

Electrical and Computer Engineering

Deep Learning Techniques in Load Forecasting

A proposal in partial fulfillment of the MScE

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# Load Forecasting Overview

Electric utilities have relied on load forecasting for over a century to plan and operate their systems. A steady supply of electricity requires storing reserve power for future use (e.g., in case of high demand or failure in the current grid supply). Other organizations that benefit from load forecasting include load aggregators, power marketers, independent system operators, regulatory commissions, industrial/commercial companies, banks, trading firms, and insurance companies [1], [2]. A number of these organizations use load forecasting for various purposes [3]–[5]. This topic has been extensively researched [1], [6]–[8]. With the advent of new smart grid technologies, load forecasting is becoming increasingly important. The deregulation of energy markets has made it difficult to predict future electricity demand patterns. Developing a forecasting model that is appropriate for a particular power network is not a simple task [4], [5], [9]. Weather (e.g., temperature), time of day, day of week, and other unpredictable factors can all affect load forecasts (i.e., coronavirus outbreak). There are several ways to forecast electricity demand: 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 >3-years) [10]. Recently, most research has focused on forecasting within 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].   ARIMA modeling [11], [12] and multiple linear regression analysis [13], [14] are examples of statistical techniques used to forecast electrical load. However, ML algorithms are more intelligent and can adapt to non-linear and complex relationships between load and other influencing factors (e.g., weather, time of day) [10].   These include Artificial Neural Networks (ANNs) [15], [16], Fuzzy Regression Models (FRM) [17], [18], SVMs (support vector machines) [19], and gradient boosting machines (GBM) [20]. The ability to learn about temporal dependencies in data inputs, and to quickly adapt to sudden changes in load patterns, have made deep learning approaches like recurrent neural networks (RNN) [21], long-short-term memory networks (LSTM) [22], and 1-D convolution neural networks (CNN) [3], [6] appealing to researchers in this field.

Tao Hong spoke about the myth of finding the best technique [1]. A universally best technique does not exist, he concluded. The approach used to forecast load should be based on the dataset and forecasting needs. No single approach will likely be useful in all load forecasting scenarios. The performance of various algorithms varies. Also, forecast errors vary greatly between utilities, utility zones, and horizons. This study compares deep learning forecasting to some conventional forecasters used by utilities to see if deep learning can better meet their needs.

# Investigation

This study compares the accuracy of deep learning forecasters to some of the current utility forecasters to see if deep learning can improve forecasting accuracy. Focus will be on STLF horizons. Three sets of data will be examined. In order to aid in reproducibility, two sets of data from an Independent Electrical System Operator in Ontario have been included. Both sets come from Ottawa [23] and Toronto [23] and cover ten years of hourly city-wide load aggregation measurements from 2010 to 2019. St. John Energy is a municipal utility reseller. As part of a larger Smart Grid Technologies project at UNB, this data is included. A little shorter than the others (3.5 years from 2018 to now), the Saint John Energy data set matches the hourly city-wide load aggregates. Weather data (temperature) from Environment Canada [24] will be used in some parts of this work. Four benchmark forecasters will be compared: a seasonal naive forecaster, an MLR forecaster, an ARIMA forecaster, and a shallow ANN forecaster (ANN). These benchmark algorithms have been used for many years by researchers and utilities [1], [4], [5], [9], [25]–[27].

This project has three phases. First, we'll implement the benchmark algorithms. Then a CNN or other deep learning algorithm will be implemented. Finally, the performance of deep learning forecasters will be compared to the performance of benchmark algorithms using available data sets. The overall and peak detection accuracy will be compared. The phases are described in detail below. For an overview of work completed, and pending, see the Gantt chart in the appendix.

## The Benchmark Algorithms

Many publications lack detailed experimental set-up information, making direct comparisons with reported results difficult. The benchmark algorithms chosen for this work are relevant and reproducible [1], [4], [5], [9], [25]–[27].

### Seasonal Naïve Forecaster

One of the most widely used benchmarks for developing more sophisticated forecasters [25], [29]–[31] is the naive forecaster [28]. When a naive forecaster outperforms a more complex forecasting model, we know that the complex model offers little value. Bracale [30] 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." The Seasonal Naive Forecaster (SNF) improves this by considering seasonal trends [32]. The SNF can be expressed mathematically as shown in (1):

where is 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, while the seasonal naive formula uses the previous season's value. That makes it ideal for predicting variables that are generally stable or vary consistently. Ineffective at forecasting time series data that fluctuate or are subject to irregularities such as temperature [29].

### Multiple Linear Regression Forecaster

MLR is one of the most widely used statistical techniques for load forecasting [14], [17], [25], [33]–[39]. 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 mean of 0 and a constant variance [14]. The sum-of-squares of actual and forecasted values is minimized in MLR models. 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 explicit user input [40]. Moreover, 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. Autocorrelation requires lags in time series research. Autocorrelation is the tendency of values within a time series to recur. For example, to forecast demand for today t, we can use demand from yesterday t-1. Like linear regression, auto-regression uses past values (lag values) as predictors. ARIMA does this by combining AR with a moving average (MA) model [41]. The result is an estimate based on a linear combination of weighted lagged values and lagged errors as delineated in (3) [42]–[44]:

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. The error terms are usually assumed to be independent, uniformly distributed variables with a mean of zero. and are the parameters of the autoregressive and moving average parts, 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 [38], [45], differencing is required. Fernandez et al. used ARIMA, polynomial, neural network, and SVM models to forecast energy load for non-residential buildings in [46]. 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. The authors also 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], [26], [38] is a popular ML load forecaster. We will use the third-generation design (G3) [49], 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:

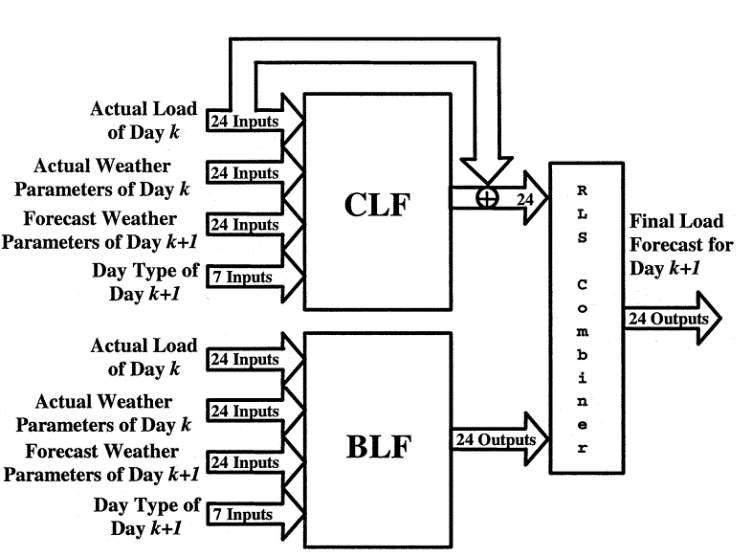


Figure :- The Block Diagram of the third generation ANNSTLF [49]

Two multi-layer perceptrons 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 [38], [50], [51]. 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. In the final forecast, a weighted average of each block's output is calculated using an RLS algorithm. In the same utility, a neural network-based approach [52] was developed alongside a regression-based approach [53]. 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 [40], [54]. According to some publications [1], [38], 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 the effects of a vanishing or exploding gradient [6], [55]. 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, say Munem [56] 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], [57]–[60]. The CNN is a feed-forward network designed to process data in a grid topology [3], [61]. However, 1D CNNs can be used on time series data [3], [62]–[64]. CNNs have deeper layers and model parameters like receptive field length and dilation, which can help interpret load data better [6], [65]. 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], [38]. The inputs and structure are the same as the ANNSTLF, but the BLF and CLF components are trained using CNNs.

## Metrics for Evaluation

MAPE, MBE, MAE, RMSE, and SD are all commonly used performance metrics for load forecasting. The MAPE value is the most commonly used load forecasting metric [1]. However, when the actuals are zero, MAPE returns undefined values. When the actuals are close to zero, it penalizes negative errors more severely than positive errors. This is because the percentage error for low forecasts cannot exceed 100%, whereas high forecasts have no such limit. MBE measures the model's overall bias and determines whether it over- or under-estimates (MBE > or < 0). Because a positive error on one pair can offset a negative error on another, a forecast model can be highly accurate while remaining biased. A forecast that is significantly biased already indicates that something is wrong with the model.

MAE is the average magnitude of forecast errors, regardless of direction. The RMSE measures the model's absolute fit, or how closely the observed and expected values match. The MAE has the disadvantage that the error amount is not always noticeable. The distinction between a major and minor error can be difficult to discern. This was addressed by including the mean absolute error as a percentage (MAPE). The MAE and MAPE risk underestimating the impact of rare but significant errors. By focusing solely on the mean, we risk missing a massive error. We included the Root Mean Square Error to account for severe errors (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 favors 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 one of the most accurate measures of dispersion. Irregularities in the time series have less impact on the standard deviation. The standard deviation is more difficult to compute and interpret than other dispersion measures. Extreme values in the time series strongly influence the standard deviation. All these are simple tools for assessing forecast accuracy, but they have limitations.

In this study, we will compare performance metrics for each forecaster globally, across forecasts, and subsets such as weekdays and weekends, mornings and evenings. It will help us identify when forecasters perform better or worse than anticipated.

# 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'll use are well-documented.

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# Appendix

## Gantt Chart

