

Electrical and Computer Engineering

Deep Learning Techniques for Forecasting Electrical Loads

A proposal in partial fulfillment of the MScE

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Table of Contents

[1 Load Forecasting Overview 1](#_Toc81313721)

[2 Investigation 2](#_Toc81313722)

[2.1 The Benchmark Algorithms 3](#_Toc81313723)

[2.1-a Seasonal Naïve Forecaster 3](#_Toc81313724)

[2.1-b Multiple Linear Regression Forecaster 3](#_Toc81313725)

[2.1-c Auto-Regressive Integrated Moving Average (ARIMA) 4](#_Toc81313726)

[2.1-d Artificial Neural Network Short Term Load Forecaster – Generation Three 5](#_Toc81313727)

[2.2 Deep Learning Algorithms 6](#_Toc81313728)

[2.3 Performance Metrics 7](#_Toc81313729)

[3 Contributions 8](#_Toc81313730)

[4 References 9](#_Toc81313731)

[5 Appendix 18](#_Toc81313732)

[5.1 Gantt Chart 18](#_Toc81313733)

Table of Figures

[Figure 1 - The Block Diagram of the third generation ANNSTLF [47] 5](file:///C:\Users\tolul\Sync\TOO\Masters\Proposal\Proposal%204.4%20-%20Final%20Version.docx#_Toc81313734)

Deep Learning Techniques for Forecasting Electrical Loads

Updated: 2021-Sep-07 by Tolulope Olugbenga

# 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.

# 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.

## 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].

### 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].

### 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:

In load forecasting, is the load, and  are explanatory variables like temperature and time of day, the s are coefficients to be estimated, and 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.

### 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]:

Here  is estimated to account for the average change between consecutive observations, the lag operator is the nth differentiated lag value of the time series, 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 and 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.

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

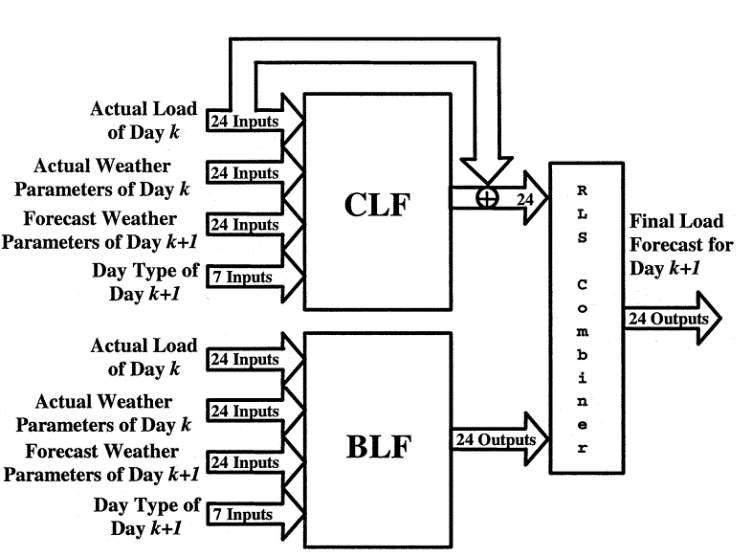
The ANNSTLF [1], [25], [37] is a popular ML load forecaster. The ANNSTLF-G3 has improved prediction accuracy and generated economic benefits for over a dozen utilities [40], [52]. In some publications [1], [37], ANNSTLF-G3 is the best short-term forecaster. We will use the third-generation design (G3) [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 - 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.

## 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.

## 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:

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Table

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].

# 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.

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# Appendix

## Gantt Chart

