Deep Learning Techniques for Forecasting Electrical Loads

by

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ABSTRACT

For over a century, load forecasting has been used to plan and operate electric grids. Load aggregators, power marketers, independent system operators, regulatory commissions, industrial/commercial firms all benefit from load forecasting for revenue projection, energy trading, rate design, and other purposes. Load forecasting has been extensively studied in the literature [1]–[9]. Forecasting load has been done using statistical and machine learning (ML) techniques and the line between the two is becoming increasingly blurred [1]. However, machine learning algorithms are more intelligent and can adapt to complex relationships between load and other influencing factors (weather) [10]. Deep learning approaches like recurrent neural networks (RNN) [11], long-short-term memory networks (LSTM) [12], and 1-D convolution neural networks (CNN) [3], [7] have recently caught the attention of researchers in this field. This study compares deep learning forecasters to some conventional forecasters used by utilities to see if deep learning better suits their needs.

DEDICATION

This thesis is dedicated to my future self; I want him to look back and understand that all his struggle, anguish, and late nights were not in vain. I adore you, and I am excited to meet the man you are going to become.

ACKNOWLEDGEMENTS

Without a doubt, this is one of the most challenging journeys I have ever completed. It has shown me how much I can grow and do when I believe in myself and put in the work. It was indeed a learning experience, and I am grateful that I did not give up but instead persisted in my efforts to cross the finish line. When I first arrived at UNB and saw what my colleagues in the lab were working on, I honestly wondered what I had gotten myself into. In addition to what I had heard from other students about taking a thesis-based master's degree. I began to doubt my ability and became concerned that I might be unable to complete it.

I want to express my gratitude to my supervisors, Dr. Dawn MacIsaac and Dr. Julian Cardenas; I would not have completed this program without them. I appreciate your patience and words of encouragement, which reminded me that everything is possible and that all I need to do is keep going. I would also like to express my gratitude to my family for standing by my side and constantly motivating me to complete this program.

If I am entirely truthful, the individual who entered the lab for the first time in December 2018 will be unable to complete this degree. To complete, I needed to improve on both a personal and intellectual level. I want to applaud myself for not throwing in the towel and giving up; I want to commend myself for persevering through difficult times and even when the going became tougher. In short, this has been an educational experience and a game of physical and cognitive development. If I have to go through it all over again, I will because I would not be the man I am today without it. As a result, I would like to convey my appreciation to my supervisors and the University of New Brunswick for providing me with this opportunity to learn and develop as a person.

Table of Contents

[ABSTRACT ii](#_Toc81832945)

[DEDICATION iii](#_Toc81832946)

[ACKNOWLEDGEMENTS iv](#_Toc81832947)

[Table of Contents v](#_Toc81832948)

[List of Tables vii](#_Toc81832949)

[List of Figures viii](#_Toc81832950)

[List of Symbols, Nomenclature or Abbreviations ix](#_Toc81832951)

[1 Introduction 1](#_Toc81832952)

[1.1 Load Forecasting Overview 1](#_Toc81832953)

[1.2 Motivation 4](#_Toc81832954)

[1.3 Investigation 5](#_Toc81832955)

[1.4 Outline of the Thesis 6](#_Toc81832956)

[2 The Benchmark Algorithms 7](#_Toc81832957)

[2.1 The Seasonal Naïve Forecaster (SNF) 7](#_Toc81832958)

[2.2 The Multiple Linear Regression Forecaster (MLR) 8](#_Toc81832959)

[2.3 The Auto-Regressive Integrated Moving Average Forecaster (ARIMA) 9](#_Toc81832960)

[2.4 Artificial Neural Network Short Term Load Forecaster – Generation Three (ANNSTLF-G3) 11](#_Toc81832961)

[3 Deep Learning Techniques 13](#_Toc81832962)

[3.1 The Long Short Term Memory Forecaster (LSTM) 14](#_Toc81832963)

[3.2 The Convolutional Neural Network Forecaster (CNN) 17](#_Toc81832964)

[4 Results and Discussion 20](#_Toc81832965)

[4.1 Performance Metrics 20](#_Toc81832966)

[5 Conclusion 23](#_Toc81832967)

[Bibliography 24](#_Toc81832968)

[Appendix Title 35](#_Toc81832969)

[Glossary 36](#_Toc81832970)

Curriculum Vitae

List of Tables

[Table 1 19](#_Toc81231713)

List of Figures

[Figure 1 - The Block Diagram of the third generation ANNSTLF [52] 10](#_Toc81226282)

[Figure 3 – An Architecture of a one dimensional CNN for time series data [79]. 14](#_Toc81226283)

[Figure 4 – The Architecture of the LSTM network [81] 16](#_Toc81226284)

List of Symbols, Nomenclature or Abbreviations

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# 1 Introduction

## 1.1 Load Forecasting Overview

Electricity is critical to our daily lives and is one of the primary drivers of a country's economy. Load forecasting is a critical component of the design, 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].

Over the recent decade, there has been an increase in the grid's adoption of renewables and distributed generation sources, as well as progress and implementation of smart grids and buildings to effectively meet expanding energy demands. To integrate these distributed energy resources without creating system disruptions, reliable load forecasting across many time horizons is required [13]. Electric load forecasting is well studied [1], [7]–[9], 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. Developing a forecasting model that is appropriate for a particular power network is not a simple task [4]–[6].

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). 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]. Short-term forecasting has been the focus in most current research, concentrating on horizons of less than two weeks [1], [10], [14]. Longer forecasting horizons are more susceptible to unanticipated changes in future demand.

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 [15], [16] exponential smoothing [17], [18], and auto-regressive integrated moving average (ARIMA) modeling [19], [20]. 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]. Examples are, Artificial Neural Networks (ANNs) [21][22], Fuzzy Regression Models [23], [24], Support Vector Machines [25], Gradient Boosting Machines [26]; they have all been applied to electrical load forecasting.

Deep learning approaches have had remarkable success in the last few of years at handling complex sequential data [27], [28]. As a result, deep learning approaches have been effectively used to load forecasting applications, where they have been shown to outperform a variety of benchmark models, including simple ANNs and standard statistical time series methods such as ARIMA [29]. With improved computational power, more datasets, and granularity of available data, deep learning models are expected to dominate the load forecasting field. Deep learning approaches like the recurrent neural network (RNN) [11], long-short-term-memory network (LSTM) [12], and the 1-D convolution neural network (CNN) [3], [7] have 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.

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

## 1.2 Motivation

This research will assess the value added by deep learning algorithms (like CNN and LTSM) by comparing their performance to traditional forecasters. 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.

## 1.3 Investigation

This work aims to determine whether deep learning approaches can improve forecasting accuracy for 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 [30], and the other is from Toronto [30], 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 the 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 [31] 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 (ARIMA) 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]–[6], [32]–[34].

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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. Overall accuracy and accuracy in peak detection 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. Details of each of these phases are delineated below. For an overview of work completed, and pending, see the Gantt chart in the appendix.

## 1.4 Outline of the Thesis

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# 2 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]–[6], [32]–[34].

## 2.1 The Seasonal Naïve Forecaster (SNF)

The naïve forecaster is a simple forecaster based on a random walk model [35]; it has often been implemented as a ground-level benchmark for developing more sophisticated forecasters [32], [36]–[38]. 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 [37] 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 the naïve forecaster by considering seasonal trends [39]. 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 [36].

## 2.2 The Multiple Linear Regression Forecaster (MLR)

Multiple linear regression (MLR) is one of the most commonly used statistical techniques for load forecasting [14], [16], [23], [32], [40]–[45]. MLR forecasters model the relationships between a continuous dependent variable and one or more independent variables. An MLR with two independent variables can be expressed mathematically as:

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  is typically assumed to have a mean of zero and a constant variance [16]. MLR models are fitted such that the sum-of-squares of differences of actual and forecasted values are minimized.

MLRs’ accuracy is largely determined by the relationships between the data and the independent variables included. Amral et al. state in [46] 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. Increasing the number of relevant independent variables generally improves predictive accuracy, but it eventually reaches a point where the improvement is negligible. However, while MLRs can simulate non-linear relationships, they cannot do so without explicit user specifications [47]. Additionally, MLRs are incapable of intelligently learning and adapting to data changes caused by newer factors.

### 2.2.1 Assumptions of the MLR forecaster

1. The dependent variable and each of the independent variables should have a linear relationship.
2. Correlations between any of the independent variables are low. Multicollinearity exists when various variables are correlated with each other and with the dependent variable. When independent variables exhibit multicollinearity, obtaining the variable that contributes to the variance in the dependent variable can be difficult.
3. The residuals have a constant variance. The magnitude of our forecast error does not change much while the independent variable's value changes.
4. Observations are autonomous. The MLR model presupposes that all observations are independent of one another; in other words, that the residuals values are also independent of one another.
5. The data is normally distributed.

## 2.3 The Auto-Regressive Integrated Moving Average Forecaster (ARIMA)

A lag feature is a fancy phrase for a variable that holds data from earlier time steps. Lags are essential in time series research because of a phenomenon known as autocorrelation. Autocorrelation is the tendency for values within a time series to relate to prior copies of itself. For example, if we want to anticipate the demand for today t, we can use the demand from yesterday t-1 as a feature.

ARIMA is arguably one of the most popular and commonly utilized statistical forecasting technique for load forecasting [41]. As the name implies, this family of techniques consists of three main components: a) a "autoregression" portion that models the series' relationship with its lagged values; b) a "moving average" portion that model the forecast as a function of lagged forecast errors; and c) a "integrated" portion that makes the series stationary. Auto-regressive (AR) modeling is like linear regression modeling but uses past values (lagged values) as predictors. ARIMA does this and includes past forecast error terms (lagged errors) as predictors when combining auto-regression (AR) with a moving average (MA) model; after some differencing has occurred [48]. The result is an estimate based on a linear combination of weighted differentiated lagged values and lagged errors as delineated in (3) [49]–[51]:

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. Generally, the error terms are assumed to be independent, uniformly distributed variables taken from a normal distribution with a mean of zero. and respectively are the parameters of the autoregressive and moving average parts; they represent the 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.* The number of lag observations in the AR portion is defined by p; q is the window size for the moving average; d specifies the number of differences used. Differencing is required since linear regression models work better when applied to stationary signals [45], [52].

In [53], Fernandez et al. forecasted energy load for non-residential buildings using an ARIMA model, a polynomial model, a neural network model, and a support vector machine model. The study analyzed energy consumption data from the Spain's University of Deusto in Donostia-San Sebastian. The goal was to forecast six days in advance at hourly intervals. The results when compared to the other models, the ARIMA model had the lowest MAPE value. Additionally, the authors noted that the ARIMA model runs 200 times quicker than the Support Vector Machine model because of the lower number of parameters. One significant disadvantage of the ARIMA model is the difficulty in determining appropriate parameters for the AR and MA components. These numbers may also vary slightly among datasets and forecast horizons. This can be frustrating and time consuming at times.

### 2.4 Artificial Neural Network Short Term Load Forecaster – Generation Three (ANNSTLF-G3)

An artificial neural network (ANN) is modeled like the human brain in that it learns the relationship between particular inputs and outputs via experience. One of the most popular ML-based load forecasters is the ANNSTLF [1], [33], [45]. The ANNSTLF-G3 has improved prediction accuracy and generated economic benefits for over a dozen utilities [47], [61]. Some publications have named ANNSTLF-G3 as the best forecaster for short-term load forecasting [1], [45]. The configuration of this load forecaster has undergone a few revisions since it was first proposed [54], [55], and we will implement the third-generation design (G3) [56], 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:

Diagram, schematic

Description automatically generated

Figure 1 - The Block Diagram of the third generation ANNSTLF [52]

Both 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 in the load demand from one day to the next. It is argued that the CLF forecaster allows the model to rapidly adapt to abrupt changes in temperature [45], [57], [58]. 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 each block's outputs, with the weights adaptively determined using an RLS algorithm.

In [59] and [60], Papalexopoulos et al. developed a neural network-based approach in addition to a regression-based approach. Both models were validated using training data from 1986 to 1990 on peak and hourly loads for 1991. It was shown that the ANN model enhanced forecasting accuracy for both peak load and hourly forecasts.

# 3 Deep Learning Techniques

According to Yann Lecun and colleagues, "deep learning enables computer models built of many processing layers to learn representations of data at different levels of abstraction" [62]. Although the concept of 'deep learning' has been bandied about for decades, it was frequently dismissed as a fanciful notion rather than a feasible technology. This was mostly due to three constraints: (i) insufficient training data, (ii) insufficient processing power, and (iii) insufficient efficient training algorithms [63]. With improvements in the semiconductor industry resulting in powerful graphics processing units (GPUs) and the rising digitization of the world, these limits have been overcome. Additionally, Geoffrey Hinton's quantum leap in inventing an effective neural network training algorithm paved the way for deep learning implementations. Deep learning models have grown in popularity during the last several years in fields such as computer vision, speech recognition, machine translation, and board game programs, where they have delivered results comparable to expert human performance, if not beyond it [64].

The significant benefit that deep learning models have over traditional models is that they acquire high-level features incrementally from data, eliminating the need for topic knowledge and time-consuming feature extraction [65]. The primary reason for utilizing deep learning models in this study is that they are superior to the conventional models in terms of their ability to (i) learn extremely non-linear relationships and (ii) learn shared uncertainties.

## 3.1 The Long Short Term Memory Forecaster (LSTM)

Recurrent Neural Network (RNNs) introduced memory into neural networks, which helps to model sequential data. RNNs have been successfully applied in the disciplines of machine translation, speech synthesis, and time series prediction [70]. Typically, back-propagation or real-time recurrent learning algorithms are used to train RNNs. These training methods expose traditional RNNs to vanishing gradient issues, reducing their effectiveness when dealing with large data sets [7], [81], [82]. The 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 [82].

LSTMs are a classification of recurrent neural networks that can learn the order of dependencies between elements in a sequence. LSTMs overcome the issue of vanishing gradients using gates that regulate the flow of input, which makes them excellent for dealing with time series data with lengthy temporal dependencies. Unlike a conventional recurrent unit, which overwrites its memory at each time step, the LSTM unit can select whether to retain existing memory via the introduced gates. The LSTM provides a model capable of storing information for an extended period and better control of gradients. Munem[82] et al. argue that LSTM is better than other deep neural networks because of its memory cell configuration.

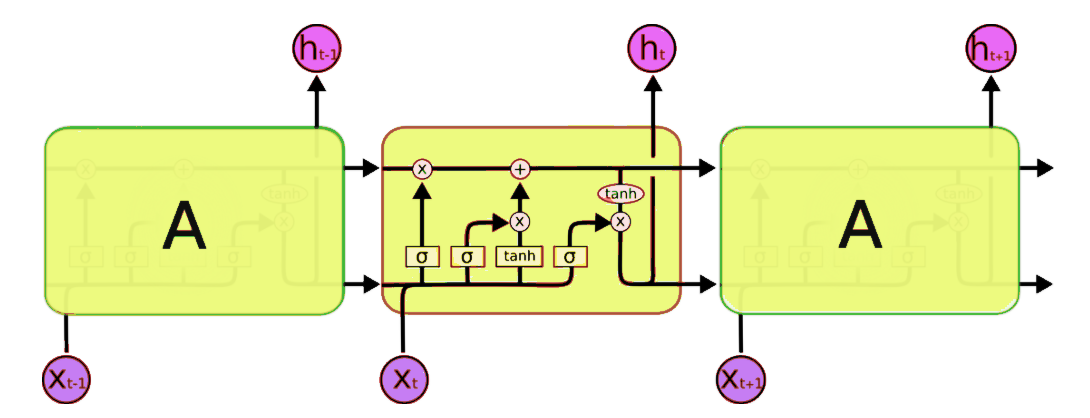


Figure 3 - The Long Short-Term Memory Structure [83]

This repeating module in standard RNNs will have a relatively simple structure, such as a single tanh layer. LSTMs have the structure as well, although the repeating module is structured differently. Rather than a single neural network layer, there are four that interact in a unique way. Each memory block is composed of the following: a memory cell, an input gate, a forget gate, and an output gate. Each line in Figure 3 represents a whole vector, from one node's output to the inputs of others. The pink circles denote operations performed at the point level, such as vector addition. The tiny yellow boxes represent layers of learned neural networks. Concatenation occurs when two lines merge, whereas forking occurs when a line's content is replicated and the copies are sent to various locations. The key to LSTMs is the cell state, represented by the horizontal line running across the diagram's top. It maintains the integrity of data travelling through it. By properly regulating gates, the LSTMs are capable of removing or adding information to the cell state. Gates typically allow information to pass through on an optional basis. They are constructed using a sigmoid neural network layer and pointwise multiplication. The sigmoid layer generates values between 0 and 1, indicating how much of each element should be allowed to pass through. A number of zero indicates that "everything is forgotten," whereas a value of one indicates that "everything is retained." Three gates protect and govern the cell state in an LSTM [7].

The initial stage in LSTM is for a sigmoid layer dubbed the "forget gate layer" to decide what information should be discarded from the cell state. It examines the preceding hidden layer and input and returns a number between 0 and 1 for each number in the cell state. The following step is to decide what new information will be stored in the cell state by merging two pieces to make a state update. The first is that a sigmoid layer known as the "input gate layer" determines which values need to be updated. The second is that a tanh layer generates a vector of new candidate values that could be inserted into the state. Following that, multiplying the old state by forgetting the items and adding the new candidate's values to update the old cell state into the new cell state. Finally, the net executes the output, which will be a filtered version of our cell state [84]. First, a sigmoid layer uses the cell state to execute outputs. Then we run the cell state through tanh and multiply it by the output of the sigmoid gate to output only the sections we want. There will be no improvement in the state cell memory if the input gate value is minimal and close to zero. In a network model, stacked LSTM can be implemented by using multiple LSTM layers [7]. The technique of forgetting and retaining information within a cell makes LSTM perfect for dealing with sequential data.

Other researchers on the smart-grid team at UNB have used the LSTM algorithm for load forecasting, but only with the Saint John dataset. We will take the present implementation and alter it to meet our datasets and input feature sets. Additionally, because the ANNSTLF structure was recognized as the best forecaster for short-term load forecasting [1], [45]; our approach mimics the ANNSTLF structure by creating a Base Load Forecaster, Change in the Load Forecaster, and RLS combiner; while using the LSTM 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 LSTMs. It will be interesting to see if this adjustment can improve forecasting performance.

## 3.2 The Convolutional Neural Network Forecaster (CNN)

In the recent years, Convolutional Neural Networks (CNNs) have gained the attention of researchers studying load forecasting [3], [29], [66]–[68]. CNNs are a type of deep learning network used for data processing with a grid-like topology [3], [69], [70]. This can comprise time series and image data, which can be viewed as a one-dimensional and two-dimensional data grid, respectively [3], [69], [71], [72]. CNN is like the ANN in that it is a feed-forward neural network that is designed to mimic human neurons [3], [62]. They have been successfully applied in computer vision, audio processing, activity recognition, natural language processing, drug discovery, video recognition, and time series forecasting, among other applications [7], [73]–[78]. In 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 [7], [79]. In at least one of its layers, CNN employs a particular linear mathematical technique called convolution [70]. Convolution is performed in CNNs by repeatedly applying filters or kernels to the input data to build a feature map.

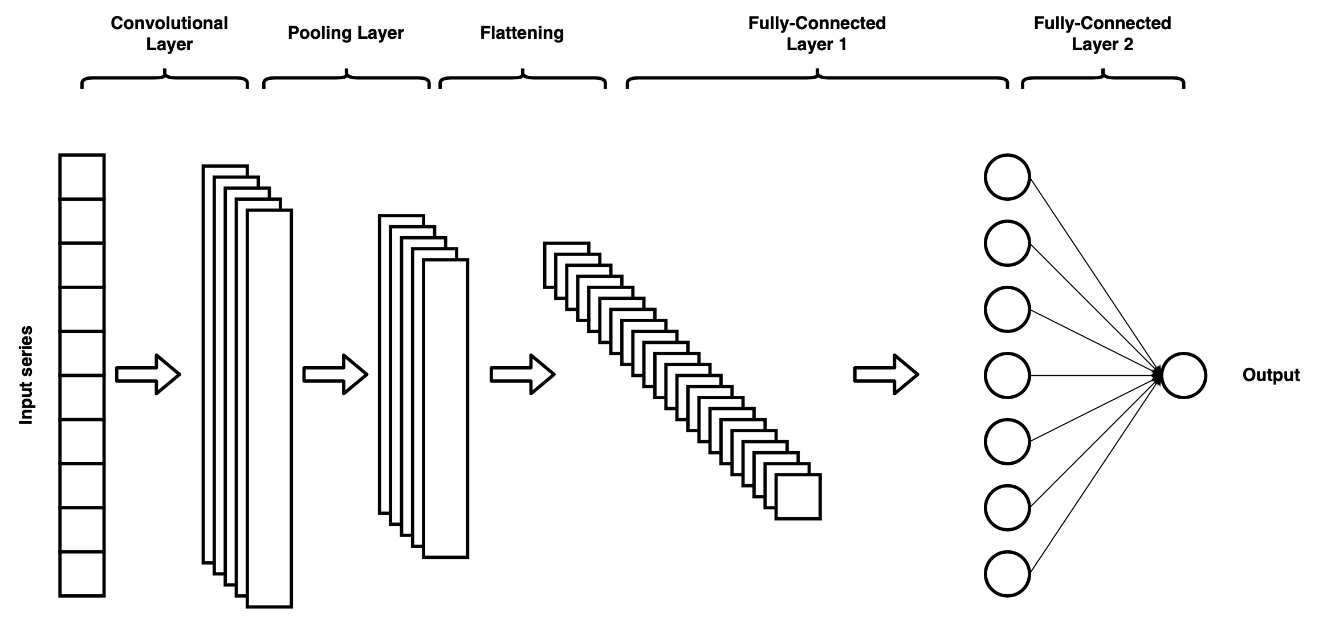


Figure 2 - An Architecture of a one dimensional CNN for time series data [80]

The convolutional layer performs three distinct actions. The feature map is created because of the first procedure mentioned above. The second stage involves activating the elements in the feature map using a nonlinear activation function, most commonly a RELU or rectified linear activation function [70]. The third stage employs a pooling procedure to smooth and minimize the dimensions of the resulting feature map. The max pooling method is commonly used; it returns an array of the maximum output values within the previous layer's rectangle neighborhood [70]. One or more convolutional layers may be present in the CNN network. After the convolutional layers generate their outputs, the hidden or fully connected layers receive them. The output layer is positioned immediately after the hidden layer and serves the same purpose as an output layer in a typical neural network. 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. We also plan to try out the CNN algorithm similarly to the LSTM using the ANNSTLF structure.

# 4 Methodology

# 5 Results and Discussion

## 5.1 Performance Metrics

This study will compare all forecasters’ performance across all forecasters and subsets of the forecasts such as weekdays, weekends, mornings, or evenings. It will assist us in identifying instances where forecasters perform better or worse than expected. 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:

|  |  |
| --- | --- |
|  |  |
|  |  |

Table 1

Mean Absolute Error (MAE) is the simplest way to measure forecast error [85], 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. The MAPE value indicates the magnitude of the forecasted values' error in percentage terms; it is also the most frequently used load forecasting metric [1]. However, MAPE returns undefined values when the actuals are zero, as is the case with demand forecasting. It produces extreme values when the actuals are close to zero and penalizes negative errors (when forecasts exceed actuals) more severely than positive errors. This is because the percentage error for forecasts that are too low cannot surpass 100%, while there is no maximum limit to overly high forecasts [1], [86]. Both the MAE and MAPE risk underestimating the effect of significant but infrequent errors. By focusing exclusively on the mean, we run the danger of being blindsided by a colossal error. To accommodate for severe, unusual errors, we incorporated the Root Mean Square Error (RMSE) [22]. With the RMSE, when we square the errors before computing the mean and then take the square root of the mean, we get an error size measure that favors significant but rare errors above the mean. However, 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 [87], [88]. MBE denotes the mean error of all forecasts across the entire forecast horizon; it quantifies the model's overall bias and determines if the model produces over-or under-estimation (MBE > 0 or MBE < 0). Since a positive error on one pair can compensate for a negative error on another, a forecast model can attain a very low bias while remaining imprecise. However, evaluating our forecast precision solely based on the MBE value will be insufficient; but a forecast that is significantly biased already indicates that something is amiss with the model.

Finally, standard deviation indicates the spread of errors by quantifying how far apart individual errors are from the mean error.  The standard deviation is calculated using the total number of values in the time series; it is one of the most accurate measures of dispersion. The standard deviation is less impacted than other measurements by irregularities in the time series.  In comparison to other measures of dispersion, the standard deviation is more difficult to compute and interpret. The standard deviation is also strongly influenced by extreme values in the time series. However, while each of these metrics have their limits, they are simple instruments for assessing forecast accuracy.

# 6 Conclusion

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Appendix Title

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Glossary

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