Original Article

Enhanced LSTM Model for Data Center Energy Consumption Forecast

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Abstract - High-energy consumption is a major challenge most sectors face, including data centers. the data center sector accounts for about 3% of the world's total energy consumption, which has been predicted to keep increasing. Most data centers are run for profit-making, and the high-energy usage makes them expensive to operate. This high-energy consumption also causes environmental pollution due to the emission of greenhouse gases. Forecasting energy consumption for data centers is important in decision-making for effective energy saving. This study considered statistical, machine learning, and deep learning algorithms. Dataset was obtained from the EnergyPlus simulation platform. the simulation was informed by the information gathered from one of the leading data centers in Lagos, Nigeria. the algorithms considered were ARIMA, SVR, and LSTM. These algorithms were compared to determine an optimal algorithm using five (5) performance evaluation metrics: MSE, RMSE, MAE, MAPE, and Accuracy. the optimal algorithm was modified and utilized to develop a model. This is a step towards producing an accurate energy consumption forecast tool for data centers.

Keywords - Algorithms, Data Centre, Energy, Machine Learning, Model.

I. INTRODUCTION

Data centers have been affirmed to have a stronghold in today's global economy**.** They are centralized facilities used for the storage and processing of data; they are computing structures that contain servers or Information Technology (IT) equipment that store, process, and manage digital data information [18] [1]. One of the most key issues data centers face is energy management. Growing energy costs and environmental responsibility have put the data center sector under pressure to improve its operational efficiency [9]. the rise in the use of personal and enterprise applications is related to more computational tasks and larger demand for storage by data centers, causing an increase in data center electricity utilization [16].

in its various ways, energy is a crucial element of modern society. the ubiquity of machines, computer devices, and various technology-driven instruments further makes the importance of electrical energy more pronounced. the connectedness of computers that has affected our lives this much would not have been possible without data centers. Data centers are homes for various servers and infrastructures that have made the internet possible. Data centers use a huge amount of energy as all the components need always to be active to make the internet available to everyone at any time. A good percentage of maintaining data centers is centered around energy costs [24].

Therefore, the importance of efficient energy usage by the data centers cannot be overemphasized. Over the years, several types of research have further clarified the need for data centers to manage their infrastructures to accommodate low cost, speed in service delivery, reduction in energy consumption, and hence minimization of carbon-dioxide emission. Energy efficiency in data centers, especially IT resources, is very important for data centers' density, scalability, and reliability [4].

Consequently, data centers account for almost 3% of the world's electricity consumption; they have a considerable impact on the environment, both negatively and positively. One of the major positive impacts of a data center is the internet. Data centers contain servers that make content hosting possible, making the internet more usable. Data centers have indirectly improved the way we learn and enhance interaction and connectivity between individuals and organizations.

The negative impact of data centers is in the energy consumption, especially when energy consumption is not rightly optimized [25]. Consequently, attention has been shifted towards techniques to reduce energy usage. Many studies have recommended different techniques that encourage reduced energy consumption and foster efficient resource utilization. the negative impact of this energy

consumption is not just about the cost of energy to power the data center but also the environmental factor, which is carbon dioxide emission. the research and market report says industries like manufacturing, transportation, and buildings are expected to increasingly use efficient data centers to help lower their own emissions footprint. the growth in artificial intelligence, machine learning, and other intelligent systems is also encouraging growth in the area [28].

II. REVIEW OF LITERATURE

Energy issue in the data center has raised concern in the research world. Many researchers have suggested techniques (hardware and software) and metrics that efficiently deploy attention to reduce energy consumption in data centers [17]. [23] examined hardware and architecture techniques and suggested methods for lower energy usage simultaneously, achieving lower PUE and satisfying cloud services. Consequently, the energy consumption model by [25] affirmed that data center architectures and server's topology and scalability are crucial in ensuring reduced power usage and equipment. [15] identified uncertainty as one of the major problems to energy optimization in data centers. the paper emphasizes the impact of effective prediction and forecast on reducing energy consumption in data centers. Although, the paper proposed using game theory for planning in data center management. Likewise, the need for prediction in policy-based was also emphasized in [6] and [5]. Energy forecasting is an approach used to predict future energy needs to achieve demand and supply balance [22]. As power cannot currently be stored in huge sums, the system administrator must always match or balance supply and demand. Accurate energy demand forecasting plays a critical part in this. Forecasting energy demand is critical for organizations. A range of factors influences electricity consumption: Weather, cost, and financial matters notably affect demand. Forecasting energy demand also requires an understanding of consumer behavior [11].

Various methods have been applied to data center energy forecast [3], [8], [12], [14], [19], [21]. the data center energy forecast approaches include machine learning, probabilistic, linear regression, and deep learning. [29] proposed an online energy-saving framework for data centers using reinforcement learning and intelligent feedback. [13] developed a predictive type of control for highly nonlinear and complex systems. An Artificial Neural Network (ANN) model that can predict and control server temperatures in significantly less time was proposed. [8] proposed a neural network for forecasting energy consumption in data centers. Their approach combined Artificial Neural networks (ANN) with Evolutionary Computation (EC). the genetic algorithm was used as the evolutionary algorithm.

[10] proposed to investigate the correlation between the weather conditions and the energy consumption in DCs. Effectively forecast the energy consumption based on the weather forecast. Provide an energy consumption forecast procedure to stakeholders and data center operators. the study exploited the effects of weather conditions to forecast the energy consumption of data centers. Multivariable linear regression was used, and to validate the model, they used live measurements from real data center datasets. However, few training sets were used for the learning process. A larger training set will enable the use of more advanced machine learning techniques like ANN and SVM. [27] used a time series probabilistic algorithm to forecast wind and solar energy consumption. the papers applied Seasonal Autoregressive Integrated Moving Average (SARIMA). Both short-term and long-term forecast was made with the SARIMA model. [26] proposed an ensemble-based energy prediction model to forecast the data center's energy demand and flexibility. the study adopted a Genetic Algorithm to generate a data center energy model heuristics.

III. DATA COLLECTION

Dataset was obtained from a simulated data center built using EnergyPlus simulation software. the simulation was informed by the information gathered from one of the leading data centers located in Lagos, Nigeria. It spans from the year 1980 to 2020. the type of dataset used is a numerical dataset in time-series format. the dataset size is 14966 rows and 6 columns. the columns are the features in the dataset. It was discovered that the dataset used contains some redundant variables or features, which makes it unsuitable for developing the proposed model that will forecast data center energy usage. the correlation feature selection method was adopted to take care of the dataset inadequacies so that only the relevant features were used. the data was split using the 80:20 ratio.

IV. ALGORITHM PERFORMANCE EVALUATION

Performance evaluation of three algorithms was carried out using the test data to determine the optimal algorithm for the data center energy consumption forecast model. the algorithms are Autoregressive Integrated Moving Average (ARIMA), Support Vector Regression (SVR), and Long Short Term Memory (LSTM). the choice of these algorithms was based on the type of data available for this study and how well they perform. the performance of the algorithms was calculated based on five performance metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Accuracy.

Table 1. Metrics value for the three Algorithms

	ARIMA	SVR	LSTM
MSE	0.874	0.049	0.016
RMSE	0.935	0.220	0.126
MAE	0.623	0.071	0.036
MAPE	0.44	0.39	0.12
ACCURACY (1 - MAPE)	56%	61%	88%

LSTM recorded the highest accuracy and lowest error values, followed by SVR and ARIMA. the generic LSTM architecture will further be modified and used to develop a model.

A. Long Short Term Memory (LSTMs) Algorithm

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network capable of learning order dependence in sequence prediction problems [7].

LSTMs have an advantage over the traditional feed-forward neural networks and Recurrent Neural networks in different manners. This is due to their property of selectively remembering patterns for long periods. LSTM networks are suitable for classifying, processing, and making predictions based on time series data since there are often lags of unknown duration between important events in a time series. Compared to Artificial Neural networks, deep learning gives a deeper representation of the network by having more hidden layers and adding more appropriate regularization methods [2] [20]. LSTM is a recurrent deep learning model, which means it can remember what has happened previously and therefore makes it a usable algorithm for energy forecasts.

B. Enhanced Long-Short Term Memory (LSTM) Model

The generic LSTM algorithm was adapted while considering the seasonality and trend factors of the forecast model. the researchers' LSTM model contains four major layers instead of the generic LSTM model, which consists of three major layers. the first layer is the forget gate layer, the second is the seasonal gate layer, the third is the input gate layer, and the fourth is the output gate layer. the four layers regulate the cell states. As with the generic LSTM model, the cell states regulate the value of the cell state that is combined with the previous values to generate the value of the next prediction.

The forget gate regulates the amount of information allowed from the previous value; the seasonal state combines the input value with the previous value and decides if to keep the seasonal state of the cell. the input gate layer creates new states to be added to the cell state, while the output layer combines the cell state with input to generate the output for the model, as shown in Fig.1.
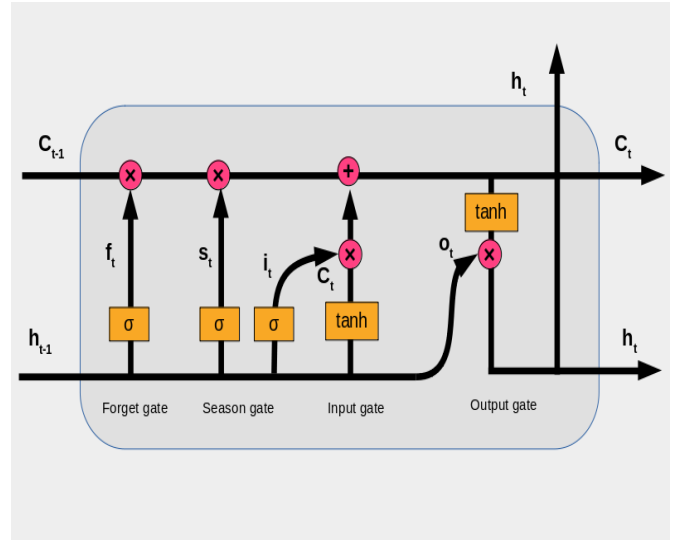

Fig. 1 Enhanced LSTM architecture

The addition and multiplication nodes are element-wise vector operations, while σ is a sigmoid operation that returns a value between [0,1]. Tanh is a function that returns values between [-1, 1]. the sigmoid formula is given in equation 1.

$$f(x) = \frac{1}{1+e^{-x}} \qquad (1)$$

Tanh function is given as in equation 2.

$$f(x) = \tanh(x) \qquad (2)$$

the mathematical representation and pseudocode for each of the layers are given below.
Building the LSTM takes two steps, which are:

1. FeedForward

2. BackPropagation

FeedForward is when the input is being combined with the weight to produce the output, whereas backpropagation is the process of learning the weight and training.

Enhanced LSTM Feedforward Algorithm

1. $X_t \leftarrow$ feature input

2. Compute current forget layer values as:

   $f_t =$ sigmoid($W_f . [h_{t-1}, x_t] + b_f$)
   Where W_f is the weight for the forget gate layer, h_{t-1} is the previously computed value, x_t is the current input values, and b_f is the forget gate bias.

3. Compute season gate layer as:

$$s_t \leftarrow \text{sigmoid}(W_s \cdot [h_{t-1}, x_t] + b_s)$$

Where W_s is the weight for the season gate layer, h_{t-1} is the previously computed value, x_t is the current input values, and b_s is the season gate bias.

4. Compute input gate layer as:

$$i_t \leftarrow \text{sigmoid}(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$C_t \leftarrow \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

where W_i is the weight for the season gate layer, W_c is the weight for the new value, b_c is the bias for the new value layer, h_{t-1} is the previously computed value, x_t is the current input values, and b_s is the input gate bias.

5. Compute output gate layer as:

$$o_t \leftarrow \text{sigmoid}(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t \leftarrow o_t \cdot \tanh(C_t)$$

Where W_o is the weight for the season gate layer, W_c is the weight for the new value, b_0 is the bias for the output layer, h_{t-1} is the previously computed value, and x_t is the current input value, b_s is the input gate bias.

Enhance LSTM BackPropagation Algorithm

The BackPropagation algorithm is performed for each layer as described in the forward pass algorithm.

Input : datapoints $(x_1, y_1)...(x_n, y_n)$, weights $W_1...W_n$

- Output: error $E_{in}(w)$ and gradient ∇E_{in} $(G^{(1)} ....G^{(n)})$
- *Step 0*. Initialize Ein=0 and $G^{(1)}$=0. $W^{(1)}$ for for l=1...L.
- *Step 1*. for each data point , do:
  Compute x(l) for l=1...L(Forward Propagation above);
  Compute $D^{(1)}$ for l=1...L (Backpropagation);

$$E_{in} \leftarrow E_{in} + \frac{1}{N}(X_n - Y_n)^2$$

for l=1...L do:
1. $G^{(1)}(X_n) = X^{(l-1)}(D^{(1)})^T$
2. $G^{(1)} \leftarrow G^{(1)} + \frac{1}{N}G^{(1)}(x_n)$

Where there are L layer and $G^{(1)}$ is the gradients at layer L.

LSTM expects sequence data; therefore, the data was converted into sequence data used in the LSTM model using 31. This value 31 was used to mimic a monthly window sequence. the resulting data was converted into a sequence tensor.

V. CONCLUSION

This paper presented an enhanced LSTM model for forecasting data center energy consumption. Seasonality was introduced to the generic LSTM architecture due to the data type available for this study. This research contributes uniquely to the body of knowledge on the subject matter. It gives a better insight into the usability of the considered algorithms in forecasting energy usage in a data center. the enhanced LSTM that was developed can also be adopted/adapted for future research works.

The enhanced LSTM model developed will be implemented and made available to data center operators to generate energy usage trends for further studies. in addition, other variants of LSTM will be compared with the enhanced LSTM model developed in this work.

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