Electrical and Computer Engineering

Deep Learning Techniques for Forecasting Electrical Loads

A proposal in partial fulfillment of the MScE

Version <4.4>
Created: 2020-Dec-14
Updated: 2021-Sep-07

Tolulope Olugbenga
Supervised By: Dr. Dawn MacIsaac, PhD
Dr. Julian Cardenas, PhD

Table of Contents

Table of Figures

Deep Learning Techniques for Forecasting Electrical Loads

Updated: 2021-Sep-07 by Tolulope Olugbenga

1 Load Forecasting Overview

Load forecasting has been used to plan and operate electric grids for over a century. Load aggregators, power marketers, independent system operators, regulatory commissions, industrial/commercial companies, banks, trading firms, and insurance companies also benefit from load forecasting for revenue projection, energy trading, rate design and other activities [1]–[5]. Load demand can be affected by weather, time of day, week, and other variables (i.e., coronavirus outbreak), and demand can be tracked and predicted across horizons of varying length: very short-term (VSTLF) (1 day), short-term (STLF) (2 weeks), medium-term (MTLF) (3 years), and long-term (LTLF > 3 years) [6]. Creating a forecasting model for a specific power network is not trivial [4], [5], [7], but it is well studied in the literature. Recent research has focused on STLF [1], [8]–[10]. Longer forecasting horizons are more susceptible to unanticipated changes in future demand.

Both statistical and machine learning (ML) techniques have been used to forecast load, and the distinction between the two is blurring [1]. Statistical techniques to forecast electrical load include auto-regressive integrated moving average (ARIMA) modelling [11], [12], and multiple linear regression (MLR) analysis [13], [14]. ML algorithms are more intelligent, and they can adapt to non-linear and complex relationships between load and other influencing factors (weather, time of day) [6]. Artificial Neural Networks (ANNs) [15], [16], Fuzzy Regression Models (FRM) [17], [18], support vector machines (SVMs) have all been applied to load forecasting [19]. Deep learning approaches like recurrent neural networks (RNN) [20], long-short-term memory networks (LSTM) [21], and 1-D convolution neural networks (CNN) [3], [8] are also appealing to researchers in this field because they can learn about temporal dependencies in inputs. Tao Hong warns about searching for a 'best' technique for load forecasting [1]. He explains that performance depends on the dataset and forecasting needs - no universal method will likely work in all load forecasting scenarios. Forecast accuracies vary greatly between utilities, zones, and horizons. This study compares deep learning forecasting to some conventional forecasters used by utilities to determine if deep learning can better suit their specific needs.

2 Investigation

An analysis of deep learning forecasting accuracy compared to current utility forecasting accuracy will be conducted, focusing on STLF horizons. Three data sets will be analyzed. Two sets from an Independent Electrical System Operator in Ontario are included to aid reproducibility (because they are publicly available). From 2010 to 2019, both sets cover ten years of hourly city-wide load aggregation measurements from Ottawa and Toronto [22]. The third dataset from St. John Energy is part of a larger Smart Grid Technologies project at UNB. This dataset includes hourly city-wide load aggregates for 3.5 years (2018 to now). In parts of this work, we will also use temperature data provided by Environment Canada [23].

The project has three stages. First, we will implement four benchmark forecasters commonly used by both researchers and utilities for years [1], [4], [5], [7], [24]–[26]: a seasonal naïve forecaster, an MLR, an ARIMA, and a shallow ANN. Then one or more deep learning algorithms will be implemented, starting with a CNN. Finally, deep learning forecasters' performance will be compared to benchmark forecaster performance using available data sets. Overall and peak detection accuracy will be compared. Peak demand forecasts are critical for securing adequate generation, transmission, and distribution capacity. Accurate peak forecasts improve capital expenditure, decision making and system reliability. Each stage is detailed below. See the Gantt chart in appendix A for an overview of completed and pending tasks.

2.1 The Benchmark Algorithms

Many publications lack experimental details, making direct comparisons with reported results difficult. The benchmark algorithms proposed for this work were selected because they are relevant but also sufficiently well documented to be reproducible [1], [4], [5], [7], [24]–[26].

2.1-a Seasonal Naïve Forecaster

The naive forecaster is a widely used benchmark for assessing more sophisticated forecasters [24], [27]–[30]. When a naive forecaster outperforms a complex model, we know the complex model offers little value. Bracale [28] et al. state 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 is the basis of the naïve forecaster. The Seasonal Naive Forecaster (SNF) improves the naïve forecaster by considering seasonal trends [31]. The naïve forecaster takes the previous value as the predicted value, but the SNF takes the value from the previous season. This makes it ideal for predicting variables that are generally stable or vary consistently, but It is ineffective at forecasting time-series data subject to irregularities such as temperature [27].

2.1-b Multiple Linear Regression Forecaster

MLR is a statistical technique that is commonly used in load forecasting [14], [17], [24], [32]–[38]. MLR forecasters model continuous dependent variables with multiple independent variables. An MLR with two independent variables can be expressed mathematically as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + e \quad (1)$$

In load forecasting, y is the load, x_1 and x_2 are explanatory variables like temperature and time of day, the βs are coefficients to be estimated, and e is an error term assumed customarily distributed, with zero mean and constant variance [14]. Amral et al. state in [39] that multi-linear regression models for short-term load forecasting are relatively simple to develop and maintain. Moreover, MLRs primary shortcoming is its reliance on the accuracy of previously recorded load and temperature data, which considerably impacts the predicted output. We can improve predictive accuracy slightly by increasing the number of relevant independent variables. However, MLRs do not readily simulate non-linear relationships [40], and they are incapable of adapting to new factors.

2.1-c Auto-Regressive Integrated Moving Average (ARIMA)

The ARIMA model is another statistical load forecaster. It combines auto-regressive (AR) modelling, differencing and moving average (MA) modelling [41]. Auto-regressive (AR) modelling is like linear regression modelling but uses past values (lagged values) as predictors. The result is an estimate based on a linear combination of weighted differentiated lagged values and lagged errors as delineated in (2) [42]–[44]:

$$y'_t = a + \beta_1 y'_{t-1} + \beta_2 y'_{t-2} + .. + \beta_p y'_{t-p} e_t + \phi_1 e_{t-1} + \phi_2 e_{t-2} + .. + \phi_q e_{t-q} (2)$$

Here α is estimated to account for the average change between consecutive observations, the lag operator y'_{t-n} is the nth differentiated lag value of the time series, e_{t-n} is the nth lag error of the time series. Typically, the error terms are supposed to be independently distributed, uniformly distributed variables with a mean of zero. The parameters β_n and ϕ_n denote the AR and MA components, respectively. Model parameters p and q represent the AR and MA orders. A differencing order, d, must also be set because linear regression models work best with stationary signals [37], [45], which can be achieved through differencing (for example, by eliminating the trend). Fernandez et al. compared an ARIMA model with polynomial, neural network, and SVM models to forecast energy load for non-residential buildings based on data from a University in Spain [46]. For six-day ahead forecasts, the ARIMA model had the highest accuracy. The authors also noted that the ARIMA model ran 200 times faster than the SVM.

2.1-d Artificial Neural Network Short Term Load Forecaster – Generation Three

The ANNSTLF [1], [25], [37] is a popular ML load forecaster. The ANNSTLF-G3 has improved prediction accuracy and generated economic benefits for over a dozen utilities [40], [52]. In some publications [1], [37], ANNSTLF-G3 is the best short-term forecaster. We will use the third-generation design (G3) [47] in this work, which uses two shallow multi-layer feed-forward ANNs with a recursive least squares (RLS) combiner to predict short-term load. The system block diagram is shown below:

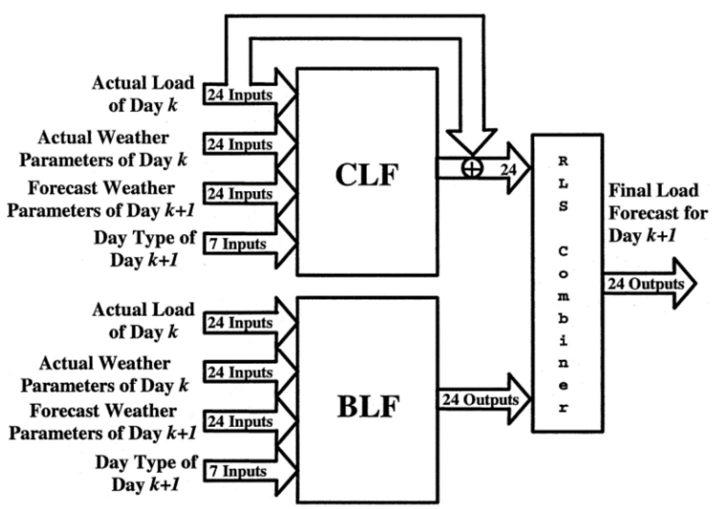

Figure 1 - The Block Diagram of the third generation ANNSTLF [47]

Two multi-layer perceptrons are trained by error back-propagation. The base-load forecaster (BLF) forecasts regular next-day load, while the change-load forecaster (CLF) forecasts daily changes in load demand. The CLF forecaster allows the model to quickly adapt to temperature changes [37], [48], [49]. Both blocks output a 24x1 vector representing hourly forecasts. To calculate the CLF's output, it adds predicted changes to last-day values. A weighted average of each block's output is calculated using an RLS algorithm in the final forecast. In [50] and [51], Papalexopoulos et al. developed a neural network-based approach in addition to a regression-based approach. Both models were tested using data from 1986 to 1990 on peak and hourly loads. The ANN model performed better in terms of peak load and hourly forecasting.

2.2 Deep Learning Algorithms

The RNN added memory to neural networks, allowing them to model sequential data. However, RNNs are vulnerable to vanishing or exploding gradients [8], [53]. This flaw led to the creation of the LSTM network. The LSTM provides a model that can store information longer and control gradients better. Its memory cell configuration makes it superior to other deep neural networks [54]. Other researchers on the smart-grid team at UNB have used the LSTM algorithm for load forecasting, but only with the Saint John dataset. As a first step in exploring deep learning forecasters for our data sets, we will modify the current implementation and compare its performance against our benchmark forecasters.

In load forecasting, convolutional neural networks (CNNs) have also gained popularity [3], [55]–[58]. The CNN is a feed-forward network designed to process data in a grid topology [3]. However, 1D CNNs can be used on time-series data [3], [59]–[61]. CNNs have deeper layers and model parameters like receptive field length and dilation, which can help interpret load data better [8], [62]. Amaradinghe et al. compared the CNN to LSTM, SVM, ANN, and other algorithms for individual building load forecasting. They concluded that CNN is a viable method for predicting load. To create the CNN, we will create a Base Load Forecaster, a Change in the Load Forecaster, and an RLS combiner to mimic the ANNSTLF structure [1], [37]. The inputs and structure will match the ANNSTLF, but the BLF and CLF components will be trained with CNNs. It will be interesting to see if this adjustment can improve forecasting performance.

2.3 Performance Metrics

This study will compare all forecasters' performance across all forecasters and subsets of the forecasts such as weekdays, weekends, mornings, or evenings. The performance will be evaluated according to accuracy in forecast values and accuracy in peak load localization. Table 1 delineates the main error measures used to quantify accuracy:

$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert forecasts - actuals\rvert$	$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left\lvert\frac{forecasts - actuals}{actuals}\right\rvert$
$MBE = \frac{1}{n}\sum_{i=1}^{n}(forecasts - actuals)$	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(forecasts - actuals)^2}$

Table 1

Mean Absolute Error (MAE) is the simplest way to measure forecast error [63], but because it is an absolute measure, it does not provide a way to compare measurements across forecast scenarios of different scales. For this reason, Mean Absolute Percent Error (MAPE) is commonly used [1] since the interpretation of comparisons is straightforward. However, MAPE is also limited in that it cannot handle 0-valued actuals, it over-emphasizes high errors during low demands, and it over-emphasizes overshoot errors compared to undershoot errors for forecasting scenarios bounded by 0 (since undershoot errors cannot be worse than 100%, but overshoot errors are unbounded) [1], [64]. Both MAE and MAPE tend to be insensitive to rare but significant errors, which are better captured with root mean square error (RMSE) [16], but RMSE is not scaled to the original error, so it is more difficult to interpret. To fully capture bias and precision, Mean Biased Error (MBE) and standard deviation (SD) can also be used [65], [66].

3 Contributions

This research will assess the value added by deep learning algorithms (like CNN and LTSM) by comparing their performance to traditional forecasters regarding accuracy in the forecasts and their ability to identify future electrical peak demands. We aim to explore deep learning approaches to see if they are more adaptive to changes in extraneous factors like annual increases in power demand or temperature shifts. The goal is to develop forecasters that can adapt to complex data relationships without explicit user intervention. This is an important goal for our Smart-Grid Project industry collaborators, and we will provide an analysis tuned explicitly to their data set. Furthermore, because we have also included analysis on data that is publicly available, this work will be reproducible, making it a valuable comparison point for future research within and beyond our smart-grid team.

4 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] 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.

[7] 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.

[8] 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.

[9] 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.

[10] 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.

[11] 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.

[12] 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.

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

[14] 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.

[15] 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.

[16] 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.

[17] 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.

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

[19] 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.

[20] 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.

[21] 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.

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

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

[24] 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.

[25] 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.

[26] 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.

[27] 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.

[28] 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.

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

[30] 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.

[31] 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.

[32] 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.

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

[34] 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.

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

[36] 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.

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

[38] 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.

[39] N. Amral, C. S. Özveren, and D. King, “Short term load forecasting using multiple linear regression,” 2007, doi: 10.1109/UPEC.2007.4469121.

[40] T. Hong, “Short Term Electric Load Forecasting,” North Carolina State University, 2010.

[41] 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.

[42] 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.

[43] 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.

[44] A. Shadkam, “USING SARIMAX TO FORECAST ELECTRICITY DEMAND AND CONSUMPTION,” 2020.

[45] 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.

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

[47] 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.

[48] 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.

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

[50] 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.

[51] 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.

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

[53] 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.

[54] 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.

[55] 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.

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

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

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

[59] 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.

[60] 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.

[61] 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.

[62] 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.

[63] S. Khan, N. Javaid, A. Chand, A. B. M. Khan, F. Rashid, and I. U. Afridi, “Electricity Load Forecasting for Each Day of Week Using Deep CNN,” 2019, doi: 10.1007/978-3-030-15035-8_107.

[64] A. Dedinec, S. Filiposka, A. Dedinec, and L. Kocarev, “Deep belief network based electricity load forecasting: An analysis of Macedonian case,” *Energy*, 2016, doi: 10.1016/j.energy.2016.07.090.

[65] S. Papadopoulos and I. Karakatsanis, “Short-term electricity load forecasting using time series and ensemble learning methods,” 2015, doi: 10.1109/PECI.2015.7064913.

[66] W. Kim, Y. Han, K. J. Kim, and K. W. Song, “Electricity load forecasting using advanced

feature selection and optimal deep learning model for the variable refrigerant flow systems,” *Energy Reports*, 2020, doi: 10.1016/j.egyr.2020.09.019.

5 Appendix

5.1 Gantt Chart