

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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# 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], [6]–[8], 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 behaviour, 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], [5], [9]. 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). Also, 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], [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]. Examples of statistical techniques applied to electrical load forecasting include multiple linear regression analysis [12], [13] exponential smoothing [14], [15], and auto-regressive integrated moving average (ARIMA) modelling [16], [17]. 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) [18][19], Fuzzy Regression Models [20], [21], Support Vector Machines [22], Gradient Boosting Machines [23] have all been applied to electrical load forecasting. In recent years, deep learning approaches like the recurrent neural network (RNN) [24], long-short-term-memory network (LSTM) [25], and the 1-D convolution neural network (CNN) [3], [6] 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.

It is not likely that one approach will be helpful in all load forecasting scenarios. 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. 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 utilities to determine if deep learning can better suit their needs.

# Investigation

This work aims to determine whether or not deep learning approaches can improve forecasting accuracy for particular 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 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 (ARIMAX) 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], [5], [9], [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. 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], [5], [9], [28]–[30].

### Seasonal Naïve Forecaster

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].

### Multiple Linear Regression Forecaster

Multiple linear regression (MLR) is one of the most commonly used statistical techniques for load forecasting [11], [13], [20], [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 [13]. MLR models are fitted such that the sum-of-squares of differences of actual and forecasted values are minimized.

The accuracy of MLRs is mainly dependent on the relationships between the data and the independent variables that have been included. Adding more relevant independent variables usually increases predicting accuracy, but it eventually reaches a threshold where the increase is minimal. Furthermore, MLRs have a restriction in that, while they may simulate non-linear relationships, they cannot do so without explicit user specification [42].  Also, MLRs cannot intelligently learn and adapt to unexpected changes in data caused by newer factors.

### Auto-Regressive Integrated Moving Average with Exogenous Variables

A lag feature is a fancy phrase for a variable that holds data from earlier time steps. The lag operator moves a time series so that the “lagged” values match the actual time series. Lags are essential in time series research because of a phenomenon known as autocorrelation, which is the tendency for values within a time series to relate to prior copies of itself. One advantage of autocorrelation is that it allows us to discover patterns within time series, which aids in determining seasonality, or the tendency for patterns to repeat at regular intervals. For example, if we want to anticipate the average demand for today t, we can utilize the demand from yesterday t-1 as a feature; this will be a lag of 1. However, we could use a lag of 7 to model today’s average demand using seven days ago as a feature.

The Auto-regressive Integrated Moving Average with Exogenous Variables (ARIMAX) is another statistical forecaster use in load forecasting [43], [44]. Auto-regressive (AR) modelling is similar to linear regression modelling but uses past values (lagged values) as predictors. The ARIMAX does this and includes past forecast error terms (lagged errors) as predictors by combining AR with a moving average (MA) model. For load forecasting, exogenous variables such as temperature, day-of-the-week, etc., are often included in the model to improve performance, yielding the ARIMAX [48]. The result is an estimate based on a linear combination of weighted lagged values and lagged errors as delineated in (3) [45]:

Here  is estimated to account for the average change between consecutive observations, is the nth lag value of the time series, is the nth lag error of the time series, and and are 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 [46], [47]. [add a statement about what kind of accuracies we can expect]

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

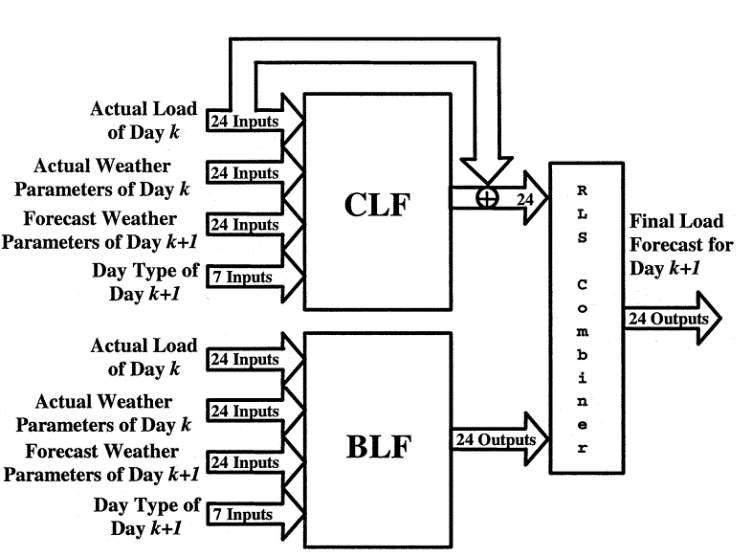
One of the most popular ML-based load forecasters is the ANNSTLF [1], [29], [41]. The configuration of this load forecaster has undergone a few revisions since it was first proposed [49], [50], and we will implement the third-generation design (G3) [51], which uses two shallow multi-layer feed-forward ANNs together with a recursive least squares (RLS) combiner to predict short-term load. The figure below shows the block diagram of the system:

Figure 1:- The Block Diagram of the third generation ANNSTLF [51]

Both of the 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 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], [52], [53]. 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 the outputs from each block, where the weights are estimated adaptively with an RLS algorithm.

Some publications have named ANNSTLF-G3 as the best forecaster for short-term load forecasting [1], [41]. [again…I think we are looking for example accuracies reported in the literature].

## Deep Learning Algorithms

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 [6], [54]. 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[55] et al. argue that LSTM is better than other deep neural networks because of its memory cell configuration. []

Convolutional Neural Networks (CNNs) have also gained the attention of researchers studying load forecasting [3], [56]–[59]. The CNN is a feed-forward network designed to process data with a grid topology; its primary application has been for image classification [3], [60]. However, CNNs can also be applied to time-series data using a 1D topology [61], [62]. 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], [63]. 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 [6], [64]. 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.

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

## Metrics for Evaluation

Standard load forecasting performance metrics include: Mean Absolute Percent Error (MAPE), Mean Error (ME), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Standard Deviation. The MAPE tells us the size of the error of the forecasted values in terms of percentage. MAPE is the most common measure used for load forecasting [1]; it works best when there are no near zeros or extreme values. ME stands for the average error of all forecasts over the entire horizon. The MAE is a calculation of the average magnitude of forecast errors without taking their direction into account. The RMSE indicates the model’s absolute fit or how similar the actual values are to the expected values. Finally, standard deviation tells how spread the errors are, measuring how far each error is from the mean error. This work will compare performance metrics applied to each forecaster we develop globally, across the forecast, and subsets of the forecast, such as weekdays and weekends, mornings, afternoons, and evenings. It will help us to identify situations where the forecasters perform better or worse.

# Contributions

Researchers will be able to compare the value added by deep learning algorithms (such as CNN and LTSM) to more traditional algorithms with the help of this research. We want to develop an algorithm (or a series of algorithms) that can easily adjust to annual increases in power demand, as well as sudden shifts in temperature and any other random variable that affects load demand. We also want to create an algorithm or algorithms capable of comprehending and interpreting complex data relationships without the need for explicit user feedback. Furthermore, this project will be a reproducible experiment that other researchers can use in the future. The main reasons for this are that two of our datasets come from an independent system operator, and the benchmark algorithms we will be working with are well-documented.

* Stage 2: implement a CNN and assess its performance using the 3 data sets.
  + 2019 is forecasted, even though we have the data so that we can measure the accuracy. Common ways to measure accuracy include MAPE, ME, MSE, RMSE, STD and will calculate all to compare performance against the benchmark algorithms and performance of other systems with the same horizon focus reported in the literature. We will also sample errors (explain) to analyze performance further.
* Stage 3: assess the performance of LSTM

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