Smart Grids, Sensors, and Neural Networks
Optimization of Load Forecasting

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Abstract

The importance of load forecasting for energy distribution company has been an integral part of the energy supply process, ensuring proper generation to meet demand and to predict and minimize cost. Historically, this has been accomplished with a time series calculation, where historical load data is used to predict future demand needs. However, the data that utility companies have used were based on hourly usage figures at best, collected post facto. A narrower variance from the actual demand would reduce the risk of blackouts and minimizes excess energy, increasing the price for suppliers and consumers alike.

With smart grid technology, companies would initiate a two-way information transfer, receiving real time data from all aspects of the supply line. This means the greater ability to monitor efficiency, the ability to remotely adjust independent modular aspects of the grid instantaneously, and to receive greater insight into the consumer behaviors through more granular demand metrics. The proposed technique for improved load forecasting installs sensors to monitor, adjust, and report lighting systems in a model commercial building floor. Using four weeks of historical usage data supplied by Consolidated Edison, Inc., we can simulate sensor generated, minute by minute data with relative accuracy. An artificial neural network can then be trained in demand behavior and predict future load estimates. When compared to current time-series processes, the artificial neural network supplied an 19% improvement over standard methods.

***Index Terms*— Smart Grid, Sensors, Neural Networks, Time Series Algorithm, Load Forecasting,**

I. SMART GRIDS: AN INTRODUCTION

The introduction of smart grids was initiated to try to solve many problems that has stemmed from energy production over the past 120 years. On the most global sense, fossil fuels needed to produce energy sources has resulted in hazardous and dangerous environmental issues such as global warming and significant pollution. More current issues have arisen that has caused significant outrage, such as the BP oil spill, fracking, and the Dakota Access Pipeline which affect natural ecosystems and environmental conservation. Clearly, a more efficient system to, at least, reduce the impact these elements have will result in measurable improvement.

A secondary element focuses on the more economical side of energy supply. A reduction in the energy needed will reduce the cost power companies would incur to generate and distribute the energy. This results in a higher margin for utility companies, which can then be passed on to its consumers.

Depending on external sources of fuel threatens national integrity on multiple levels. Aside from catastrophes like oil spills, importing oil reduces reliance on local energy sources, impacting the national economy. With the amount of oil consumed by the United States, a shift to local supply would reduce imports, bolstering the American economy. Additionally, importing always contains the risk of security breaches, exposing the government to potentially significant consequences.

On the demand side, a system that enables the consumer to be more cognizant of energy consumption, and is motivated to take significant but simple measures to reduce their own consumption would reduce unnecessary usage. Incentivizing consumers to amend their behavior is always a worthwhile effort, but under current conditions is mostly infeasible other than light suggestions.

Finally, the inability to discern accurate demand levels can cause blackouts, sometimes severe causing millions of dollars of lost business and presenting potentially dangerous and hazardous scenarios.

A new system which reduces the amount of energy needed and improved efficiency of energy distribution and consumption would have a profound impact on the environmental, economical, and security of society. With the current technologies, we have the means of implementing a system that is able to limit the elements that cause inefficient or unnecessary generation, transfer, and usage.

II. FACTORS THAT INFLUENCE COST

A. Supply side

The current energy grid is nearly 100 years old, and the techniques and methods of delivering power are antiquated, and the asset conduits that are no longer capable of handling the complexity and volume of the current demand.

There are several elements that contribute to the inefficiencies. The loss of energy that occurs when energy is supplied is significant, given the age of the lines and inability to know when an asset needs to be maintained. In fact, some systems only know about power loss when they receive inquiries from customers. The inability to determine which lines are faulty or inefficient means that more energy would have to be produced than otherwise necessary.

Similarly, the inability to receive accurate, real time demand trends means that power companies may produce more energy than is necessary. Not only does this mean more energy is produced, but sometimes entire power plants are turned on to meet the increased demand, generating extremely high operational costs, when it is otherwise unnecessary.

Even something as simple as meter readings generates a significant amount of expenditure for utility companies. In the era where you can see the amount of data that you used on your phone, regardless of your location, needing to employ staff to document meter levels generates salary costs, motor vehicle costs, and the lost opportunity cost of having that data immediately.

This is also ignoring the perspective where consumers can generate their own energy, reducing the taxing load on the utility's aging lines and an external power source for a power company to use when necessary.

B. Demand Side

While plenty of homes have smart appliances, able to automate its schedule and minimize usage when not in use, consumers are less likely to use these specifications. This is partially because consumers are not able to see how much energy these items use and how much they can save by adjusting the optimal automation features. Because the meter system employed by utility companies is a simple meter reading for the entire unit's consumption, it is harder to correlate an increase in microwave automation and a reduction in the final bill. Likewise, consumers are unaware when prices are higher and lower, and are not likely to adjust their usage based on an unclear cost.

III. Smart Grids: Benefits

With current technologies, we are able to employ several elements that will vastly improve the different components of the electric grid system.

A. Two-way, real time information

One of the core foundations of the Smart Grid system is that it removes the one-sided flow of information. By installing sensors, both on utility assets and in consumer environments, all parties get a better understanding on how the flow of energy is occurring and gives the ability to adjust that flow accordingly.

Customers can receive a bill detailing how much each appliance used, enticing them to employ automation features and use costly items less.

A power company can now know which power lines are optimally performing and which are not, and can adjust the transfer of energy so that minimal power is lost in transfer. When a distribution center fails, the company can be alerted immediately, limiting the potential repercussions. The need for meter readings vanishes since they now receive granular usage data in real time.

Most importantly, that granular data provides the utility with vital information that can improve load forecasting, reducing excess generation and minimizing risk of universal energy loss. They can also entice customers to limit high consumption appliances in times of high peak loads, something that would not be possible without detailed information.

B. Plug and Play

With the ability of the utility company to see consumer behavior, it enables them to introduce external sources of energy. Now that it can see how much energy is being produced from solar, wind, and hydraulic energy sources, it is able to adjust its supply to those locations. Additionally, it can incentivize consumers to incorporate external sources by providing discounts, enabling them to use the externally generated power allocated towards the entire grid.

C. Automation and Remote Control

Sensors installed on supply and consumption assets provide the ability to control energy usage in a wider array of ways. Aside from consumers setting up scheduled tasks and uses, intelligent home automation systems are now being introduced that use machine learning and artificial intelligence to optimize consumption behavior.

When power companies find that the peak demand threatens to exceed estimates, it has the ability to adjust supply lines and even consumer appliances in order to ease the burden and minimize potential risks.

IV. Building a Model Floor

In order to extrapolate our techniques to a larger scope, the authors designed a blueprint for a standard commercial office floorplan. The model concentrates on installing sensors that moderate, adjust, and report electrical activity for the lighting systems. With the model, the number of sensors can be calculated dependent on the area of each designated space, resulting in the number of lights and sensors that must be installed. This will illuminate the amount of energy produced over the model floor, allowing the energy savings to be derived from governmental estimates for sensor technology in lighting systems. The model can be expanded to include HVAC systems and other energy consumption systems and appliances once the data for energy savings is calculated or derived.

The initial stage is to calculate the lighting needs of this model office floor. Using guidelines from an electrical engineering website [1], we find that the standard commercial building lighting procedures dictate that the area has to be illuminated to 250 lux. Consider an office area with a total length of 120 meter, a total width of 100 meter and a height of three (3) meter. Because lighting over work spaces need to have greater intensity, the distance between the ceiling and each desk measures two (2) meters. The lighting specifications for such a floorplan using twin lamp 32 Watt CFL luminaries are as follows:

Lux of lamp	250 lux
Twin lamp	32 W
SHR (Space Ratio)	1.25
Maintenance factor	0.63
Utilization Factor	0.69

The number of lighting fixtures needed to illuminate the model floor can be calculated by determining the lumens produced by each fixture with each fixture's efficiency, and the area of the floorplan.

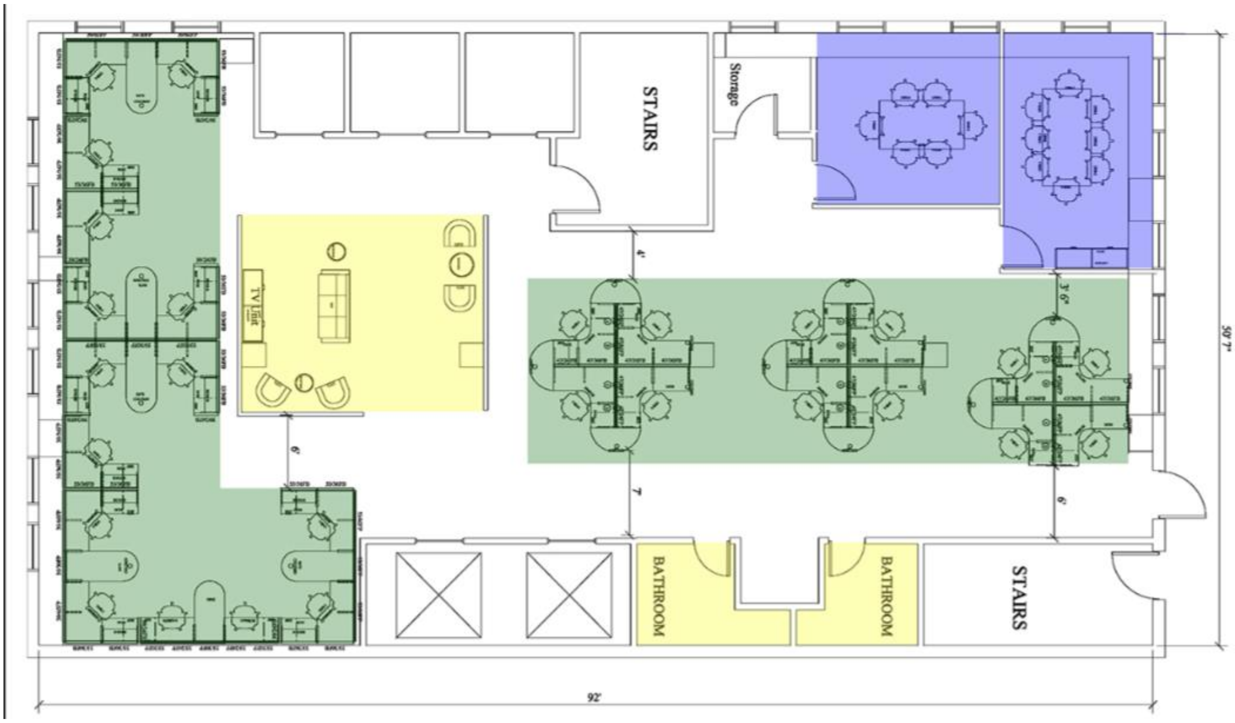
Once the number of fixtures is derived, the next step is to decide how many sensors are necessary to install to monitor and report accurately. This can be done by determining the optimal placement of the lighting fixtures throughout the office area.

The following table details the calculation steps for deciding the total number of lights and total number of sensor required for the model floor:

Total Wattage per Fixtures	**Number of lamps * Lamp Wattage**	**Fixture Wattage**
	2 Lamps per Fixture * 32 Watts	64
Lumen per Fixtures	**Lumen Efficiency (Lumen per Watt) * Fixture Wattage**	**Fixture Lumens**
	85 Lumen/Watt * 64 Watts	5440
Required Number of Fixtures	**Required Lux * Room area / MF x UF x Lumen per fixture**	**Number of Fixtures**
	(250 x 120 x 100) / (0.63 × 0.69 × 5440)	1268.623391
Minimum Spacing Between Fixtures	**Ceiling-to-Desk Height * Space-Height Ratio**	**Meters Between Fixtures**
	2 * 1.25	2.5
Number of Rows Required	**Width of Room / Maximum Spacing**	**Rows Required**
	100 / 2.5	40
Fixtures per Row Required	**Total Fixtures / Number of Rows**	**Number of Fixtures**
	1268.6233/40	31.71558478
Axial Spacing Between Fixtures	**Length of room / Number of fixtures in each row**	**Axial Spacing in Meters**
	120 / (31.7156)	3.7836288
Transverse Spacing Between Fixtures	**Width of room / Number of fixtures in row**	**Transverse Spacing in Meters**
	100 / (31.7156)	26.42965399
Number of Sensors Required	**Number of lights / 4**	**Number of Sensors**
		317.1558478

<u>**Model Floorplan of an Office Building**</u>

(Violet = Conference Room; Yellow = Restroom and breakroom; Green = Open Office area):



Once the number of sensors are determined, the savings that the sensors can be generated. The data for sensor savings for lighting fixtures was obtained through governmental estimates published [2], each figured determined by room type and purpose. By using the above dimension and figures for room measurements, lighting requirements, and sensors needed to maximize utility, we can build a model reflecting the model floorplan. This can be adjusted for any floorplan by amending the floor area designations:

	Total Area	Conference Room	Corridor	Breakroom	Open Office	Private Office	Restroom	Storage
Area (Square Meters)	120000	1100	1000	800	5500	2000	800	800
Savings (Percent)	**28.84**	45	40	29	10	35	60	70

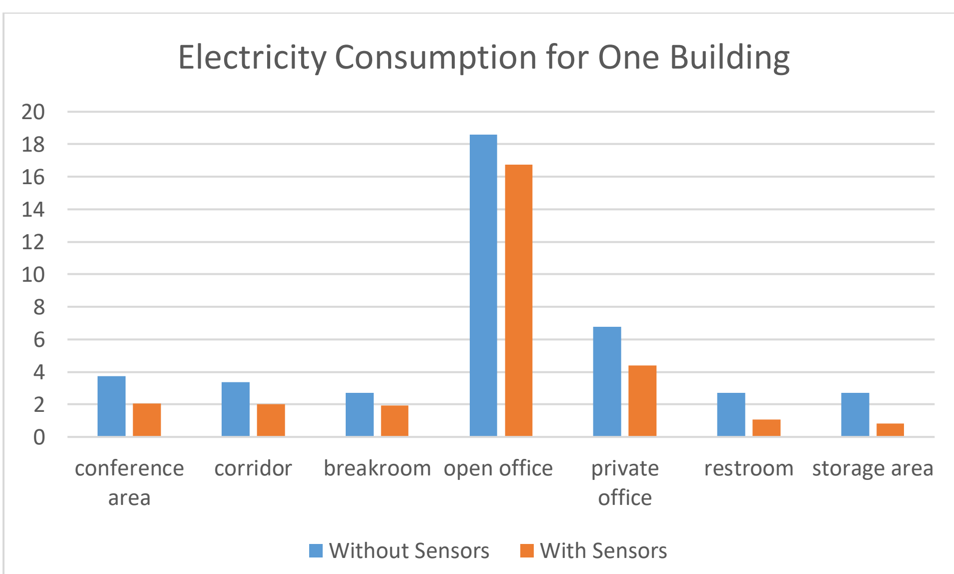
The above table details the savings generated by using occupancy sensors in different room types. The dimensions of the model used is specified and enumerates the energy savings for each room type after the occupancy sensors have been installed. The difference in savings can be attributed to room purpose, usage behaviors, and other elements detailed in the government report.

Electricity Consumption by Room Type and Area

Before and After Sensors installation

Electricity Consumption (kWh)	Total Area	Conference Room	Corridor	Breakroom	Open Office	Private Office	Restroom	Storage
W/O Sensors	40.6	3.72	3.38	2.71	18.61	6.77	2.71	2.71
With Sensors	**29.04**	2.05	2.03	1.92	16.75	4.4	1.08	0.81

The above table documents the calculated energy consumption and savings for different room types based on the area of each respective room type. As noted, the use of sensors reduces the energy consumption by over 10 kWh. The graph below illustrates a Comparison for electricity consumption in the model floorplan both with and without sensors:



V. Model Explanation

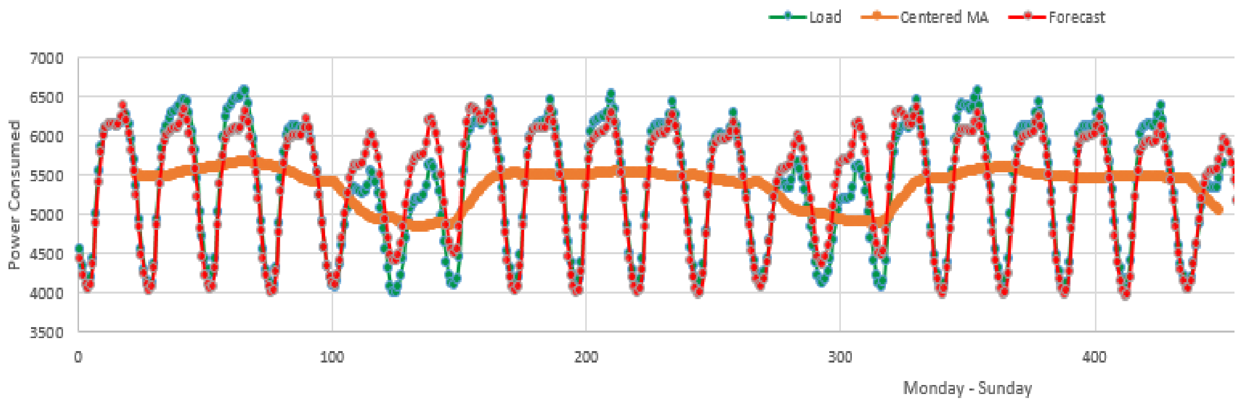
A. Time Series Analysis

The ability to estimate how much energy needed to be generated and supplied is essential to the core of the power utility industry. Through inserting historical and external data, the company can calculate a best-guess as to the anticipated demand. Historically, load forecasting has been accomplished with a time series methodology, where the data generated sequentially in time. It assumes that, in the absence of major disruptions to critical factors of a recurring event, past data will be relationally replicated in the future, and can be expressed via models developed from the past events.

There are several problems with this approach, however. Companies that use time series forecasting are doing so with hourly data, collected well after the span it represents. This results in less accurate predictions, and the inability to adjust models in real-time situations. Additionally, time series does not recover well from wide variations in energy consumption behavior, most notably, taking weekday values to forecast weekend demand. Even slight deviations from actual load data can result in significant output disparity for utility companies. Clearly, any increase in forecasting accuracy can translate into large production shifts over the course of a year.

Below is a time series forecasted trend measured against the actual load data it intended to predict. The model contains five weeks' worth of actual load data, four weeks of data to base the predicted fifth week of energy consumption upon. The green line represents the actual load data and the red line represents the predicted load. While the predictions are mostly accurate, there is still room for optimization. There are also days where the difference between the actual data and the forecast. For example, the fifth and sixth curve shows a very high disparity, equaling a significant loss to the production company. By minimizing the error by supplying more accurate predictions, utility companies can adjust their production levels according, reducing over or under-production.

<u>Time Series Forecast</u>



B. Neural Network Optimization

There is a growing tendency towards unbundling the electricity system. This is continually confronting the different sectors of the industry (generation, transmission, and distribution) with increasing demand on planning management and operations of the network. The operation and planning of a power utility company requires an adequate model for electric power load forecasting. Load forecasting plays a key role in helping an electric utility to make important decisions on power, load switching, voltage control, network reconfiguration, and infrastructure development.

Many methods have previously been used for load forecasting. These include statistical methods such as regression and similar-day approach, fuzzy logic, expert systems, support vector machines, econometric models, end-use models, etc.

Methodologies of load forecasts can be divided into various categories; included are short-term forecasts, medium-term forecasts, and long-term forecasts. Short-term forecasting, the focus of this paper, gives a forecast of electric load one day ahead of time. These forecast can assist decision making aimed at preventing imbalance in the power generation and load demand, leading to greater network reliability and power quality.

The method used in the scope of this paper is a supervised Artificial Neural Network (ANN). Here, the neural network is trained on input data along with the associated target values. The trained network can then make predictions based on the relationships learned during training. The model is built on five weeks' worth of data collected from nyiso.com on hourly basis. The data is broken down to represent minute-by-minute usage statistics, simulating sensor data that transmits the load consumption each minute. The increased granularity improves the prediction accuracy. The proposed model's aim is then contrasted with current time series methods most commonly used, highlighting the improvement in forecasting attempts.

Further sections of this paper discuss the load forecasting problem in greater detail, introduce the concept of artificial neural network and its application to load forecasting, address the pre-processing of data series that were used in this study, and present the results and conclusions of the forecast obtained through this project.

C. Load Forecasting Problem

As mentioned, utility companies face an obstacle in power generation in that its predictions are based on antiquated and over-generalized data that makes accurate representation of current environments difficult at best. Even if the company was able to obtain the data in real time, the fact that meter data is in hour increments decreases the ability to account for large shifts within a given hour. The cumulative effects of these inaccurate predictions decreases efficiency, taxes the grid unnecessarily, and generates increased environmental and security threats. This is the catalyst to build a model to obtain a very accurate prediction of load. By installing occupancy sensors the floors of commercial buildings, minute-by-minute data can be collected and reported in real time to get a precise load monitoring.

D. Data Pre-processing

Historical hourly load data was collected from energyonline.com [3] for New York City. In order to reduce this accurate data to a minute basis, the data was processed by dividing each hour by 60, representing an approximate value for one minute. Using the RANDBETWEEN excel function, each minute was randomized with values between -3 and +3 of the divided value. For example:

1. The hourly load at 12:00 PM – 1:00 PM on September 16th is 3242.41758241758

2. To get an average minute value for that hour, divide the number by 60, giving us an average value of 54.04029 per minute in our sample hour.
3. Using RANDBETWEEN, we obtain a +/- 3 range of 51.04029 - 57.04029 per minute
4. To ensure that the randomized values produced truly represent the original data, a formula is used that sums the 60 randomized values, requiring the sum to equal the original hourly value. The formula stated is Minute 1/SUM(Minute 1:Minute 60)*Hourly Data

This gives us a simulated minute-by-minute data that accurately represents a data set that would be collected by sensors.

E. Artificial Neural Networks

Time Series predictions only takes into account the previous months or days and finds a pattern in it to forecast the future demands, a method that we previously determined is inaccurate.

Artificial Neural Networks (ANNs) refer to a class of statistical models inspired by the biological nervous system. The models are composed of numerous computing elements, typically described as neurons. Each neuron has several inputs, one output, and a set of nodes called synapses that are connected to the inputs, output, or other neurons.

A linear combiner produces a weighted sum of the inputs from which the threshold value associated with the neurons is subtracted to compose the activation of the neuron, resulting in a single value from all of the inputs. The activation signal is passed through an activation function to produce the output of the neuron. The chosen activation function is normally a non-linear function (i.e. a sigmoid function), a feature that allows the ANN to represent more complex problems.

Most ANN models relating to short-term forecasting use multi-layer perceptron (MLP) networks. The attraction of MLP can be explained by the ability of the network to learn complex relationships between input and output patterns, something difficult to model with conventional methods. Inputs to the networks are generally present and past load values and the network is trained using actual load data from the past.

F. Load Forecasting Using Neural Networks

The back-propagation algorithm is a supervised learning algorithm used to change or adjust the weights of the neural network. In back-propagation, the gradient vector of the error surface is calculated. This vector points along the direction of steepest descent from the current point, so that a movement over a short distance along it decreases the error. A sequence of such moves will eventually find a minimum error point.

The following data were selected as network inputs:

1. The load of the previous hour.
2. The load of the previous day
3. The load of the previous week
4. The day of the week, and
5. The hour of the day

This results in a total of five (5) ANN input values. The Neural Network has an input layer where the values to be trained are given as input. Hidden layers are then used to set the weightage of each nodes and are effectively and automatically trained. Once trained, the model's optimized output is given to the output layer.

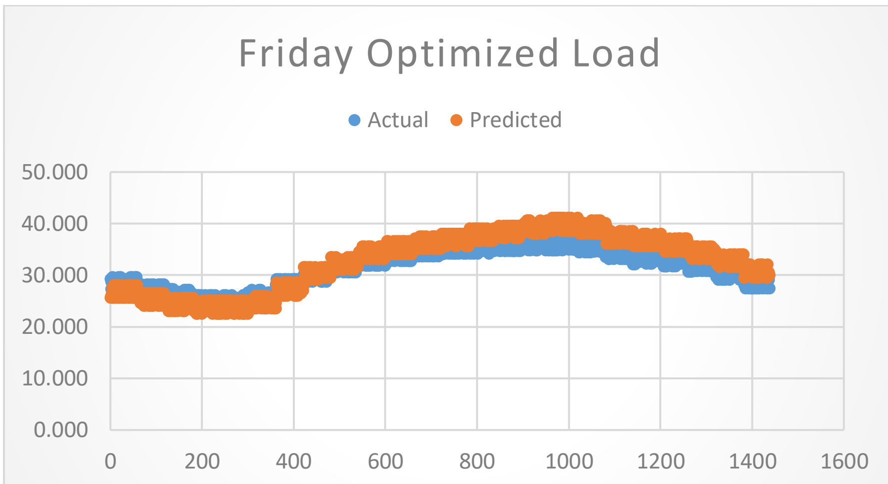
The model was run using the NeuroXL predictor Excel Add-in. Previous months load data, broken down into minute increments, were given to the predictor with the train model option, training the model using the input data and the corresponding time. Once the training of the node is completed, the model prediction was applied to future dates to predict expected values.

G. Results

The next day load data was run for a single weekday (Friday) and a single weekend (Sunday) to highlight this paper's findings.

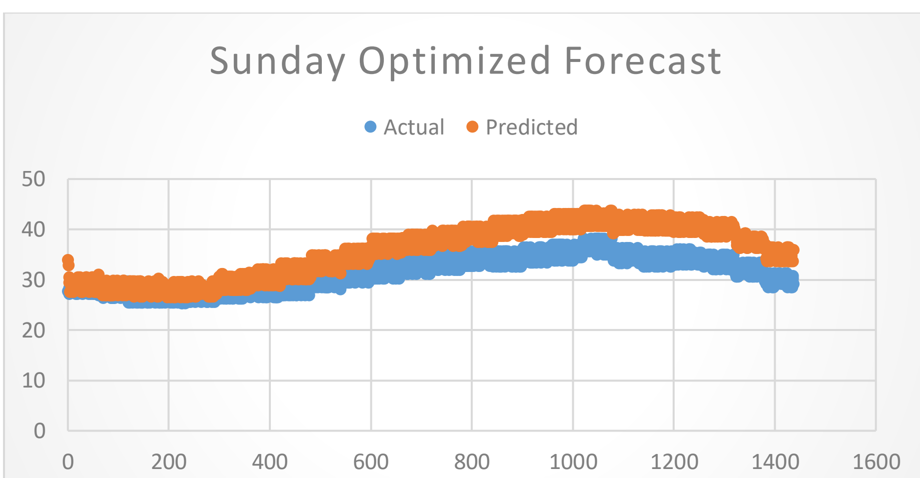
1) *Load forecast for Friday*

The findings represented in the graph blow shows that the ANN prediction method is more accurate than the time series model detailed previously.



2) *Sunday Forecast*

Though the prediction is not as accurate as the weekday values detailed above, it still is far more precise than the output produced by a time series model.



VI. Cost Saving

Given the data provided by Consolidated Edison, Inc., we find that the model floor realizes a 32.1% reduction in cost over the course of a year when sensors are installed to regulate lighting usage. When the model is run with US average electricity prices, it reflects a 31.5% savings.

When we employ the use of sensors in both in commercial building and residential building, the rate of savings increases significantly. Residential spaces typically contain more lights per square foot than commercial building, increasing the original power consumption and thereby increasing the amount of savings incurred. Additionally, electricity prices cost up to 50% more in residential buildings, increasing the value of savings a consumer will realize.

VII. Conclusion and future development

In this paper, we presented an accurate model for power consumption prediction. Transparency about the consumption is becoming increasingly important for paving the way to make adjustments in order to optimize grid efficiency. Hence, the capability to precisely forecast load is vitally important for electric power systems. The objective of this model is to provide more accurate predictions of the load in minutes through an adaptive neural network training process, enable companies to apply preventative upgrades and increase grid reliability.

The proposed methodology of this model aims to predict total power demand sixty seconds into the future, thereby giving sixty-second forecast ability with low error using this model, it has theoretical possibility enable companies to minimize experienced peak demand.

Some of the future work directions are the inclusion of background knowledge which are various external potential data sources that are influential to power consumption. Those factors can be divided into four categories. Time factors, such as different seasons of the year and holiday schedules. Weather factors, for instance, temperature, humidity, wind, precipitation, solar radiation and light intensity. However, the impact of weather on electricity demand is complex and highly nonlinear, the principal weather variables that have impacts on short term loads are temperature, humidity and wind speed. For different types of consumers, the model need to be adjusted to fit either residential or industrial consumers. Besides, since economic growth requires the availability of energy, it plays an important role in energy consumption as well. Other factors regarding to economic would be per capita growth, electricity rates, etc. Except these four categories, an anticipated construction to this model can boost the accuracy of the predicted load.

The proposed model is entirely scalable and can be implemented for predicting the load that are caused by other types of sensors, such as appliances, HVAC systems. If it is implemented on a large scale and across building/Industrial facility energy management systems, such as city municipalities or other large energy end users, the benefits would be maximized by applying efficient and reduced power generation capacity. In other words, it would undoubtedly be invaluable for pointing out where adaptations are necessary to make the grid future-proof, as well as for contributing to improve the energy sustainability for local municipalities and communities.

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