

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

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 behavior, which needs to be considered to predict future electricity demand. Finding an appropriate forecasting model for a specific electricity network is not a trivial 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) modeling [16], [17]. 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 have also become enticing to researchers in this field. The Recurrent Neural Network (RNN) introduced memory into neural networks, which helps model sequential data. However, RNNs have a weakness in that they are susceptible to the effects of vanishing or exploding gradient [6], [24]. 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[25] 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], [26]–[29]. The CNN is a feed-forward network designed to process data with a grid topology; its primary application has been for image classification [3], [30]. CNNs can also be applied to time-series data using a 1D topology [ref]. For electrical load forecasting, they 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], [31]. 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.

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. 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 [ref the access point], and the other is from Toronto [ref the access point], 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 Saint John load aggregates. 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], [32]–[34].

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.

## 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], [32]–[34].

### Seasonal Naïve Forecaster

The naïve forecaster is a simple forecaster based on a random walk model [ref]; it has often been implemented as a ground level benchmark for developing more sophisticated forecasters [32], [35]–[37]. 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 [36] et al. points 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 on this by taking seasonal trends into consideration [38]. 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 are taking 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. [add a statement about what kind of accuracies we can expect]

### Forecaster

(MLR) forecasters .

In the case of load forecasting, load such as temperature and time-of-daycoefficientsan termminimized [add a statement about what kind of accuracies we can expect]

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

The Auto-regressive Integrated Moving Average with Exogenous Variables (ARIMAX) is an other statistical forecaster use in load forecasting [ref]. Auto-regressive (AR) modeling is similar to linear regression modeling, but uses past values (lagged values) as predictors. The ARIMAX does this, but also includes past forecast error terms (lagged errors) as predictors by combing AR with a moving average (MA) model. The result is an estimate based on a linear combination of weighted lagged values and lagged errors as delineated in (2) [39]:

where 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 terms 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 [40], [41]. For load forecasting, exogenous variables such as temperature, day-of-the-week, etc., are often also included in the model to improve performance, yielding the ARIMAX. [42]. [add a statement about what kind of accuracies we can expect]

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

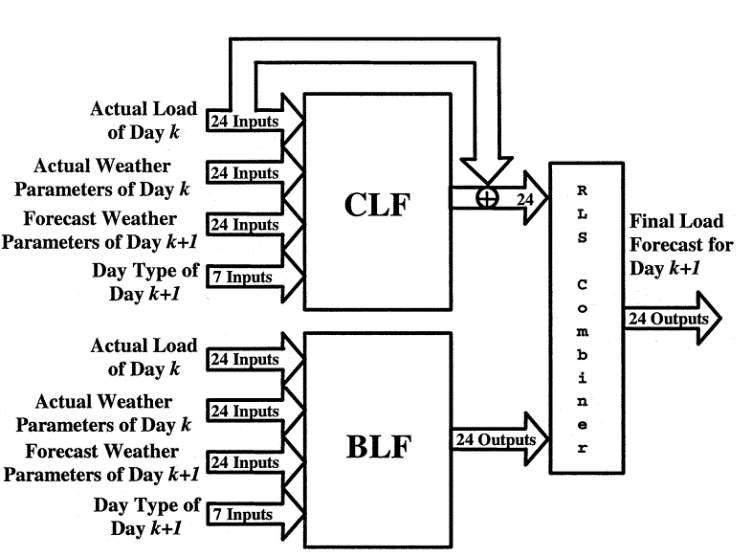
One of the most popular ML-based load forecasters is the ANNSTLF [1], [33], [44]. The configuration of this load forecaster has undergone a few revisions since it was first proposed [47], and we will implement the third generation design [ref to the paper we use to implement] which uses two shallow multi-layer 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 [47]

Both of the ANN blocks are multi-layer perceptrons, 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 [44], [48], [49]. Both blocks are presented with the same 79 inputs (see figure), and output a 24x1 vector representing hourly forecasts. The CLF sums predicted changes to 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. [add a statement about what kind of accuracies we can expect]

## Deep Learning Algorithms

// Find a better way to say it

Over the previous years, we have noticed a rising trend in the power demand at most utilities due to new systems and more sophisticated equipment been added. Therefore, it is essential to create algorithms that could adapt quickly to these changes as they occur [10].

We will start with the CNN and LSTM [6] algorithms, as these are two of the most popular ones. This comparison will help us figure out how much extra value deep learning adds to the forecasts compared to the benchmarks. First, by implementing all the algorithms, we compare their performances on three datasets and observe when one performs better or worse. We can then make improvements based on the new information we find.

### Convolutional Neural Networks (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 [6], [50]. 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], [51]. 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], [44]. 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.

### Long Short-Term Memory (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 [6], [24], [25]. 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 [25]. 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 [6].













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 [6].

## Data Sets and Metrics for Evaluation

Three time-series datasets were selected, they are sampled on an hourly horizon, and they also contain the temperature variable as changes in temperature plays a huge role in load forecasting. The authors of the ANNSTLF algorithm mentioned that the algorithm works best when trained with at least three years of data. Two datasets were obtained from the Ontario independent system operator [51]; one was from Toronto, and the other was from Ottawa. Both datasets run from January 2010 until December 2019. The third dataset was obtained from Saint John Energy [52]; this dataset runs from January 2018 until December 2020. The weather variables were obtained from the Government of Canada’s website [53].

The selected global metrics are: 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. Standard deviation tells how spread the errors are, measuring how far each error is from the mean error.

Since the global metrics only show one value that was gotten from the entire dataset. There is the need to classify the errors on hourly, daily, and monthly horizons. This approach gives us a better picture of the distribution of errors for each hour, month, and day. It also helps us to identify situations where the algorithms 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.

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