the spread of errors by quantifying how far apart individual errors are from the mean error.  The standard deviation is calculated using the total number of values in the time series; it is one of the most accurate measures of dispersion. The standard deviation is less impacted than other measurements by irregularities in the time series.  In comparison to other measures of dispersion, the standard deviation is more difficult to compute and interpret. The standard deviation is also strongly influenced by extreme values in the time series. While each of these indicators has limits, they are simple instruments for assessing forecast accuracy.

This work will compare performance metrics applied to each forecaster we develop globally, across the forecast, and forecast subsets such as weekdays and weekends, mornings, afternoons, and evenings. It will assist us in identifying instances where forecasters perform better or worse than expected.

# Contributions

Researchers will be able to compare the value added by deep learning algorithms (such as CNN and LTSM) to more traditional algorithms with the help of this research. We want to develop an algorithm (or a series of algorithms) that can easily adjust to annual increases in power demand, as well as sudden shifts in temperature and any other random variable that affects load demand. We also want to create an algorithm or algorithms capable of comprehending and interpreting complex data relationships without the need for explicit user feedback. Furthermore, this project will be a reproducible experiment that other researchers can use in the future. The main reasons for this are that two of our datasets come from an independent system operator, and the benchmark algorithms we will be working with are well-documented.

# References

[1] T. Hong and S. Fan, "Probabilistic electric load forecasting: A tutorial review," *Int. J. Forecast.*, vol. 32, no. 3, pp. 914–938, 2016, doi: 10.1016/j.ijforecast.2015.11.011.

[2] S. Singh, S. Hussain, and M. A. Bazaz, "Short term load forecasting using artificial neural network," 2018, doi: 10.1109/ICIIP.2017.8313703.

[3] K. Amarasinghe, D. L. Marino, and M. Manic, "Deep neural networks for energy load forecasting," 2017, doi: 10.1109/ISIE.2017.8001465.

[4] J. Zhang, Y. M. Wei, D. Li, Z. Tan, and J. Zhou, "Short term electricity load forecasting using a hybrid model," *Energy*, 2018, doi: 10.1016/j.energy.2018.06.012.

[5] C. Kuster, Y. Rezgui, and M. Mourshed, "Electrical load forecasting models: A critical systematic review," *Sustainable Cities and Society*. 2017, doi: 10.1016/j.scs.2017.08.009.

[6] A. Almalaq and G. Edwards, "A review of deep learning methods applied on load forecasting," *Proc. - 16th IEEE Int. Conf. Mach. Learn. Appl. ICMLA 2017*, vol. 2017-Decem, pp. 511–516, 2017, doi: 10.1109/ICMLA.2017.0-110.

[7] B. Yildiz, J. I. Bilbao, and A. B. Sproul, "A review and analysis of regression and machine learning models on commercial building electricity load forecasting," *Renewable and Sustainable Energy Reviews*. 2017, doi: 10.1016/j.rser.2017.02.023.

[8] A. Baliyan, K. Gaurav, and S. Kumar Mishra, "A review of short term load forecasting using artificial neural network models," 2015, doi: 10.1016/j.procs.2015.04.160.

[9] I. K. Nti, M. Teimeh, O. Nyarko-Boateng, and A. F. Adekoya, "Electricity load forecasting: a systematic review," *J. Electr. Syst. Inf. Technol.*, 2020, doi: 10.1186/s43067-020-00021-8.

[10] Z. Deng, B. Wang, Y. Xu, T. Xu, C. Liu, and Z. Zhu, "Multi-scale convolutional neural network with time-cognition for multi-step short-Term load forecasting," *IEEE Access*, vol. 7, pp. 88058–88071, 2019, doi: 10.1109/ACCESS.2019.2926137.

[11] T. Hong, J. Wilson, and J. Xie, "Long term probabilistic load forecasting and normalization with hourly information," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 456–462, 2014, doi: 10.1109/TSG.2013.2274373.

[12] S. Kumar, S. Mishra, and S. Gupta, "Short term load forecasting using ANN and multiple linear regression," 2016, doi: 10.1109/CICT.2016.44.

[13] A. Y. Saber and A. K. M. R. Alam, "Short term load forecasting using multiple linear regression for big data," *2017 IEEE Symp. Ser. Comput. Intell. SSCI 2017 - Proc.*, vol. 2018-Janua, pp. 1–6, 2018, doi: 10.1109/SSCI.2017.8285261.

[14] P. Ji, D. Xiong, P. Wang, and J. Chen, "A study on exponential smoothing model for load forecasting," 2012, doi: 10.1109/APPEEC.2012.6307555.

[15] J. F. Rendon-Sanchez and L. M. de Menezes, "Structural combination of seasonal exponential smoothing forecasts applied to load forecasting," *Eur. J. Oper. Res.*, 2019, doi: 10.1016/j.ejor.2018.12.013.

[16] L. Tang, Y. Yi, and Y. Peng, "An ensemble deep learning model for short-term load forecasting based on ARIMA and LSTM," 2019, doi: 10.1109/SmartGridComm.2019.8909756.

[17] B. Nepal, M. Yamaha, A. Yokoe, and T. Yamaji, "Electricity load forecasting using clustering and ARIMA model for energy management in buildings," *Japan Archit. Rev.*, 2020, doi: 10.1002/2475-8876.12135.

[18] A. Badri, Z. Ameli, and A. Motie Birjandi, "Application of artificial neural networks and fuzzy logic methods for short term load forecasting," 2012, doi: 10.1016/j.egypro.2011.12.965.

[19] P. H. Kuo and C. J. Huang, "A high precision artificial neural networks model for short-Term energy load forecasting," *Energies*, 2018, doi: 10.3390/en11010213.

[20] T. Hong and P. Wang, "Fuzzy interaction regression for short term load forecasting," *Fuzzy Optim. Decis. Mak.*, 2014, doi: 10.1007/s10700-013-9166-9.

[21] M. Hanmandlu and B. K. Chauhan, "Load forecasting using hybrid models," *IEEE Trans. Power Syst.*, 2011, doi: 10.1109/TPWRS.2010.2048585.

[22] A. Yang, W. Li, and X. Yang, "Short-term electricity load forecasting based on feature selection and Least Squares Support Vector Machines," *Knowledge-Based Syst.*, 2019, doi: 10.1016/j.knosys.2018.08.027.

[23] V. Mayrink and H. S. Hippert, "A hybrid method using Exponential Smoothing and Gradient Boosting for electrical short-term load forecasting," 2017, doi: 10.1109/LA-CCI.2016.7885697.

[24] W. Kong, Z. Y. Dong, Y. Jia, D. J. Hill, Y. Xu, and Y. Zhang, "Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 841–851, 2019, doi: 10.1109/TSG.2017.2753802.

[25] J. Zheng, C. Xu, Z. Zhang, and X. Li, "Electric load forecasting in smart grids using Long-Short-Term-Memory based Recurrent Neural Network," 2017, doi: 10.1109/CISS.2017.7926112.

[26] "IESO - Hourly Zonal Demand Report." http://reports.ieso.ca/public/DemandZonal/ (accessed Jun. 05, 2021).

[27] "Historical Climate Data - Climate - Environment and Climate Change Canada." https://climate.weather.gc.ca/ (accessed Jan. 05, 2021).

[28] T. Hong, P. Wang, and H. L. Willis, "A naïve multiple linear regression benchmark for short term load forecasting," 2011, doi: 10.1109/PES.2011.6038881.

[29] K. Methaprayoon, W. J. Lee, S. Rasmiddatta, J. R. Liao, and R. J. Ross, "Multistage artificial neural network short-term load forecasting engine with front-end weather forecast," *IEEE Trans. Ind. Appl.*, 2007, doi: 10.1109/TIA.2007.908190.

[30] A. K. Singh, Ibraheem, S. Khatoon, M. Muazzam, and D. K. Chaturvedi, "Load forecasting techniques and methodologies: A review," 2012, doi: 10.1109/ICPCES.2012.6508132.

[31] G. Papacharalampous, H. Tyralis, and D. Koutsoyiannis, "Predictability of monthly temperature and precipitation using automatic time series forecasting methods," *Acta Geophys.*, 2018, doi: 10.1007/s11600-018-0120-7.

[32] P. Wang, B. Liu, and T. Hong, "Electric load forecasting with recency effect: A big data approach," *Int. J. Forecast.*, 2016, doi: 10.1016/j.ijforecast.2015.09.006.

[33] A. Bracale, G. Carpinelli, P. De Falco, and T. Hong, "Short-term industrial load forecasting: A case study in an Italian factory," 2017, doi: 10.1109/ISGTEurope.2017.8260176.

[34] M. Rana and I. Koprinska, "Forecasting electricity load with advanced wavelet neural networks," *Neurocomputing*, 2016, doi: 10.1016/j.neucom.2015.12.004.

[35] Da Liu, K. Sun, H. Huang, and P. Tang, "Monthly load forecasting based on economic data by decomposition integration theory," *Sustain.*, 2018, doi: 10.3390/su10093282.

[36] T. Hong, M. Gui, M. E. Baran, and H. L. Willis, "Modeling and forecasting hourly electric load by multiple linear regression with interactions," *IEEE PES Gen. Meet. PES 2010*, pp. 1–8, 2010, doi: 10.1109/PES.2010.5589959.

[37] M. Abuella and B. Chowdhury, "Solar power probabilistic forecasting by using multiple linear regression analysis," 2015, doi: 10.1109/SECON.2015.7132869.

[38] K. Panklib, C. Prakasvudhisarn, and D. Khummongkol, "Electricity Consumption Forecasting in Thailand Using an Artificial Neural Network and Multiple Linear Regression," *Energy Sources, Part B Econ. Plan. Policy*, 2015, doi: 10.1080/15567249.2011.559520.

[39] X. Sun, Z. Ouyang, and D. Yue, "Short-term load forecasting based on multivariate linear regression," 2017, doi: 10.1109/EI2.2017.8245401.

[40] G. Dudek, "Pattern-based local linear regression models for short-term load forecasting," *Electr. Power Syst. Res.*, 2016, doi: 10.1016/j.epsr.2015.09.001.

[41] R. Weron, *Modeling and forecasting electricity loads and prices: A statistical approach*. wiley, 2006.

[42] T. Hong, "Short Term Electric Load Forecasting," North Carolina State University, 2010.

[43] K. Goswami, A. Ganguly, and A. K. Sil, "Day ahead forecasting and peak load management using multivariate auto regression technique," *Proc. 2018 IEEE Appl. Signal Process. Conf. ASPCON 2018*, no. 1, pp. 279–282, 2018, doi: 10.1109/ASPCON.2018.8748661.

[44] G. N. Shilpa and G. S. Sheshadri, "ARIMAX Model for Short-Term Electrical Load Forecasting," *Int. J. Recent Technol. Eng.*, 2019, doi: 10.35940/ijrte.d7950.118419.

[45] H. Cui and X. Peng, "Short-Term City Electric Load Forecasting with Considering Temperature Effects: An Improved ARIMAX Model," *Math. Probl. Eng.*, 2015, doi: 10.1155/2015/589374.

[46] A. Shadkam, "USING SARIMAX TO FORECAST ELECTRICITY DEMAND AND CONSUMPTION," 2020.

[47] R. Bonetto and M. Rossi, "Parallel multi-step ahead power demand forecasting through NAR neural networks," *2016 IEEE Int. Conf. Smart Grid Commun. SmartGridComm 2016*, pp. 314–319, Dec. 2016, doi: 10.1109/SmartGridComm.2016.7778780.

[48] I. Fernández, C. E. Borges, and Y. K. Penya, “Efficient building load forecasting,” 2011, doi: 10.1109/ETFA.2011.6059103.

[49] A. Khotanzad, R. C. Hwang, A. Abaye, and D. Maratukulam, "An Adaptive Modular Artificial Neural Network Hourly Load Forecaster and its Implementation at Electric Utilities," *IEEE Trans. Power Syst.*, 1995, doi: 10.1109/59.466468.

[50] A. Khotanzad, R. Afkhami-Rohani, T. L. Lu, A. Abaye, M. Davis, and D. J. Maratukulam, "ANNSTLF - A neural-network-based electric load forecasting system," *IEEE Trans. Neural Networks*, 1997, doi: 10.1109/72.595881.

[51] A. Khotanzad, R. Afkhami-Rohani, and R. Af, "ANNSTLF - Artificial neural network short-term load forecaster - generation three," *IEEE Trans. Power Syst.*, vol. 13, no. 4, pp. 1413–1422, 1998, doi: 10.1109/59.736285.

[52] A. Khotanzad, E. Zhou, and H. Elragal, "A neuro-fuzzy approach to short-term load forecasting in a price-sensitive environment," *IEEE Trans. Power Syst.*, vol. 17, no. 4, pp. 1273–1282, Nov. 2002, doi: 10.1109/TPWRS.2002.804999.

[53] P. R. J. Campbell and K. Adamson, "Methodologies for load forecasting," 2006, doi: 10.1109/IS.2006.348523.

[54] A. D. Papalexopoulos, S. Hao, and T. M. Peng, "An implementation of a neural network based load forecasting model for the EMS," *IEEE Trans. Power Syst.*, 1994, doi: 10.1109/59.331456.

[55] A. D. Papalexopoulos and T. C. Hesterberg, "A regression-based approach to short-term system load forecasting," *IEEE Trans. Power Syst.*, 1990, doi: 10.1109/59.99410.

[56] B. F. Hobbs, "Analysis of the value for unit commitment of improved load forecasts," *IEEE Trans. Power Syst.*, 1999, doi: 10.1109/59.801894.

[57] D. L. Marino, K. Amarasinghe, and M. Manic, "Building energy load forecasting using Deep Neural Networks," *IECON Proc. (Industrial Electron. Conf.*, pp. 7046–7051, 2016, doi: 10.1109/IECON.2016.7793413.

[58] M. Munem, T. M. Rubaith Bashar, M. H. Roni, M. Shahriar, T. B. Shawkat, and H. Rahaman, "Electric power load forecasting based on multivariate LSTM neural network using bayesian optimization," *2020 IEEE Electr. Power Energy Conf. EPEC 2020*, vol. 3, 2020, doi: 10.1109/EPEC48502.2020.9320123.

[59] H. J. Sadaei, P. C. de Lima e Silva, F. G. Guimarães, and M. H. Lee, "Short-term load forecasting by using a combined method of convolutional neural networks and fuzzy time series," *Energy*, 2019, doi: 10.1016/j.energy.2019.03.081.

[60] I. Koprinska, D. Wu, and Z. Wang, "Convolutional Neural Networks for Energy Time Series Forecasting," 2018, doi: 10.1109/IJCNN.2018.8489399.

[61] M. Vos, C. Bender-Saebelkampf, and S. Albayrak, "Residential Short-Term Load Forecasting Using Convolutional Neural Networks," 2018, doi: 10.1109/SmartGridComm.2018.8587494.

[62] W. He, "Load Forecasting via Deep Neural Networks," 2017, doi: 10.1016/j.procs.2017.11.374.

[63] G. H. Yann LeCun, Yoshua Bengio, "Deep learning (2015), Y. LeCun, Y. Bengio and G. Hinton," *Nature*, 2015.

[64] R. Fukuoka, H. Suzuki, T. Kitajima, A. Kuwahara, and T. Yasuno, "Wind Speed Prediction Model Using LSTM and 1D-CNN," *J. Signal Process.*, 2018, doi: 10.2299/jsp.22.207.

[65] A. Brunel *et al.*, "A CNN adapted to time series for the classification of Supernovae," 2019, doi: 10.2352/ISSN.2470-1173.2019.14.COLOR-090.

[66] N. Singh, C. Vyjayanthi, and C. Modi, "Multi-step Short-term Electric Load Forecasting using 2D Convolutional Neural Networks," 2020, doi: 10.1109/HYDCON48903.2020.9242917.

[67] A. Gasparin, S. Lukovic, and C. Alippi, "Deep Learning for Time Series Forecasting: The Electric Load Case," 2019, [Online]. Available: http://arxiv.org/abs/1907.09207.