

Analysis and Prediction of Electricity Load Forecasting

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ABSTRACT

The monetary growth of every country is relatively associated with its strength infrastructure, community, and availability considering that strength has emerge as the relevant part of normal existence in this modern world. Consequently, the worldwide demand for power for residential and commercial purposes has seen an exceptional increase. Electricity charges hold fluctuating during the last years and no longer citing the inadequacy in strength generation to meet global call for. As a approach to this, numerous studies geared toward estimating future electric power demand for residential and business purposes to enable strength generators, vendors, and suppliers to plot successfully beforehand and promote strength conservation some of the users.

Keywords

Electricity, Grids, Prediction, LSTM

Introduction

Residential buildings make up enormous proportion of cease-use energy demand. The U.S. strength information management tasks that around 30% of worldwide energy cease use might be attributed to residential region with the aid of 2020 but, the residential strength sector has visible restrained research hobby compared to commercial and industrial sectors among the forecast studies which focused the residential sector, the primary recognition have been on mixture local or district level energy loads over medium time period (per week to a year in advance) to long time (more than a yr in advance) horizons because of the shortage of economic hobbies, little emphasis has been given to individual family stage intake analysis and forecasts on the other hand, with the recent development of clever grid technology, there may be a growing hobby for expertise residential strength intake at person family degree. mainly, the evaluation and correct prediction of power loads at character household stage can enhance the effectiveness of clever grid packages; this include clever domestic energy management structures, battery electricity control equipment, and demand response operations on the same time, there was a excellent enlargement within the deployment of clever meters globally.

Many governments mandate utilities to equip their customers with superior metering infrastructures (AMI) which is a essential tool to deal with clever grid technologies and help networks in responding and shaping future's residential strength demand. AMI can display the load at diverse statistics resolutions, and transmit and receive consumption records between the software corporations and households. AMI facts permits household consumption analysis at high resolutions which can be efficiently used for terribly short (much less than an hour in advance) and brief-term (an hour to per week beforehand) intake forecasts individual household

strength load profiles reveals excessive volatility. specially as compared to larger scale masses along with industrial buildings, substations or nearby power loads, load variance and uncertainty is tons more on the family level.

Previous load forecast research on individual families which applied smart meter and climate information within device learning fashions, or clever meter based totally fashions (SMBM), in particular worked with a particular statistics decision; with common forecast horizons selected to be both one hour and 24 hours ahead

- To manipulate this growing demand effectively, so-referred to as smart grids are used.
- The cardinal feature of call for-side control in clever grids is load forecasting, because it permits the operators of the smart grid to make efficient and powerful decisions, that's the topic of hobby of this challenge.
- Load forecasting is a way utilized by energy businesses to are expecting the power or strength had to balance the deliver and cargo demand at all the times. it's far obligatory for correct functioning of electrical enterprise
- Load forecasting is a complex multi-variable and multi-dimensional estimation problem wherein forecasting strategies together with curve fitting the usage of numerical methods do no longer offer correct effects as they fail to song the apparently random traits appropriately, which is something system studying algorithms are better at.

Smart Grids

The growing use of renewable strength assets with variable output, which includes sun photovoltaic and wind electricity era, requires smart Grids that efficaciously manage flexible hundreds and energy storage. The capacity to forecast intake at one of a kind places in distribution structures can be a key functionality of clever Grids.

The goal of this paper is to benchmark modern day strategies for forecasting energy call for on the household degree throughout different granularities and time scales in an explorative way, thereby revealing ability shortcomings and find promising instructions for destiny studies in this region. We follow a number of forecasting strategies which includes ARIMA, neural networks, and exponential smoothening the use of numerous strategies for training information choice, specifically day type and sliding window based strategies[11].

Categories

There are three one of a kind categories of load forecasting, namely quick-time period load forecasting (STLF, starting from a few hours to a few days), medium-time period load forecasting (MTLF, numerous days up to 3 months), and long-time period load forecasting (LTLF, extra than or identical to twelve months).

Literature Review

Number of studies are focused on electricity Load Forecasting. there's a clear pass toward hybrid methods, which integrate or extra of the techniques. studies in a paper published via Hung Nguyen in an IEEE conference in 2017 used Autoregressive included moving common (ARIMA) and Seasonal Autoregressive integrated transferring average (SARIMA) for load forecasting.

An ARIMA is usually a statistical evaluation model which has time series statistics to both higher apprehend data set or expect future trends. Whereas a SARIMA is a Seasonal ARIMA which is

like an extension of ARIMA that supports univariate time collection records with seasonal additives. Over the years, the course of studies has shifted, by changing vintage approach with new and efficient approaches. This have a look at to research ARIMA and SARIMA supplied an average absolute percent errors (MAPE) of 9.13% and 4.36% respectively. The LSTM fashions added in this examine bring this MAPE metric all the way down to 1.975%.

LSTM version (lengthy brief-term model) is an artificial recurrent Neural network structure used in deep getting to know[11]. LSTM is used as it is suitable for statistics classification, processing and making predictions based totally on time collection statistics. Marino made the first attempt in the direction of the equal load forecasting trouble via the use of LSTM and confirmed similar results.

The effectiveness of the two pioneering works become simplest confirmed at the metric of root imply square blunders (RMSE) as opposed to the more not unusual metric of MAPE, which makes it tough to contrast to different works. Very lately, deep getting to know-primarily based techniques start to emerge inside the load forecasting network. the weight forecasting accuracy for business customers might be advanced through using deep neural network.

The industrial energy intake styles are a lot more normal than residential ones, so that a miles more accurate end result of approximately 8.85% MAPE on common is accomplished compared to the results. Marino et al. made the primary try toward the identical load forecasting trouble via using LSTM and reveal comparable consequences.

The LSTM can capture the diffused temporal consumption pattern persisting in single-meter load profile and convey the pleasant forecasts for the majority of instances.

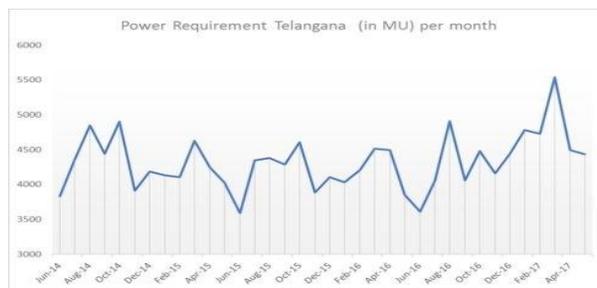


Figure.1

The fig.1 shows the time collection version recorded for energy load forecasting the usage of LSTM . evidently this time collection could likely be described using an additive model, as the seasonal fluctuations are roughly regular in size through the years and do not seem to depend on the level of the time series, and the random fluctuations also seem to be roughly regular in size over the years. Do not use abbreviations in the title or heads unless they are unavoidable. Primarily based at the touchy nature of strength demand forecasting within the power industries, there's a need for researchers and professionals to become aware of the challenges and possibilities in this area.

The purpose is to provide end customers (marketplace demands) with safe and strong power. Load forecasting is a technique used by power corporations to are expecting the power or energy needed to stability the supply and load call for at all of the times, it is far obligatory for proper

functioning of electrical enterprise. Electricity call for forecasting is a significant and vital system for planning periodical operations and facility expansion within the power region.

Architecture

The long short-term memory (LSTM) architecture was first introduced by Hochreiter when reminiscence cellular became protected and similarly advanced by means of Gers with an extra overlook gate. It's been the most a hit RNN architecture and received huge reputation in lots of next programs.

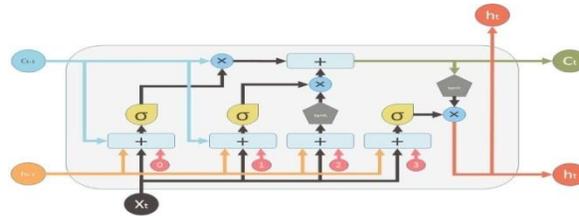


Figure.2

The above fig.2 is the diagram of a LSTM building block. The un-rolled LSTM structure connecting records of the subsequent time factor is proven in the above figure. The weights of the un-rolled LSTM are duplicated for an arbitrary variety of time steps. All the weights and biases are learnt through minimizing the variations between the LSTM outputs and the real training samples via this un-rolled structure, statistics of the modern-day time step can be stored and maintained to affect the LSTM output of the destiny time steps. At a primary sight, this appears intimidating. Retaining that aside, have a look at the inputs and outputs of the unit. The community takes three inputs. The enter of the modern time step, the output from the previous LSTM unit and the reminiscence of the previous unit.

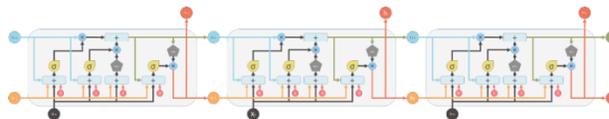


Figure.3

This (Fig.3) shows the data preprocessing for the inputs. Coming to the outputs of this structure- the output of the contemporary community and the memory of the present day unit are it. consequently, this unmarried unit makes selection by way of considering the cutting-edge input, previous output and former reminiscence.

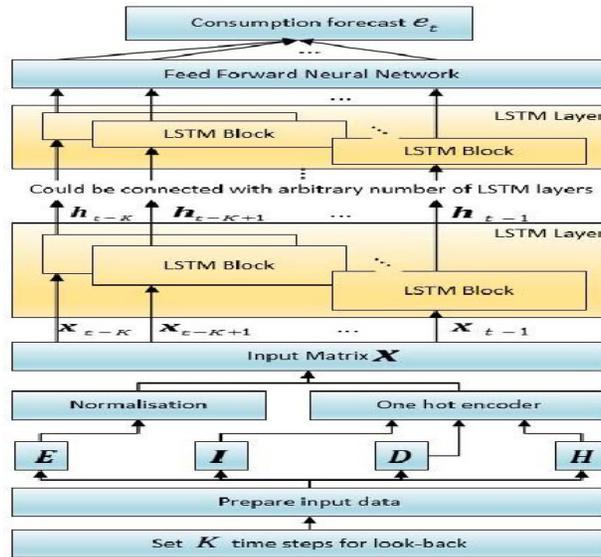


Figure.4

Subsequently we recommend a protracted brief-time period reminiscence (LSTM) recurrent neural network-primarily based framework(Fig.3), that's the cutting-edge and one of the most popular strategies of deep learning, to tackle this difficult issue. The proposed framework is tested on a publicly to be had set of actual residential clever meter facts, of which the overall performance is comprehensively as compared to diverse benchmarks including the country-of-the-arts within the subject of load forecasting. As a result, the proposed LSTM technique outperforms the alternative listed rival algorithms in the project of brief-term load forecasting for person residential families.

Methodology

Step one closer to developing a machine getting to know version for load forecasting is to apprehend the diverse parameters on which energy demand relies. We can be the use of beyond strength tendencies, correlated climate records and a timestamp for our predictions. We used a dataset supplied with the aid of the American Electric Power (AEP) , in which the estimated energy intake in Megawatts during the last 15 years is particular at the side of the Date and Time.

TRAINING THE LSTM MODEL

For time series forecasting our training dataset will usually comprise of a single column data frame values i.e. $A = [a_1, a_2, a_3, \dots, a_n]$. Suppose the length of the vector A is $l = 5$, then input = $[x(1), x(2), x(3), x(4), x(5)]$ and we want the output sequence to be of period one, as we understand LSTM version is recurrent in nature, the characteristic S might be implemented five instances as proven under.

$$(H^s, C^s) = S(S(S(S(S(H^{(0)}, C^{(0)}, x^1)x^2)x^3)x^4)x^5$$

Figure.5

After feeding inside the inputs, the mistake is calculated via a loss function and it is then back propagated through the network to replace the weights for last iterations with the help of a few gradient descent kind schemes.

MODELLING THE LOAD AND TEMPERATURE TIME SERIES

The processed information in preceding segment is used to model the time series the use of extraordinary fashions together with ARMA, SARIMA, ARMAX, and LSTM. ARMA and SARIMA use handiest the weight time collection to model and forecast. whereas, the ARMAX and LSTM additionally use temperature TS as an exogenous variable. all the techniques use 12 months records for modeling or schooling, and the thirteenth month statistics is used to evaluate and validate the forecast. The goodness of fits and the forecast uncertainties are compared. To validate the forecasts in every case, the forecasted records is converted back to the original form from the algorithmic converted form. The logarithmic transformation on the start of statistics processing turned into used to convey the fashions to balance at some stage in estimation and now not to put off Heteroscedasticity. handiest LSTM technique, as the target of this work, is explained inside the following subsequent subsections. whereas, the modeling using above referred to strategies and forecasts using these fashions is used to evaluate with the LSTM forecasts.

TRAINING THE LSTM NETWORK

The LSTM network is supposed to research both the long-time period and quick-term features of the education information. Towards this give up, the kind of input facts has relevance to the effectiveness of getting to know. If the statistics is provided which is leading towards wrong route or isn't enough to make the features clear, the LSTM or RNN will analyze as a result and could not expect or forecast accurately. for example, the every year seasonality inside the provided statistics is most effective for twelve months. The LSTM will don't forget it a continuing fashion and will expect wrongly and will lead in the direction of zero values regularly. but, if the data of more than one 12 months is given, LSTM can discover ways to are expecting the every year seasonality too. in addition, the selection of enter records additionally contributes in identifying the accuracy of the network overall performance. The education method uses DS2 level of information processing that consists of all styles of seasonality and traits except the yearly seasonality. For all the fashions, the data is split into two parts. The 365 days facts are used for schooling/modelling reason, and the 13th month facts is used for forecast validation while, for different fashions together with ARMA, SARIMA, and ARMAX, the DS5 level of information processing is used.

Data Analysis

The load forecasting has each commercial and technical implications and if not finished well, it could result in bad planning and inefficient operation of the electric energy structures. The accuracy of the burden forecasting is crucial to each the application agencies in addition to the clients. Because of this, it is able to be necessary to maintain on adjusting based totally on seasons and other elements that could affect the manner clients use the energy. Similarly, the forecast should rely on accurate statistics and excellent forecasting practices. Prediction at a

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particular timestamp is strongly structured upon electricity consumption on preceding timestamps. Subsequently, electricity intake at 5 preceding timestamps is also included at the same time as making predictions. the primary version uses LSTM layers and aims to tune greater complicated styles in power call for whilst the second one model is a easy single layer LSTM model. The first version is anticipated to outperform the second one model however it might take considerably greater time to train and utilizes more resources. We can test each models to see if the distinction among a complex community and a easy model is negligible or now not. The forecasts generated by using the LSTM are in comparison with the results of conventional strategies the use of RMSE and MAPE for all of the forecast horizons. The outcomes of some of experiments display that the LSTM based totally forecast is higher than other techniques and feature the ability to further improve the accuracies of forecasts.

$$APE = \left| \frac{y(i) - \hat{y}(i)}{y(i)} \right| \times 100\%,$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y(i) - \hat{y}(i)}{y(i)} \right| \times 100\%,$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n |y(i) - \hat{y}(i)|^2},$$

Figure.6

APE, MAPE, and RMSE formulae are shown in the figure 6.

Results and Discussions

This Fig.7 shows the energy consumption with respect to the year. It shows the different trends that can be observed in the Energy levels demand, over the past 15 years.

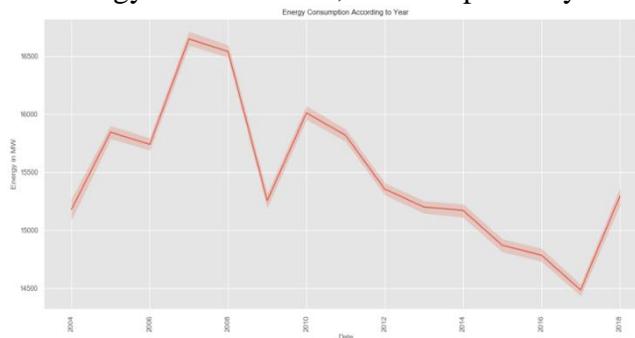


Figure.7

The graph, Figure 8 depicts the Energy Consumption from the years 2004-2006.

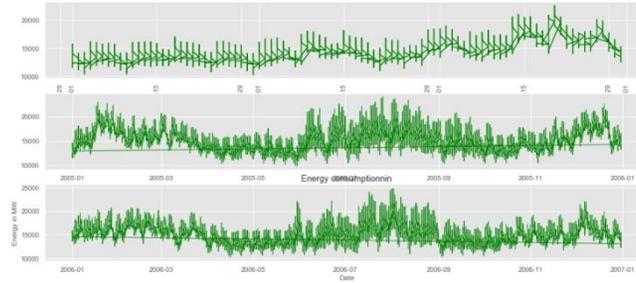


Figure 8

The graph (Figure.9) depicts what our machine learning algorithm has achieved through the given data set. Green line indicated the actual consumption and red line indicates the prediction of the next two months of consumption. As you can see that it is pretty accurate and it is learning in every curve and points.

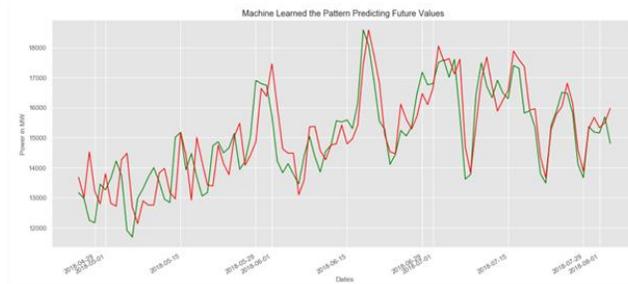


Figure 9

Conclusion

Table 1. ERCOT Dataset

Model	MAPE	RMSE
ARMA	9.13	3451
SARIMA	4.36	1638
Simple LSTM	2.638	716.534
Complex LSTM	1.664	229.630

Energy consumption at fifty preceding timestamps is also integrated even as making predictions. ARIMA calls for a sequence of parameters (p,q,d) which should be calculated based on

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information, whilst LSTM does not require placing such parameters. LSTM networks are nicely-applicable to classifying, processing and making predictions based totally on time series statistics. After viewing the results, we will see that LSTMs offer considerably improved effects compared to the ARMA and SARIMA models. we will see that LSTMs provide considerably stepped forward outcomes as compared to the ARMA and SARIMA models. We can also see that our “easy model”, that is greater sincere and less compute extensive to teach, gives outcomes near the more complex version and may be used in which sources are confined. In similarly observe, the proposed version may be progressed via accumulating and including greater applicable factors that may have an effect on the load alternate. at the equal time, that allows you to train the neural community greater effectively, a new loss function training method is designed to reduce the schooling time of the model. it can even be considered for random load forecasting, such as electric powered motors.

References

- [1] Das, Utpal Kumar; Tey, Kok Soon; Seyedmahmoudian, Mehdi; Mekhilef, Saad; Idris, Moh Yamani Idna; Van Deventer, Willem; Horan, Bend; Stojcevski, Alex (2018-01-01). "[Forecasting of photovoltaic power generation and model optimization: A review](#)".
- [2] Shahidehpour, Mohammad; Yamin, Hatim; Li, Zuyi (2002). *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management*. Wiley.
- [3] Weron, Rafał (2014). [Open Access]. "[Electricity price forecasting: A review of the state-of-the-art with a look into the future](#)". *International Journal of Forecasting*.
- [4] Seyedmahmoudian, Mehdi; Jamei, Elmira; Thirunavukkarasu, Gokul Sidarth; Soon, Tey Kok; Mortimer, Michael; Horan, Ben; Stojcevski, Alex; Mekhilef, Saad (May 2018).
- [5] VanDeventer, William; Jamei, Elmira; Thirunavukkarasu, Gokul Sidarth; Seyed Mahmoudian, Mehdi; Soon, Tey Kok; Horan, Ben; Mekhilef, Saad; Stojcevski, Alex (2019-09-01). "[Short-term PV power forecasting using hybrid GASVM technique](#)".
- [6] Dedinec A, Filiposka S, Dedinec A, Kocarev L (2016) Deep belief network based electricity load forecasting: an analysis of Macedonian case. *Energy* 115:1688–1700. <https://doi.org/10.1016/j.energy.2016.07.090>
- [7] Zaman MU, Islam A, Sultana N (2018) Short term load forecasting based on internet of things (IoT). BRAC University, Dhaka
- [8] Kumar CHJ, Veerakumari M (2012) Load forecasting of Andhra Pradesh grid using PSO, DE algorithms. *Int J Adv Res Comput Eng Technol*
- [9] Jevgenijs S, Joeri deW, Kochnakyan A, Vivien F (2017) Forecasting electricity demand: an aid for practitioners.

- [10] Shah RB (2019) A technological literature review on load forecasting in power system using artificial intelligence. Paripex-Indian J Res 8:14–15
- [11] Kshirsagar PR, Akojwar SG, R. Dhanoriya, “Classification of ECG-signals using Artificial Neural Networks”, https://www.researchgate.net/publication/317102153_Classification_of_ECGsignals_using_Artificial_Neural_Networks, International Conference on Electrical, Computer and Communication Technologies. 2017 .