

Electrical and Computer Engineering

Deep Learning Techniques in Load Forecasting

A proposal in partial fulfillment of the MScE

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

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Deep Learning Techniques in Load Forecasting

Updated: 2021-Aug-14 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 forecasts 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 [1], [8]–[10]. Recent research has focused on STLF.

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 [1]. He concludes that performance depends on the dataset and forecasting needs - no universal method will likely work in all load forecasting scenarios. Forecast errors 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 were 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 this work, we will also use temperature data from Environment Canada [23]. Four benchmark forecasters will be compared: seasonal naive, MLR, ARIMA, and shallow ANN. Researchers and utilities have used these benchmark algorithms for years [1], [4], [5], [7], [24]–[26].

The project has three stages. First, we will implement the benchmark forecasters. 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. 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. The SNF is mathematically expressed as (1):

where  are the time series and m is the seasonal period (m=24 for hourly data if taken the day before). This formula uses the previous season’s value. This makes it ideal for predicting variables that are generally stable or vary consistently. It is ineffective at forecasting time series data that fluctuate or are 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 is shown below:

In load forecasting, is the load, and  are independent variables like temperature and time of day, s are coefficients estimated, and is an error term. The error term has a constant variance and a mean of 0 [14]. The relationships between the data and the independent variables determine MLR accuracy. Increasing the number of relevant independent variables improves predictive accuracy, but only marginally. MLRs can also simulate non-linear relationships, but only with direct user input [39]. Also, MLRs are incapable of intelligently learning and adapting to newer factors.

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

Any variable that contains data from previous time steps is called a lag feature. Like linear regression, auto-regression uses past values (lag values) as predictors. ARIMA does this by combining AR with a moving average (MA) model [40]. The result is an estimate based on a linear combination of weighted lagged values and lagged errors as delineated in (3) [41]–[43]:

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. Typically, the error terms are supposed to be independently distributed, uniformly distributed variables with a mean of zero. The parameters and denote the autoregressive and moving average components, respectively. The AR order, p, the MA order, q, and the differencing order, d, are all model parameters. Because linear regression models work best with stationary signals [37], [44], differencing is required. Fernandez et al. used ARIMA, polynomial, neural network, and SVM models to forecast energy load for non-residential buildings [45]. The study used data from the University of Deusto in Donostia-San Sebastian, Spain. The goal was to forecast six days ahead of time. Among the other models, the ARIMA model had the lowest MAPE. They noted that the ARIMA model runs 200 times faster than the SVM model due to fewer parameters.

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

The ANNSTLF [1], [25], [37] is a popular ML load forecaster. We will use the third-generation design (G3) [46], 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:

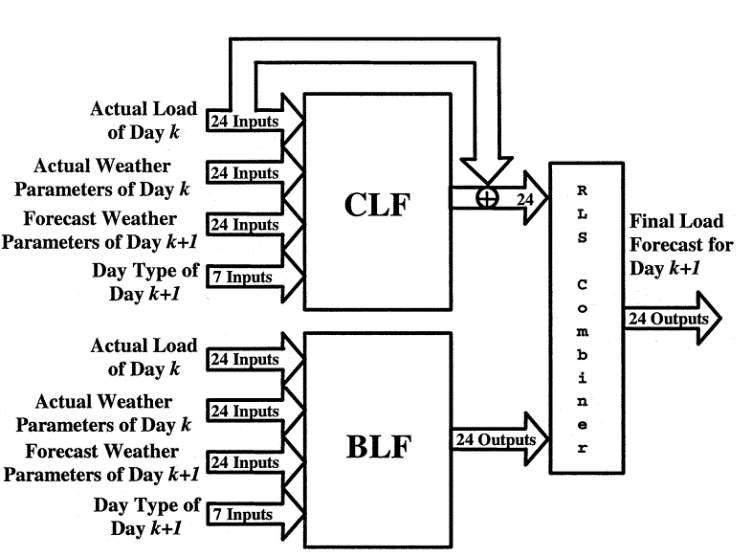


Figure 1:- The Block Diagram of the third generation ANNSTLF [46]

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], [47], [48]. Both blocks (Figure 1) 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 the same utility, a neural network-based approach [49] was developed alongside a regression-based approach [50]. Both models were validated using peak and hourly loads from 1986 to 1990. The ANN model improved peak load and hourly forecasting accuracy. The ANNSTLF-G3 has improved prediction accuracy and generated economic benefits for over a dozen utilities [39], [51]. In some publications [1], [37], ANNSTLF-G3 is the best short-term forecaster.

## 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], [52]. 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, said Munem [53] et al. Our UNB graduate student used the LSTM algorithm for a similar project with load forecasting. We will modify his current implementation to fit our datasets and input features.

In load forecasting, convolutional neural networks (CNNs) have also gained popularity [3], [54]–[57]. 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], [58]–[60]. CNNs have deeper layers and model parameters like receptive field length and dilation, which can help interpret load data better [8], [61]. 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 created 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 are the same as the ANNSTLF, but the BLF and CLF components are 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 metric is widely used in load forecasting [1]. When the actuals are zero, MAPE returns undefined values. The algorithm penalizes negative errors more severely than positive errors near zero because low forecasts have a maximum percentage error of 100%, whereas high forecasts have no such limit. MBE measures the model’s overall bias and whether it over-or under-estimates (MBE > or < 0). A forecast model can be highly accurate while remaining biased due to the offset effect of positive and negative error pairs. A significantly biased forecast indicates a model flaw.

MAE is the average magnitude of forecast errors. An absolute fit is measured by the RMSE of the observed and expected values. With the MAE, the error amount is not always noticeable, and the difference between major and minor errors can be hard to tell. The mean absolute error as a percentage was included to address this (MAPE). The MAE and MAPE may underestimate rare but significant errors. We risk missing a massive error by focusing solely on the mean. To account for severe errors, we included RMSE. By squaring the errors before computing their mean and then taking the square root of the mean, we get an error size measure that favours significant but rare errors above the mean. Finally, standard deviation measures the spread of errors by comparing them to the mean. The standard deviation is a good measure of dispersion. Time series irregularities have less impact on standard deviation. Extreme values in the time series strongly influence the standard deviation. Unlike other dispersion measures, the standard deviation is difficult to compute and understand. All these are simple tools for assessing forecast accuracy, but they have limitations.

This study will compare performance metrics for each forecaster globally, across forecasts and subsets such as weekdays and weekends, mornings, and evenings. It will show us when forecasters perform better or worse than expected.

# Contributions

This research will allow researchers to compare the value added by deep learning algorithms (like CNN and LTSM) to more traditional algorithms. We want to create an algorithm (or a set of algorithms) that can easily adjust to annual increases in power demand, temperature shifts, and other random variables. We also want to develop algorithms that can understand and interpret complex data relationships without explicit user input. This project will also be a reproducible experiment for future researchers. Two of our datasets come from an independent system operator, and the benchmark algorithms we will use are well-documented.

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# Appendix

## Gantt Chart

