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Implementing the Optimum LSTM Optimizer for Power Consumption

Dr Kanmani P[1], Anjali.S[2], Sakchi Choudhary[3]

[1]*Department of Data Science and Business Systems, SRM Institute of Science and Technology, Chennai, India*
[2] *Department of Data Science and Business Systems, SRM Institute of Science and Technology, Chennai, India*
[3] *Department of Data Science and Business Systems, SRM Institute of Science and Technology, Chennai, India*

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Abstract - Electricity is an essential component that can't be overlooked in any home anywhere in the world. It is one of the most important attributes that determine a person's overall standard of living. When we look at the quantity of energy consumed in a certain household, one of the most significant factors to take into consideration is the amount of power consumed. The term "power consumption" refers to the amount of electrical energy that is used during a particular period of time. The department for power supply can better comprehend the power consumption of residents and also predict whether or not there will be any anomalous power consuming phenomena by analyzing the power consumption of any individual household.

The utilization of energy in homes is responsible for roughly one third of the total demand for primary energy on a global scale and has a substantial impact on the environment. The purpose of this article is to determine which optimizer produces the most accurate results when estimating the amount of electricity that will be used over the next 12 days by building an LSTM model. LSTM is one of the deep learning models that is utilized most frequently. It is also one of the best models to employ for projecting events that will occur in the near future.

Key Words: power consumption, LSTM, Adam, Adadelta, SGD, RMSprop

1.INTRODUCTION

Electricity is a fundamental factor of nature and one of the most extensively employed types of energy. Electricity is a secondary source of energy used by humans and is produced by converting primary energy sources including coal, natural gas, oil, and nuclear energy. Primary sources are the first natural sources of electricity. Numerous villages and cities were constructed next to waterfalls, which were used as the main source of mechanical energy for water wheels and before the advent of electricity generation a little more than 100 years ago, kerosene lights were used to illuminate homes, iceboxes were used to keep food cold, and wood or coal burning stoves were used to heat rooms. Electricity has grown to play a significant role in improving people's quality of life and reviving the country's economy.

There has been a lot of progress and development in the usage of electricity thanks to the discoveries of scientists, and this is all due to the discovery of electric energy, which sparked the creation and invention of technologies that changed their era. The light bulb, invented by Thomas Edison, is widely regarded as one of the most significant innovations in human history. The telegraph, created by Samuel Morse in 1837, was eventually wired to continents as far apart as Europe, the United States, and India. In 1876 A.D., physicist Alexander Graham Bell developed a method to transport sound over great distances using electrical current flowing in copper wires and converting sound to electrical current. The generation, transmission, and use of alternating electricity (AC) and the resulting reduction in the cost of transporting electricity over long distances were all contributions made by Nikola Tesla, whose inventions enabled people to power their homes' interior lighting and factories' industrial machinery.

Energy utilization is measured in terms of its usage over a given time period. In digital systems, power consumption is crucial. The amount of electricity used by portable equipment like cell phones and laptops determines how long their batteries will last. Power usage is typically reported in watts (W) or kilowatts (kW). Always more power isconsumed by machines than is necessary. Since no machine can function flawlessly, this is inevitable. Some portion of the input energy is lost as heat, vibrations, and/or electromagnetic radiation. A light bulb, for instance, generates some heat in addition to light when electricity is transformed by it.

The mapping of energy flows in a structure or system can be accomplished through measuring energy usage. Unnecessary energy use and irregular consumption patterns become apparent. Even more so, a clear picture of a world where systems are out of sync emerges. When monitoring consumption at different sites or buildings, it is possible to make useful comparisons. Reduced energy usage, lower energy expenditures, and better operational results are the direct result of analysing monitoring data and implementing solutions.

Forecasting the power consumption of a particular household is also important to be prepared for upcoming challenges that may be faced in the future. LSTM is one of the best models to be used for short- term forecasting and to give a good forecasting performance we need to use the best possible optimizer. In this study we are using the household power consumption dataset to determine the optimum LSTM optimizer to be used to get the best results.

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MOTIVATION

The need for electricity in our everyday lives is only going to rise significantly; we have an increasing responsibility to conserve as much of it as we possibly can for use in the future. Efficient use of power can significantly benefit from sustainable development's many positive effects. The Long Short-Term Memory Model, sometimes known as LSTM, is frequently employed for short-term forecasting. If this model is constructed using the most effective optimizer, then the model will have the capability of precisely predicting the amount of electricity that will be consumed over the course of the following couple of days. The process of forecasting takes a significant amount of time in and of itself; utilizing the most effective LSTM optimizer will make the process much simpler. The users will also be able to anticipate the potential power crises that they may face in the not-too-distant future with the help of the model

2.OBJECTIVE

In view of the ever-increasing presence of electrical equipment in modern life, the ability to monitor one's own electricity consumption has become an essential skill to have. The power supply department is able to better comprehend the power usage of residents with the help of household power consumption. When the cost of a family's power bill is unreasonably high and they have not made sufficient preparations for such a scenario, it may be challenging for the family to make ends meet and maintain their standard of living. This project intends to facilitate future prediction and forecasting with an LSTM model and be well prepared for forthcoming issues by selecting the most effective optimizer for this model.

3.LITERATURE SURVEY

Steemers, K. and Yun, G.Y. established the various variables and to what extent these variables affect the energy performance of a housing stock with the help of a statistical analysis. The residential sector in the US is used to evaluate how socioeconomic status and behavioral traits of various people affect these variables. The Residential Energy Consumption Study (RECS), a current comprehensive survey conducted by the US Department of Energy, is used to examine the energy consumed in household heating and cooling. This dataset contains data on actual energy use as well as specific energy-related details about the residential units and the people who live in them.

Saoud, L.S., Al-Marzouqi, H. and Hussein, R. introduced an innovative technique utilizing machine learning models based on transformers and the stationary wavelet transform (SWT) to predict power usage for a specific household at various resolutions. Deep transformers are utilized to predict the SWT sub-bands. The data on actual and projected home power consumption is decomposed and rebuilt separately with the help of the SWT and its inverse. According to the experimental results, this hybrid strategy outperforms other power consumption prediction algorithms.

Kotsila, D. and Polychronidou, P. discussed that over the last few decades, the contemporary manner of life and the advancement of technology have increased the use of power. Excessive power use harms the environment by accelerating climate change and increasing carbon footprint. Given how much the residential sector contributes to energy usage, it is important to look into the socioeconomic factors, climatic factors, and household-specific electricity consumption patterns. Two statistical models were created from the data that was gathered from 1801 homes across all of Greece for this study. According to both the authors, the majority of important factors impacting electricity usage are the number of occupants, the dwelling size, the kind of heating used, the number of hours spent on heating and cooling, and the weather.

Tewathia, N. analyzed the factors that affect a household's power usage with the help of a questionnaire research with 395 Delhi households chosen using a stratified random selection technique. In order to describe the pattern of residential power consumption, a multiple regression model was created. According to the study's findings, a household's collection of appliances is what accounts for the majority of its power use.

Han, X. and Wei, C. intended to evaluate the state, evolution, and upcoming themes in this field by a network analysis of 1134 retrieved papers from the years 1983 to 2018. Recent research has also shown that, among the contributing nations, China and USA have the strongest relationships and the greatest global academic influence. The study may benefit from new and innovative research on behavioral therapies, energy efficiency, energy poverty, the environment, and power usage.

Qin, J. established an extendable framework for experimental analysis and studied the data in a visual manner. This experiment studied the impact of the neural network model and the linear regression model on several variables. According to the study's findings, the linear regression model performed worse than the neural network model for the experimental dataset.

Payne, J.E. discussed a study on empirical literature and a discussion of the numerous theories proposed to explain the causal link between electricity use and economic growth. The study focused on characteristics such as nation coverage, model specifications, econometric techniques and various methodological issues. According to the survey's findings for the particular nation, 31.15% of respondents backed the neutrality hypothesis, followed by 27.87% who supported the conservation hypothesis, 22.95% who supported the growth hypothesis, and 18.03% who supported the feedback hypothesis.

Fischer, C. proposed the most effective feedback type. He provided a psychological model that clarifies how different types of feedback function and why they are important. The usefulness of feedback may depend on a number of pertinent characteristics, including its breakdown, medium, frequency, duration, presentation method, and interaction with other tools. The study goes on to examine global practice in order to uncover actual data regarding the best types of feedback. The most effective feedback appears to combine the following features: it is presented in a clear and appealing manner, it provides an appliance-specific breakdown, it is given frequently and over a long period of time, and it uses computerized and interactive tools, despite the fact that there were significant data limitations and research gaps.

Ghosh, S. examined the Granger causation between electricity consumption per capita and Gross Domestic Product (GDP) per capita for India utilizing annual data spanning from the years 1950–51 to 1996–97. After logarithmic transformation, Phillips-Perron tests showed that both series are non-stationary as well as individually merged into a single series. According to this analysis, there is no long-run equilibrium link between the variables, but there is a one-way Granger causal relationship that connects economic development and electricity consumption without any negative feedback. Therefore, initiatives for energy conservation can be implemented without having negative economic side effects.

Ma, X., Wang, M. and Li, C. contradicted between energy supply and demand. This work uses the bibliometric method to examine the growth of this research field utilizing the literature published in the field of domestic energy consumption between the years 1970 and 2018 as per the databases of Science Citation Index Expanded and Social Sciences Citation Index

4. EXPERIMENT

4.1 About the Dateset

This dataset contains values of electric power consumption in intervals of minutes for 4 years from December 2006 to November 2010. Different electrical entities like Global Reactive Power, Global Active Power, Voltage, Global Intensity and few sub-metering values are also available. The characteristics of the dataset include multivariate analysis and time series analysis. This dataset contains all calendar timestamps but a few timestamps are missing such as April 28, 2007.

4.2 Methodology

First, all the necessary libraries are imported. Date and time columns are combined as dt after reading the dataset and formatting it into datetime format. We remove all the null values and fill the missing values with the mean value. A new column is created as power consumption using the formula:

EQ1 = (Global Active Power x 1000)/60

EQ2 = Sub Metering 1+Sub Metering 2 + Sub Metering 3

Power Consumption = EQ1 - EQ2

Second, we remove the data for the year 2006 as it is very limited and could hinder further analysis. Then, we remove

every column except dt and power consumption and create a new dataset. The new dataset is resampled into daily averaged data, MinMaxScaler is used for data preprocessing.

Third, we are splitting the new resampled data into training and test data transform a range of values to a dataset matrix. We size timesteps at twelve.

Finally, the code for LSTM is executed and the RMSE of each optimizer is determined, after which the RMSE values from each optimizer are compared to one another to determine which optimizer is the most suitable for the LSTM model in predicting future power consumption. The optimizers compared are Adam, Adadelta, SGD and RMSprop

Fig. 1 Methodological Structure of LSTM Model

4.3 LSTM Architecutre

There are various kinds of architectures, and the ones that are utilized are determined by the problem that needs to be solved. In this study, architecture is utilized in order to determine the

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best feasible optimizer for LSTM by forecasting it for a short period of time.

The forget gate f_t is responsible for removing information from the cell stateThe forget gate accepts two inputs; h(t-1) representing the previous cell's output or a hidden state and x(t) representing the input at that period of time as shown in Fig.2. These two inputs are multiplied with weight matrices and summed with a bias. Then, a sigmoid function is used to to determine which information to retain and which to drop. If the output is '0,' the forget gate aids the cell state in dropping the information; if the output is '1,' the forget gate aids the cell state in retaining the complete piece of information. Different optimizers are used to tune the weights and learning rate to reduce the loss.

The input gate i_t is responsible for adding information to the cell state using a sigmoid function. A vector containing perceived values from h(t-1) and x(t) is constructed and added to the cell state with the help of the tanh function, which returns values between -1 and +1. The sigmoid gate value is then multiplied with the tanh function vector and placed into the cell state.

At the output gate O_t, the tanh function is used to create a vector with values between -1 and +1. It creates a filter from the values of h(t-1) and x(t), so that it can add the values from the vector using a sigmoid function.

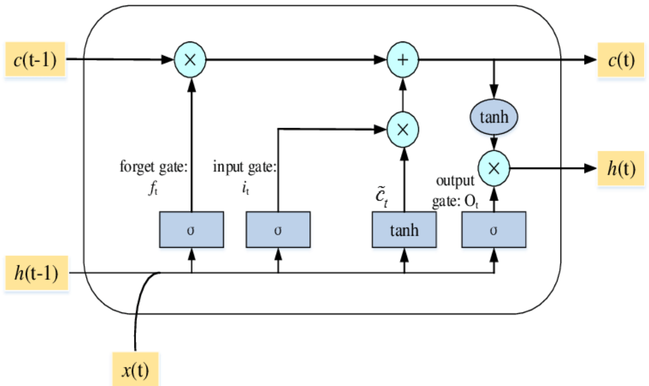

Fig. 2 LSTM Architecture

The basic overview of how the structure of the model built is shown in Fig.3

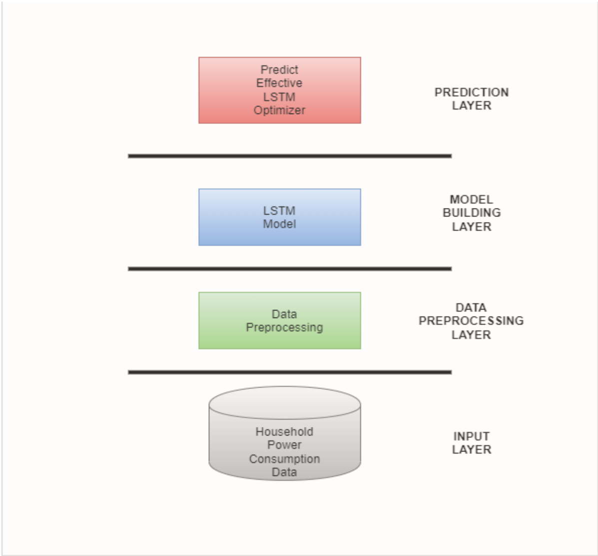

Fig. 3 Overview of the LSTM Model Structure

5. RESULTS

The LSTM model was built with four different optimizers namely, Adam, Adadelta, SGD and RMSprop. The error metrics used to compare the optimizers was RMSE (Root Mean Square Error), the equation defining this metric is as below:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - a_i)^2}$$

where *n* is the number of samples to be predicted and, *pi* and *ai* are the predicted and actual values of the i-th sample, respectively.

Table.1 shows the optimizers with their respective RMSE values and it is depicted in the decreasing order. We can conclude from the table that the most effective optimizer for LSTM model is Adam with an RMSE value of 1.735 and the second best optimizer is SGD with an RMSE value of 1.783.

OPTIMIZER	RMSE
ADAM	1.735
SGD	1.783
RMS PROP	1.838
ADADELTA	5.464

Table 1. Comparison Table of Different Optimizers used for the LSTM Model

Fig. 4 shows the comparison of RMSE values of different optimizers. Adam, SGD and RMSprop have a comparatively good RMSE value than Adadelta.

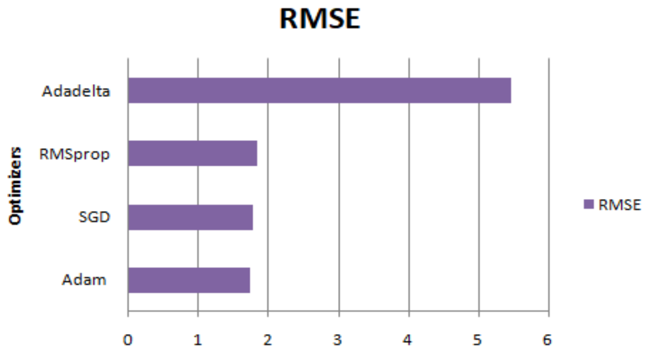

Fig. 4 Comparison Graph of Different Optimizers used for the LSTM Model

Fig.5 shows the graph between the predicted and actual values of the average power consumed in a day using the Adam optimizer. It is clearly seen that the values are almost close and it proves that Adam optimizer is the most effective optimizer.

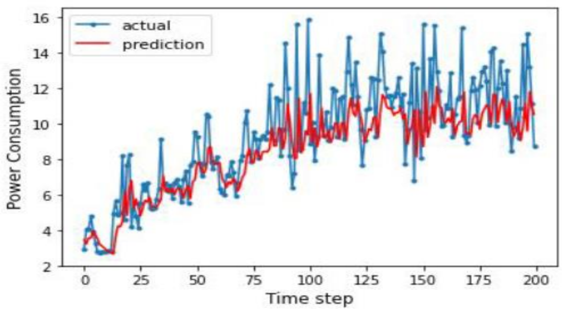

Fig. 5 Actual vs Predicted Graph using Adam Optimizer

Fig.6 shows the graph between the predicted and actual values of the average power consumed in a day using the SGD optimizer. It is clearly seen that compared to Adam the SGD optimizer predicts values less accurately.

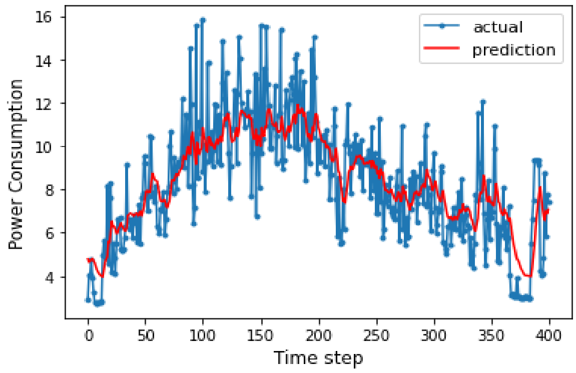

Fig. 6 Actual vs Predicted Graph using SGD Optimizer

Fig.7 shows the graph between the predicted and actual values of the average power consumed in a day using the RMSprop optimizer. It is clearly seen that the values are not predicted as accurately as Adam or SGD

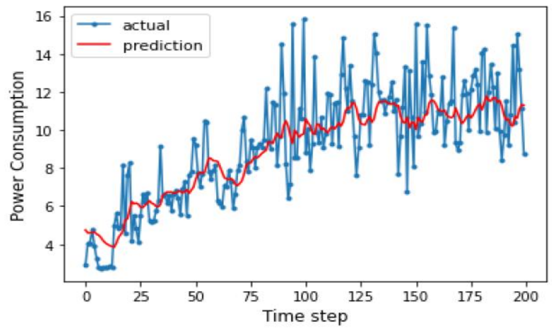

Fig. 7 Actual vs Predicted Graph using RMSprop Optimizer

Fig.8 shows the graph between the predicted and actual values of the average power consumed in a day using the Adadelta optimizer. It is clearly seen that there is no link between the predicted values and the actual values

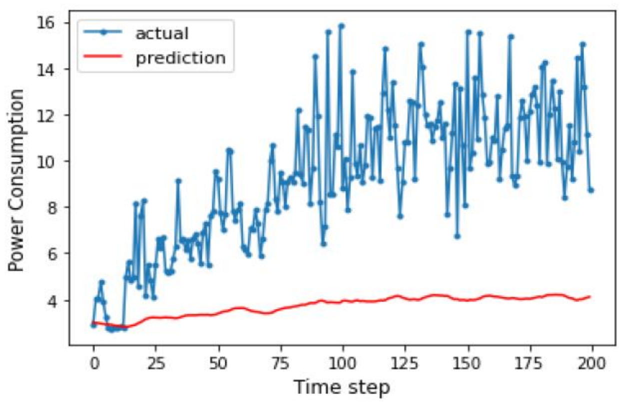

Fig. 8 Actual vs Predicted Graph using Adadelta Optimizer

6. CONCLUSION

Optimization methods such ADAM, SGD, Root Mean Square Propagation, and ADADELTA were used to execute the survey. There are optimization algorithms that can be utilized to resolve complicated issues. Then, in order to gain a better analysis of the many features of the algorithms, a thorough survey was carried out. Results of the optimization techniques are better when local optimal solutions prevent trapping. In terms of optimizing numerical functions, ADAM outperforms the other algorithms that were chosen. We want to use it in the future to evaluate the algorithm's performance using a subsample of the dataset. This makes it feasible to determine which algorithm is drawing out more data from the data

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