Predicting Energy Consumption Using LSTM and CNN Deep Learning Algorithm

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Abstract - Innovations in technologies that rely on electricity have led to an uncontrollable rise in power usage. In order to predict future electricity demand and enhance the power distribution system, analysis and forecasting of energy consumption systems are necessary. Several issues with the present energy consumption prediction methods make it difficult to anticipate actual energy usage with any degree of accuracy. In order to master the energy prediction method, this study examines fourteen years' worth of hourly energy usage data from a Kaggle open source dataset. In addition, a Long Short Term Memory (LSTM) and Convolution Neural Network (CNN) based method for estimating energy consumption based on actual datasets is presented in the research. The empirical findings demonstrate which LSTM and CNN architectures can improve energy consumption forecasting accuracy.
Keywords –Power consumption, LSTM, CNN, prediction

1. INTRODUCTION

The rapid developments of motorized cars, extensive machine systems and international market trade have all contributed to the current tremendous growth in energy demand. This has been made possible by the Smart Meter Infrastructure [1], which combines smart grids with active power distribution systems to provide effective and reliable short-term energy forecasting systems [2]. Power framework specialists should create and execute new strategies as the quantity of machines expansions to really control power use in light of buyer interest. A methodology for modern energy the executives to think about this issue could be energy use examination and estimates. However, creating an effective mathematical model of energy consumption is difficult task since it has nonlinear uniqueness and is dependent on a number of elements [3]. Therefore, it's essential to consider the primary aspects that influence energy use before developing a sound consumption forecasting strategy. Statistical machine learning techniques have been more popular recently [4] because of their accomplishments in the fields of computer vision and energy consumption prediction. The Machine Learning (ML) techniques used by [5] to predict energy consumption were Support Vector and Gradient Boosting Machines (SVM & GBM), RF and ML Regression. Compared to other ML algorithms, GBM fared better in this case. [6] looked on the relationship between equipment and occupant behavior and energy use. Additionally, [7] has presented a classification method based on the power usage patterns of 15500 plus built-up homes using a K-means cluster and SVM algorithms. This method is used to categorize the energy consumption rating. As a result of their inability to handle more complex data, statistical machine learning algorithms, on the other hand, are constrained in their ability to provide answers that are more correct. Deep learning methodologies, as an advanced methodology, can replace statistical approaches due to its significant contribution to the pattern recognition and prediction processes. As a result, a strategy is used that uses LSTM and CNN technology with hourly historical energy use data. Data pre-processing and data rearrangement processes are combined in the initial section of our study. In the second stage, LSTM and CNN networks were used, and the rearranged data was fed into the recommended network to efficiently learn the sequence pattern of input. The prediction is then tested using error metrics by comparing the real and forecasted data series acquired from our suggested network. The outcomes of our experiment show that the recommended LSTM & CNN algorithm successfully improves energy consumption forecast accuracy and identifies which is optimal. "Estimation of Energy Utilization in Machine Learning," by EvaGarca-MartnaCrefeda FaviolaRodriguesb, GrahamRileyb, and HkanGrahna are the current software tools (RNN) that provide energy estimation values. They also present two application examples that expand on the study of energy consumption in machine learning. Machine learning for energy consumption prediction and scheduling in smart buildings" was written by SafaeBourhnane, Mohamed RiduanAbid, RachidLghoul, Khalid Zine-Dine, NajibElkamoun, and DrissBenhaddou. "They employ hypothetical models that have been validated against real-world data from a PV system and SB electrical appliances." The prediction accuracy of this model is low due to the small size of the data set. This can be used to create practical SB test beds as well as investigate machine learning and energy planning. In their paper titled "Predicting Electricity Consumption Using Deep Recurrent Neural Networks," AnupiyaNugaliyadde, UpekaSomaratne, and Kok Wai Wong present the newest software tools (LSTM) that give energy estimation values as well as two use cases that

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improve the study of energy consumption in machine learning. "Energy consumption prediction using machine learning for smart buildings: Case study in Malaysia," by Mel Keytingan The prediction model's methodology was developed by ShapiaAzuana M. LilikJ.Awalin using three techniques: k-Nearest Neighbor, Ramlib Support Vector Machine, and Artificial Neural Network. Two tenants from a commercial building serve as case studies to demonstrate real-world application in Malaysia. The RMSE, NRMSE, and MAPE metrics are used to compare the performance of each technique. The experiment results show that the distribution of energy use varies by tenancy. Based on these papers, the PJM Hourly Energy Consumption Data was chosen as the dataset. PJM Interconnection LLC (PJM) is an American regional transmission company (RTO). It maintains an electric transmission network that serves parts of the United States as part of the Eastern Interconnection grid. PJM provides information on hourly electricity consumption in megawatts (MW). Because the territories have changed over time, statistics for each region may only be available for a few specific dates.

PROBLEM STATEMENT

Project can be used in places where there is

i. i. Overconsumption: The energy issue is the result of multiple demands being made on our natural resources, not just one. Pollution is caused by the over use of fossil fuels like oil, gas, and coal, which deplete our oxygen and water supply.

ii. Overpopulation: The issue has been made worse by the increase in global population as well as the demand for products and fuel. No matter the food or product you use, whether it is fair trade, organic, or made in shops with fuel materials, none of them can be produced or shipped without putting a significant strain on our energy resources.

iii. Poor Infrastructure: Another source of energy constraints is the infrastructure of aged power generation technology. The majority of energy-producing businesses still rely on antiquated equipment, which restricts energy output. Infrastructure maintenance and modernization must be done while assuring optimum performance, according to utilities.

iv. Alternatives to Renewable Energy That Have Not Been Examined: Most nations are currently underutilizing renewable energy. Energy is primarily derived from nonrenewable resources like coal. As a result, it is still the best option for producing energy. If don't take renewable energy seriously, then won't be able to solve the energy situation. Renewable energy sources can assist us in lessening both our reliance on fossil fuels and our carbon impact.

v. Power Plant Commissioning Delays: In a few countries, the commissioning of new power plants that can close the gap between energy demand and supply is experiencing a severe delay. Old plants are therefore under a lot of stress to produce enough electricity each day. When supply and demand are out of balance, load shedding and breakdown occur

vi. Energy Waste: The majority of people worldwide are ignorant of the value of energy conservation. Books, the internet, newspaper ads, lip service, and seminars are the only sources of information. Until take it seriously, nothing is going to change anytime soon. Utilizing daylight as much as possible, walking short distances rather than driving, switching to CFLs from incandescent bulbs, and installing energy-efficient insulation can all help cut down on energy usage.

vii. Poor Distribution System: A poor distribution system frequently experiences tripping and failure.

2. *MOTIVATION*

The past few decades have seen an exponential rise in the use of electricity. Electrical wholesalers are under a lot of pressure as a result of this increase. As a result, the electricity distributor will have an advantage by estimating future electricity use. A blackout will occur if the amount of electricity provided to the grid does not match the amount of electricity used. This has became much more difficult with the rise of renewable energy, which can vary dramatically depending on the weather. Traditional power plants must make up for these swings since significant amounts of electricity cannot be stored for extended periods of time. The electrical frequency increases when there is an imbalance between the amount of power used and the amount that is transferred into the grid. Power plants have a potential of disconnecting from the grid after a while because they are made to operate within a specific frequency range. Our application, along with its use in electric grids and by energy suppliers to stay on guard through consumption projection, can help small business owners, office building owners, and even little colonies or houses keep track of their usage, in addition to its use in these areas. They may fill out the form with all the necessary information and get a statistical breakdown of their energy usage, which may help them figure out why their bill was so high at any given moment.

3. *DEEP LEARNING MODELLING*

A. *LSTM*

Power distributors must be able to predict energy demand for their clients' short- and long-term energy management and conservation. As a result of noise or other unforeseen circumstances, data may become jumbled, making it impossible to forecast real energy use and, in some cases, erroneous projections. Furthermore, systems typically have a limited short-term memory and must occasionally learn from scratch. This study has begun to employ LSTM, a type of recurrent neural network (RNN) that has seen tremendous success in the field of machine learning, to address these challenges. An LSTM network's output is typically affected by contextual cells that correlate previous knowledge with current prediction results. This way of operation generates more precise forecast results in the context of energy consumption prediction since load prediction is based on customer propensity. The recommended network's special gating structure also prevents the vanishing gradient issue, leading to predictions that are more precise. Figure 1 illustrates the exact structure of the LSTM-based energy consumption projection. In order to forecast energy use for the following time stamp, the proposed network uses three LSTM layers to constantly train and extract characteristics from hourly energy consumption data. The core architecture of the LSTM handle and analyse data from the input energy usage dataset using long or short term memory cell gates. The forget gate, the input gate, and the output gate control the LSTM IN input node. The forget gate Fg, which is the first step of the LSTM, receives the output from step Pt1 and the later input of the current state Nt. It then executes a sigmoid operation to keep or discard data based on a value between 0 and 1, depending on the value. In eq 1, the forget gate Fg's output is displayed.

$F_{g} = \alpha(W_{Fn}N_t + W_{Fp}P_{t-1} = b_f)$ ------- (1)

The hyperbolic tangent function, or tanh, is then used by the input gate Ig to update the value of the current state, as illustrated in eq 2.

$I_{g} = \alpha\ (W_{iN}N_t+W_{Fp}P_{t-1} = b_i)$ -------- (2)

Finally, the output gate Og performs both the sigmoid and tanh functions to calculate the output based on the cell state stated in eq 3.

$O_{g} = \alpha\ (W_{On}N_t+W_{Op}P_{t-1} +b_o)$ ------- (3)

The forget, input, and output gates' biases are bf, bi, and bo, respectively, while the weight matrices are WfN, WfP, WiN, WiP, WoN, and WoP.

The output gate's elementwise multiplication and tanh operations result in the intermediate output Yout of internal memory cell state St1, which is denoted by the equation 4.

$Y_{out} = \varphi(S_{t-1})\theta O_g$------- (4)

A leaky ReLU layer that conducts a threshold operation for which the input is multiplied by a fixed scalar if it is less than zero is being utilised as the activation function. This is demonstrated in eq 5.

$F(Y_{out}) = \{\ Y_{out}\ ,\ \ Y_{out}>= 0\ \&\alpha * Y_{out,} Y_{out}<0$

B. *CNN*

The network employs the convolutional mathematical approach, hence the name "convolutional neural network." Convolutional neural networks are having Convolutional layers, Fully connected layers and Receptive field.

PROPOSED OPTIMIZATION METHOD

In order to determine which time of day uses the most energy and to display a time-by-time graph of energy consumption, we need to be able to analyze over 15 years' worth of energy consumption data from our source (a csv file) and visualize it in the form of graphs and tables that show year-over-year energy consumption, month-over-month energy consumption, and variation in energy consumption throughout the day. Finally, using the CNN deep learning algorithm, forecast energy consumption for the upcoming year based on the data from the previous year that is contained in our csv file. Shallow CNN, a two-layer feed forward network is used together with multiple regressions to produce the same results. Next, locate a better version to optimize using LSTMA feed forward neural network is a type of artificial neural network where there is no looping in the connections between the nodes. It differs from its offspring, recurrent neural networks, as a result. The first and most basic artificial neural network to be created was the feed forward neural network. Information only moves forward in this network. As a result, they don't have as many variables, which lowers the prediction's accuracy. To overcome this issue, which has never been done before in any of the research articles have looked at, we'll learn how to design an LSTM network.LSTMs would be more precise than CNN because they are designed specifically to deal with the issue of long-term reliance. It comes naturally to them, so they don't have to work very hard to remember things for a long time. The LSTM's repeating module has a unique structure. It is possible to add more variables because there are four neural network layers instead of only one, each of which interacts differently. Such a method will deal with the issues of speed and accuracy that the CNN architecture will experience. It is essential to be able to predict an area's energy consumption since it enables locals to conserve energy and reduce waste. Due to uncertainty and disorderly noise, it can be difficult to estimate where energy consumption will be.The method for estimating energy consumption in residential structures that is suggested in this article uses a deep extreme learning machine (DELM). The suggested method has four main layers: data collection, preprocessing, prediction, and performance assessment. The specific data used in the experimental work at the data acquisition layer. Moving average was employed in the preprocessing layer to filter out data oddities. To improve the accuracy of the findings for energy consumption, the deep extreme learning machine (DELM) has been proposed for the prediction layer.

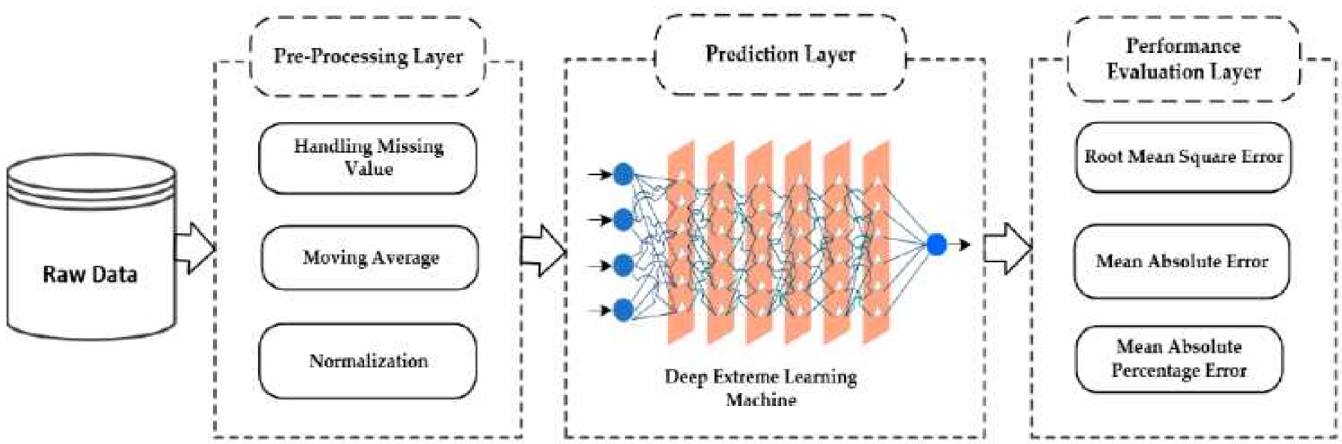

Fig 1: Flowchart showing how Deep Learning Works

4. RESULTS

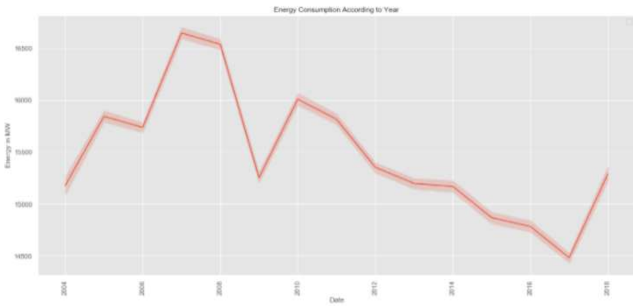

Fig 2: Energy Consumption of yearly basis

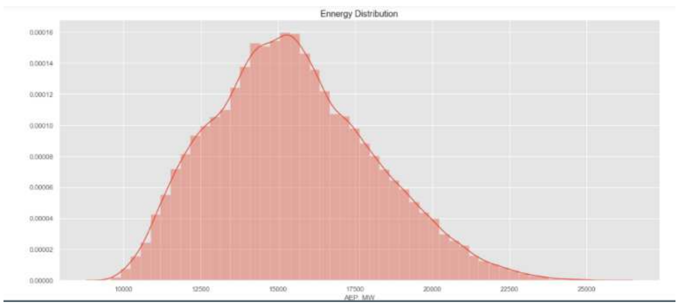

Fig 3: Energy Distribution

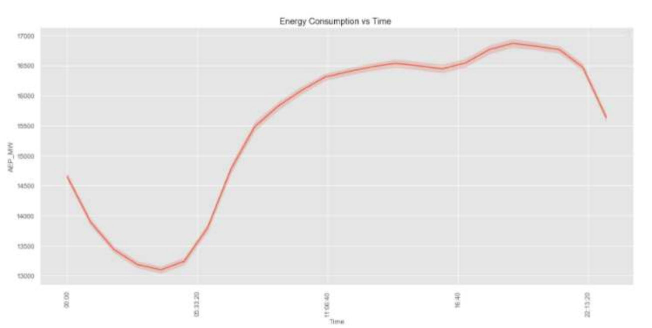

Fig 4: Energy distribution of hourly basis

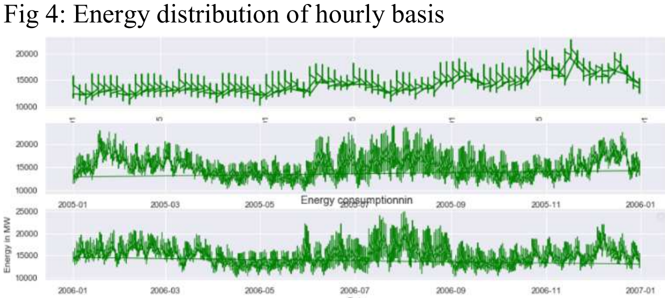

Fig 5: Energy distribution of year 2014, 2015 and 2016

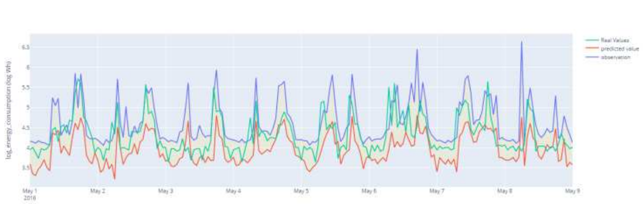

Fig 6: Energy predicted using CNN

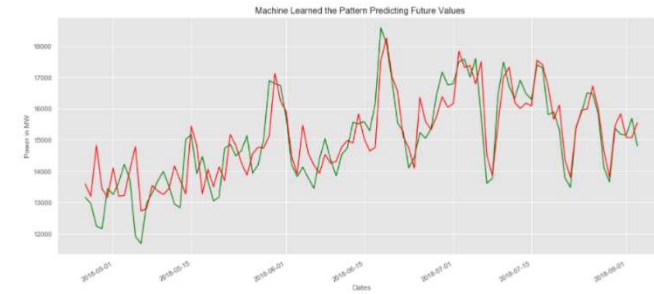

Fig 7: Energy predicted using LSTM

5. RESULT ANALYSIS

According to our initial hypotheses, the results are as expected. LSTM outperformed CNN in prediction tasks like energy prediction because it excels at dealing with sequential data and takes previous inputs into account to get the required output.

Type	Error
LSTM	0.45%
CNN	4.27%

6. CONCLUSION

Due to noise and variability, predicting energy consumption in a region is a challenging undertaking. In order to improve forecast accuracy, A model in this study is created for estimating energy use in residential projects. Data collection, preprocessing, prediction, and performance evaluation were the four stages of the suggested model. To test the model and examine the results, data was gathered using smart meters in a chosen building in the data collecting layer.Some preprocessing operations were carried out at the preprocessing layer to decrease abnormalities in the data.A deep extreme learning system is proposed for estimating one-week and one-month energy consumption in second stage regions using pre-processed data. It was intended to increase the accuracy of the results for practical applications by utilizing a variety of machine learning techniques.

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