Deep Learning Techniques for Forecasting Electrical Loads

by

Tolulope Oluwaseun Olugbenga

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Supervisor: Dr. Dawn MacIsaac, Ph.D., Electrical and Computer Engineering

Dr. Julian Cardenas, Ph.D., Electrical and Computer Engineering

Examining Board: (name, degree, department/field), Chair

(name, degree, department/field)

(continue as required)

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ABSTRACT

For over a century, load forecasting has been used to plan and operate electric grids. Load aggregators, power marketers, independent system operators, regulatory commissions, industrial/commercial firms all benefit from load forecasting for revenue projection, energy trading, rate design, and other purposes. Load forecasting has been extensively studied in the literature [1]–[9]. Forecasting load has been done using statistical and machine learning (ML) techniques and the line between the two is becoming increasingly blurred [1]. However, machine learning algorithms are more intelligent and can adapt to complex relationships between load and other influencing factors (weather) [10]. Deep learning approaches like recurrent neural networks (RNN) [11], long-short-term memory networks (LSTM) [12], and 1-D convolution neural networks (CNN) [3], [7] have recently caught the attention of researchers in this field. This study compares deep learning forecasters to some conventional forecasters used by utilities to see if deep learning better suits their needs.

DEDICATION

This thesis is dedicated to my future self; I want him to look back and understand that all his struggle, anguish, and late nights were not in vain. I adore you, and I am excited to meet the man you are going to become.

ACKNOWLEDGEMENTS

Without a doubt, this is one of the most challenging journeys I have ever completed. It has shown me how much I can grow and do when I believe in myself and put in the work. It was indeed a learning experience, and I am grateful that I did not give up but instead persisted in my efforts to cross the finish line. When I first arrived at UNB and saw what my colleagues in the lab were working on, I honestly wondered what I had gotten myself into. In addition to what I had heard from other students about taking a thesis-based master's degree. I began to doubt my ability and became concerned that I might be unable to complete it.

I want to express my gratitude to my supervisors, Dr. Dawn MacIsaac and Dr. Julian Cardenas; I would not have completed this program without them. I appreciate your patience and words of encouragement, which reminded me that everything is possible and that all I need to do is keep going. I would also like to express my gratitude to my family for standing by my side and constantly motivating me to complete this program.

If I am entirely truthful, the individual who entered the lab for the first time in December 2018 will be unable to complete this degree. To complete, I needed to improve on both a personal and intellectual level. I want to applaud myself for not throwing in the towel and giving up; I want to commend myself for persevering through difficult times and even when the going became tougher. In short, this has been an educational experience and a game of physical and cognitive development. If I have to go through it all over again, I will because I would not be the man I am today without it. As a result, I would like to convey my appreciation to my supervisors and the University of New Brunswick for providing me with this opportunity to learn and develop as a person.

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# Introduction

## 1.1 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], [7]–[9], 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]–[6]. 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). 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], [13].

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 [14], [15] exponential smoothing [16], [17], and auto-regressive integrated moving average (ARIMA) modeling [18], [19]. 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) [20][21], Fuzzy Regression Models [22], [23], Support Vector Machines [24], Gradient Boosting Machines [25] have all been applied to electrical load forecasting. In recent years, deep learning approaches like the recurrent neural network (RNN) [11], long-short-term-memory network (LSTM) [12], and the 1-D convolution neural network (CNN) [3], [7] 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.

## 1.2. Motivation

This research will assess the value added by deep learning algorithms (like CNN and LTSM) by comparing their performance to traditional forecasters. 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.

## 1.3 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]–[6], [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]–[6], [28]–[30].

## The Seasonal Naïve Forecaster (SNF)

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].

## The Multiple Linear Regression Forecaster (MLR)

Multiple linear regression (MLR) is one of the most commonly used statistical techniques for load forecasting [13], [15], [22], [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 [15]. 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. Amral et al. state in [42] 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. Increasing the number of relevant independent variables generally improves predictive accuracy, but it eventually reaches a point where the improvement is negligible. However, while MLRs can simulate non-linear relationships, they cannot do so without explicit user specifications [43]. Additionally, MLRs are incapable of intelligently learning and adapting to data changes caused by newer factors.

## The Auto-Regressive Integrated Moving Average Forecaster (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.

The ARIMA is another statistical load forecaster. 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 [44]. The result is an estimate based on a linear combination of weighted lagged values and lagged errors as delineated in (3) [45]–[47]:

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], [48].

In [49], 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 (ANNSTLF-G3)

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 [50], [51], and we will implement the third-generation design (G3) [52], 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:

Diagram, schematic

Description automatically generated

Figure 1:- The Block Diagram of the third generation ANNSTLF [52]

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], [53], [54]. 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.

In [55] and [56], Papalexopoulos et al. developed a neural network-based approach in addition to a regression-based approach. 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 [43], [57]. Some publications have named ANNSTLF-G3 as the best forecaster for short-term load forecasting [1], [41].

# Deep Learning Techniques

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 [7], [58]. 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[59] 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], [60]–[63]. The CNN is a feed-forward network designed to process data with a grid topology; its primary application has been for image classification [3], [64]. However, CNNs can also be applied to time-series data using a 1D topology [3], [65]–[67]. 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 [7], [68]. 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.

## The Convolutional Neural Network Forecaster (CNN)

CNN shares some similarities with the ANN; it is a feed-forward neural network that mimics the human neurons in its design. CNN has been applied in image and audio processing, natural language processing, and video recognition [7], [69]. CNNs are usually used with image data, but time-series data can be arranged to mimic image data, and it can then be fed into a CNN [3], [67]. CNNs usually process data with a grid topology; images are two-dimensional grids and time series data are one-dimensional, making the time series conversion necessary. In this research study, the CNN architecture consists of six layers: the image input layer, the 2D convolution layer, the rectified linear unit activation layer (relu), the max-pooling 2D layer, and fully connected, and a regression layer.

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

## The Long Short Term Memory Forecaster (LSTM)

The Recurrent Neural Networks (RNNs) are typically trained using either a Back-propagation or Real-Time Recurrent Learning algorithm. The issue is, training with these methods usually fails due to the vanishing gradient [7], [58], [59]. This LSTM is an RNN created to fix vanishing gradient problems and store information for long periods. Its memory cell configuration helps retain information more than any other deep neural network currently available [59]. We also plan to try out the LSTM algorithm similarly to the CNN using the ANNSTLF structure. The computational graph of the LSTM consists of five critical elements: 1) input gate, 2) forget gate, 3) output gate, 4) cell and 5) state output. The cell memory state is responsible for operations such as writing, reading, and erasing. The equations below give a mathematical representation of the model [7].













Where  represents the input of the input gate,  represents the input of the forget gate,  represents the output gate's input,  represents the update signal,  represents the state value at a time  , and  represents the output of the LSTM cell. The input gate's decision to use a sigmoid feature with an on/off state will change the memory state. There will be no improvement in the state cell memory  if the input gate value is minimal and close to zero. In the network model, stacked LSTM can be implemented by using multiple LSTM layers [7].

### How do LSTMs deal with vanishing / exploding gradients?

// To be filled

# Results and Discussion

## Performance Metrics

This study will compare all forecasters’ performance across all forecasters and subsets of the forecasts such as weekdays, weekends, mornings, or evenings. It will assist us in identifying instances where forecasters perform better or worse than expected. 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:

|  |  |
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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. 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 [1], [64]. 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) [16]. 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. However, 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]. 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.

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.

# 5. Conclusion

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Appendix Title

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Glossary

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**Curriculum Vitae**

Candidate's full name: Tolulope Oluwaseun Olugbenga

Universities attended:

BSc in Computer Science Engineering, University of Debrecen, 2018

Publications: None

Conference Presentations: None