# Predicting server energy consumption using machine learning

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**Abstract**

With the application and great expansion of digital transformation in various sectors around the world because of its benefits to improve work efficiency and meet market demands, concerns have arisen about its impact on the environment due to the increasing demand for computing resources involving data centers, which have a direct impact on the environment through the generation of greenhouse gas emissions and the frequent use of non-renewable energy sources. This paper aims to contribute to reducing the environmental impact of digital transformation, specifically by focusing on the energy consumed by the server and proposing a predictive model to estimate the energy consumed by the server using machine learning algorithms. By accurately measuring and predicting energy use, organizations can take actions and make informed decisions to manage their energy usage, reduce their environmental footprint, and enhance environmental sustainability. In this paper, some papers related to the environmental impact of digital transformation and studies related to the prediction of energy consumption were also mentioned and reviewed.

**Keywords:** Digital Transformation, Data centers, server, Energy consumption, Machine learning

## 1 Introduction

"Digital transformation" is the process of modifying an organization's system to benefit and improve quality by using many technologies. To clarify the concept more, "modifying business processes" means adding new or changing business processes, organizational culture, and customer experience. Many organizations benefit from digital transformation by increasing efficiency, opening up more valuable ideas for their business, and gaining a better understanding of their customers and market, which helps to satisfy stakeholders. [1]

Every time digital transformation occurs, it's expected to affect the sustainability triangle, and one of the sides is the environment. For example, digital technologies such as artificial intelligence, the Internet of Things (IoT), and others aid in environmental sustainability by developing models to predict emissions, weather, etc. On the other hand, the more digital technologies are used without careful planning, the more they will negatively affect the environment because there are many studies that prove that the stage of production of information technology products involves the impact of earth resources, such as: in the production stage of electronic devices, they use many metals, chemicals, and plastics to create these devices; for this reason, these materials may be in demand [2]. Not only that, many electronic devices such as routers, servers, and datacenters need more energy, and many studies show that after 10 years, the use of electricity and energy for these devices will use up to 50 percent of global electricity, contributing to global warming and an increase in carbon dioxide emissions. [2] Also, it's one of the reasons for increasing the amount of electronic waste, which is considered a major environmental problem that negatively affects health and the environment. [3]

Most businesses now employ data centers to store and analyze vast amounts of organizational data; they also aid in the operation of applications and offer a variety of additional advantages. Every data center contains many components, such as servers, cooling systems, network devices, and others. Servers in data centers are considered the heart of data centers because they store and provide data and other services to the devices connected to the network. In our generation, servers can store and handle large amounts of data.[4]

On the other hand, data centers have many disadvantages. One of these is that they generate a high amount of energy and heat to compile their servers, which causes bad effects on the environment such as the spread of carbon dioxide emissions, climate change, and global warming. If this problem increases without continuous monitoring and treatment, it may affect the sustained viability of electronics, modern technologies, and the digital economy. [5]. Several studies and research have demonstrated that the energy used by datacenters comes from the servers, which use close to 45 percent of the total energy consumed in datacenters. [6].

One of the methods for reducing server energy consumption is to predict energy consumption using modern technologies such as machine learning algorithms and techniques. Predicting server energy consumption using related factors may help in optimize the energy consumption, reduce costs, and minimize environmental footprint. [5]

The objective of this paper is to use machine learning algorithms and techniques to predict server energy consumption by using data that contains values of server energy consumption and related factors. This paper covers specific questions: what are the related factors for server energy consumption to use in building the predictive model? Can machine learning algorithms accurately predict server energy consumption based on other relevant factors? which machine learning algorithms are most effective in predicting server energy consumption in data centers?

The rest of the paper is structured as follows: Section [2] explains the related studies, and section [3] describes the method that was used and the study procedure used in this paper. Section [4] describes the results of the proposed machine learning models. Finally, Section [5] provides a summary of the results that were obtained in the study, the implications of our findings, limitations, and future work.

## 2 Lecture Review

In this research paper, we hope to enhance current understanding and suggest unique insights by examining the contributions of prior studies that are related to our field. In paper[6], The authors talk about the servers, which are one of the most energy-consuming parts and account for 45 percent of the energy consumed in data centers. Their goal was to create a meter that includes a network of sensors, a microcontroller, the "MQTT communication protocol," and an energy measurement module. From this meter, they measured some features related to the server's energy consumption, such as voltage (V), current (A), power (PA), Watts (W), frequency (Hz), active energy (KWh), and power factor. After that, they implemented four types of linear regression algorithms to predict the server's energy consumption.

In the paper [7], the authors discovered a way to predict energy consumption on global servers using the Romonet simulation model and global data center traffic. In their method, the Romonet simulation model was used in the study to define the dynamic global average power usage effectiveness (PUE) and the high latitude (PUE). After that, they predicted the energy consumption of global datacenters using the polynomial fitting method and global datacenter traffic.

In paper[8], the authors searched for a way to reduce the power consumption of data centers and their elements such as servers and cooling systems. Their method is to build an energy efficient data center system that contains its construction, function, and power consumption model. After that, they merged the linear regression and the wavelet neural network techniques in a prediction method (MLWNN) to predict the data center workload. Additionally, they implemented a resource management method and an online energy efficient job scheduling algorithm for heuristic energy efficient job scheduling with workload prediction.

In the paper [9], the authors made a study to show if there is a relationship between the weather conditions and the energy consumption of data centers and how it affects the energy consumption by using the FIESTA-IoT platform. They proposed a model to predict the energy consumption depending on dominant weather condition parameters by using multivariable linear regression process. They also planned to validate their results using live measurements from the realDC testbed.They found that there are some weather conditions that have a big effect on the energy consumption of data centers.

In paper[10], the authors clarified the importance of using virtual machines to decrease the energy consumption of datacenters.So they predicted virtual machine energy consumption by using one of the machine learning techniques, which is regressive predictive analysis. Their method provided more accurate future value forecasts by utilizing the multi-layer perception (MLP) regressor, which has a 91 percent prediction accuracy rate. In their paper, they used many regression methods in their prediction process, such as regression types, random forest regressors, and KNN regression.

In the paper [11], the authors made an energy consumption model that depends on feature selection and deep learning. They stated that they were focused on 12 energy-related features and they implemented deep neural network architecture to leverage large amounts of data for model training. They separated their approach into three phases, which are: monitoring the performance and getting the energy related features; selecting the important features; and building and improving the model. They also mentioned that their approach had state of the art predictive capability when they compared it with other models.

## 3 Methodology

With the use of digital transformation in various sectors and organizations around the world, many concerns have been raised regarding its environmental effect as a result of the growing demand for computing resources, including data centers, which have a direct influence on the environment through the creation of greenhouse gas emissions. In this paper, the objective is to predict the server energy consumption by using machine learning algorithms to decrease the environmental impact of the data centers by making the organizations take action and make informed decisions to manage their energy usage, reduce their environmental footprint, and enhance environmental sustainability.

In the methodology section, the implementation of the experiment, such as the method that was used and the experimental procedure as shown in the figure [1] were described. The suggested prediction model employing machine learning algorithms attempts to give accurate estimations of energy consumption, allowing organizations to make educated decisions and reduce their environmental impact. By using data related to server energy consumption and related features related to energy consumption, the prediction model is trained and used for future predictions.

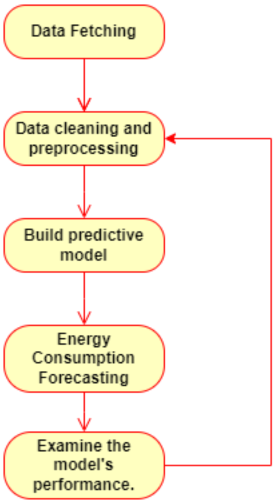


**Fig. 1**: Methodology used in this paper

## 3.1 Data collection

The first step in this study is to get data that is related to server energy consumption and contains several features related to energy consumption. Collecting reliable data ensures the quality and reliability of the data to be used to build the predictive model and obtains a reliable model that gives reliable results.

The data used in this study is from Learning-based Energy Consumption Prediction paper. They collected the data by creating a meter that contains a network of sensors that include a microcontroller, MQTT communication protocol, and an energy measurement module to measure the server's energy consumption and some related features to energy consumption as shown in Table [1], while a dashboard was used to show the energy measurements in real-time. The hardware, which comprises a network of sensors, is based on the ESP32 module. The MQTT communication protocol was used to connect devices to each other. The energy measurement module used to measure energy consumption in their study was the PZEM004T module.

Data was collected from a workstation located at the information technology center ESPOL in Ecuador for 120 days with a sampling frequency of one value per minute. Table [1] provides a summary of the energy consumption variables that were recorded together with their appropriate units of measurement.

"Active energy" is the target variable in this study to build the predictive model. Active energy describes the amount of energy consumed by the server over a specific period of time, which is 120 days. Active energy is measured in kilowatts per hour (KWh). As shown in the figure [2], the Active energy variable consumed is plotted over days.

**Table 1**: Energy consumption variables with their appropriate units of measurement in the selected data

| Variable number | Variable name | measurement unit |
|---|---|---|
| 1 | Voltage | (V) |
| 2 | Current | (A) |
| 3 | Power | (W)- Watts |
| 4 | Frequency | Hertz(Hz) |
| 5 | Active Energy | kilowatts per hour (KWh) |
| 6 | Power factor | Dimensional |
| 7 | ESP32 temperature | Centigrade Degrees(°C) |
| 8 | Workstation CPU | Percentage |
| 9 | CPU power consumption | Percentage |
| 10 | CPU temperature | Centigrade Degrees (°C) |
| 11 | GPU consumption | Percentage |
| 12 | GPU power consumption | Percentage |
| 13 | GPU temperature | Centigrade Degrees (°C) |
| 14 | RAM memory consumption | Percentage |
| 15 | RAM memory power consumption | Percentage |

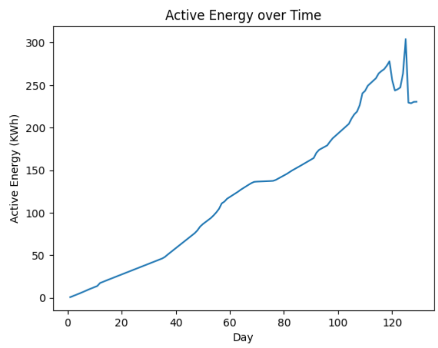


**Fig. 2**: Active Energy over days

Also, as shown in figure [3], the distribution of active energy values was represented to gain some insights and define some patterns.

## 3.2 Data Preprocessing

In this section, several preprocessing techniques on the data were implemented to ensure data quality improvement and help improve the performance of the predictive model. These data preprocessing techniques used in the paper include normalization and feature selection.

Normalization of values in the dataset was implemented due to existing features that contain percentage values in the data, such as CPU consumption (maximum value is 100), which differ from the range of values for other non-percentage values such as voltage or current (maximum value is more than 100), which affect the result of

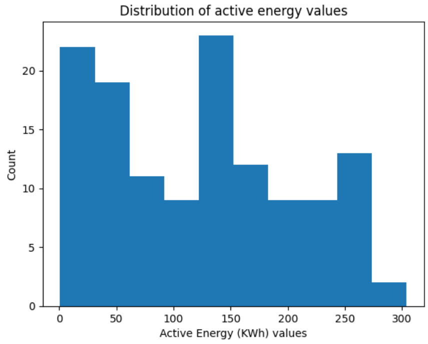


**Fig. 3**: Distribution of active energy values in the dataset

the predictive model and give more importance to the non-percentage variables when predicting energy consumption. The normalization was implemented in this study using the minimum and maximum values of each of the variables in our data as shown in the equation below:

$$X_{\text{scaled}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \tag{1}$$

where,

$$\begin{aligned} X &: \text{indicates the original value of a feature in the data} \\ X_{\text{scaled}} &: \text{indicates the scaled value of the feature} \\ X_{\text{min}} &: \text{indicates the minimum value of the feature in our dataset} \\ X_{\text{max}} &: \text{indicates the maximum value of the feature in our dataset} \end{aligned}$$

The normalized data of the target variable (active energy) in days is shown in figure [4]. The normalized target variable is shown in the range between 0 (the minimum value) and 1 (the maximum value). On the other hand, the normalized data of the CPU power consumption variable (percentage variable) in days is shown in figure [5]. It shows the normalized CPU power consumption between the range 0 and 1 (0 means 0 percent of CPU power consumption and 1 means 100 percent of CPU power consumption), which is the same range as the target variable.

The correlation between variables was estimated using the heatmap chart as shown in figure [6], which shows the correlation coefficient values between all the variables in the data. The best variables were selected to build the predictive model in this study based on the correlation between features and their feature importance. Variables that have a high correlation with the target variable were removed because a high correlation value means that the values of the two variables are similar, so the focus was on removing the variables with high correlation values with the target variable, and if there are two independent variables where the correlation between them is high,

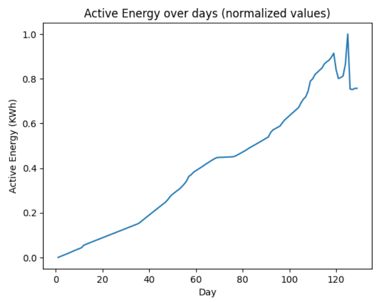


**Fig. 4**: Active Energy over days (normalized values)

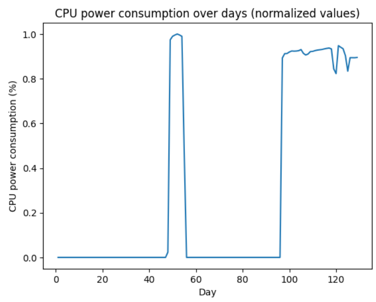


**Fig. 5**: CPU power consumption over days (normalized values)

the variable with the lowest feature importance was removed and the other remains.

The emphasis is on selecting only the best five independent variables to use in the predictive model to predict the server's energy consumption. The reason for only selecting five features is to prevent overfitting, reduce the complexity of our data, and improve the performance of the machine learning model. The five selected independent variables were: voltage, power, power factor, ESP32 temperature, and workstation CPU. Other variables were removed because of their high correlation with the target feature or because they had the lowest feature importance when predicting energy consumption.

## 3.3 Machine learning models

In this paper, we proposed Random Forest Regressor and Gradient Boost as our supervised learning approach to build the predictive model. Regression learning is widely used in applications that relate to continuous results. Random forest and gradient boost were chosen in our paper based on their suitability and capability to handle complex cases such as relationships between variables are complex. In this study, the data was split into training and testing sets as follows: with the training set accounting for 70 percent of the data and the testing set accounting for 30 percent.

A random forest regression model was built using the training data at different time intervals (minute, hour, day, and week). In minutes, different numbers of decision trees in the random forest (n-estimators) were performed, and the best option that improved the performance of the random forest model was selected. The best option was to use 249 decision trees in the random forest to build the model. In hours and days, the best option was to use 202 decision trees in the random forest model. In weeks, the best option was to use 157 decision trees in the random forest model.

Also, the gradient boost model was trained using the training data at different time intervals (minute, hour, day, and week). In minutes, different learning rates and numbers of decision trees in the gradient boost (n-estimators) were performed

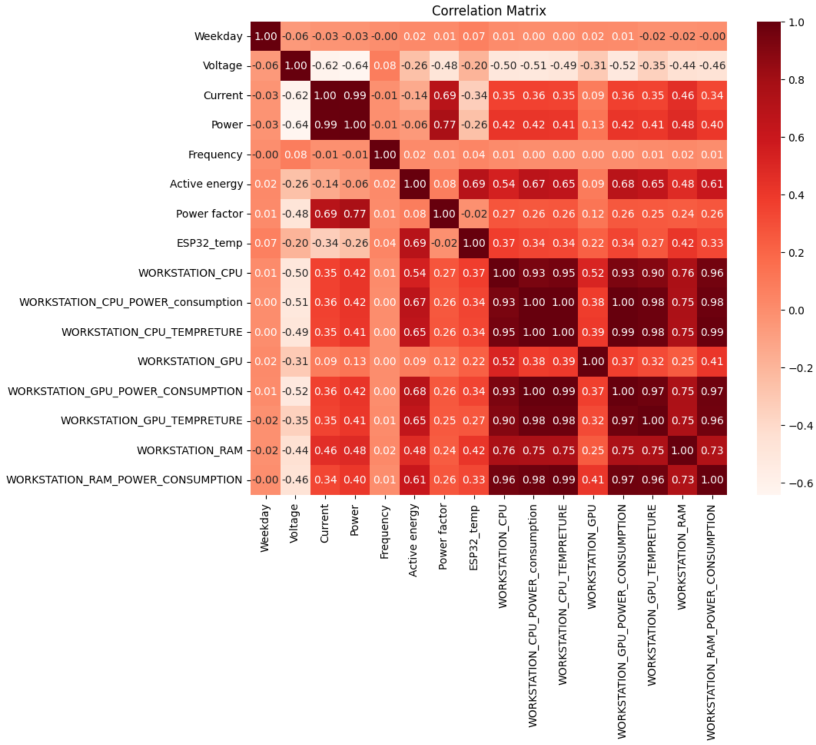


**Fig. 6**: Correlation between variables

to select the best option that gave the best performance and the fewest errors in predicting energy consumption. The best option was to use a 0.2 learning rate and 150 decision trees in the gradient boost. In hours, the best option was to use a 0.05 learning rate and 174 decision trees in the gradient boost model. In days, the best option was to use a 0.1 learning rate and 229 decision trees in the gradient boost model. In weeks, the best option was to use a 0.2 learning rate and 101 decision trees in the gradient boost model.

After training the random forest and gradient boost models, we were able to predict the server's energy consumption in minutes, hours, days, and weeks. The prediction model was verified using the testing data (compare the actual server energy consumption values with the predicted energy consumption values).

# 4 Results and discussion

In this section, the results of the random forest and gradient boost models are presented. Root mean squared error (RMSE) and mean squared error (MSE) were used to evaluate the performance of the two models (random forest regression and gradient boost regression). In addition, our predictive models results were compared to a benchmark [6].

The performance of random forest regression and gradient boost regression in predicting server energy consumption at different time intervals (minutes, hours, days, and weeks) was evaluated. As shown in the two figures [7] and [8], the RMSE and MSE values for both the random forest model and the gradient boost model were compared over different time intervals .

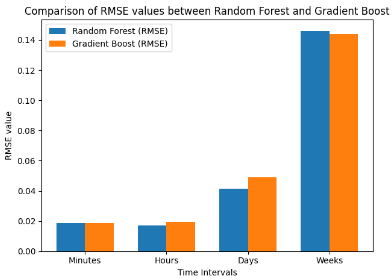


**Fig. 7**: Comparison of RMSE values between Random Forest and Gradient Boost

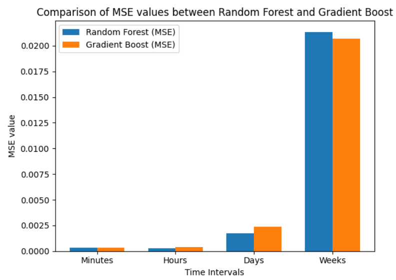


**Fig. 8**: Comparison of MSE values between Random Forest and Gradient Boost

The numerical values of both RMSE and MSE of the random forest and gradient boost models in this paper are shown in the table [2]. The unit of RMSE values is [KWh] because the RMSE takes the unit of the target variable, which is the "target variable". On the other hand, the unit of MSE values is [$(KWh^2)$].

**Table 2**: Performance of random forest and gradient boost models in terms of RMSE and MSE over different time intervals

| Time Interval | Random Forest (MSE) | Random Forest (RMSE) | Gradient Boost (MSE) | Gradient Boost (RMSE) |
|---|---|---|---|---|
| Minutes | 0.0003 | 0.018 | 0.0004 | 0.019 |
| Hours | 0.0003 | 0.017 | 0.0004 | 0.019 |
| Days | 0.0017 | 0.04 | 0.0024 | 0.05 |
| Weeks | 0.021 | 0.15 | 0.020 | 0.14 |

Additionally, to make sure that the random forest model and gradient boost model performance is good and reliable to use to predict energy consumption, the performance of the benchmark model [6] was compared based on RMSE value. They used the same data but different models, which are four linear regression models, but they selected the robust linear model at the end to predict the energy consumption by days and hours because their robust linear regression gave the best performance among all the other regression models. As shown in the table [3], the performance of the random forest model and the gradient boost model were compared with the benchmark robust linear regression model depending on RMSE value to determine which was the best model that had the lowest error when predicting energy consumption.

**Table 3**: RMSE values of our models VS Benchmark

| Machine learning model [kWh] | Hour | Day |
|---|---|---|
| Random Forest regression (Our model) | 0.017 | 0.04 |
| Gradient boost regression (Our model) | 0.019 | 0.05 |
| Linear Regression - Robust Linear (Benchmark) | 0.026 | 3.25 |

In their paper, they stated an RMSE of (0.026 [kWh]) for hourly predictions and (3.25 [kWh]) for daily predictions. When comparing the random forest and gradient boost model results with their robust linear regression model, the random forest and gradient boost models outperformed their robust linear regression model regarding the RMSE value.

Overall, the random forest model in this study had the best performance in terms of getting the lowest error when predicting the server energy consumption when compared with the gradient boost model and benchmark model (robust linear regression), because the random forest model is considered very powerful against outliers, noise, and missing values, efficient in dealing with large and complex data, and also powerful against overfitting. These benefits of random forest contributed to getting the best performance among other models like gradient boost and linear regressions.

Random forest and gradient boost models were very effective in predicting server energy consumption by using some related features to server energy consumption because these two models are ensemble methods that merge multiple models to produce predictions, which leads to higher performance compared with other models like linear regression and their capability to deal with complex data like server energy consumption data that contains non linear relationships between variables.

# 5 Conclusion and Recommendations

In this paper, the objective was to predict server energy consumption by using machine learning algorithms to decrease the environmental impact of digital transformation. This paper also proposed some questions to cover: what are the related factors for server energy consumption to use in building the predictive model? Can machine learning algorithms accurately predict server energy consumption based on other relevant factors? which machine learning algorithms are most effective in predicting server energy consumption in data centers?

By using features that are related to server energy consumption, like voltage, power, CPU workstation consumption, and others, the predictive model can be built and can predict the server energy consumption. Machine learning algorithms provide state-of-art results in predicting server energy consumption when the data is reliable and doesn't have any issues like null values, duplicate values, and others. In this paper, random forest and gradient boost models were implemented to predict the server's energy consumption at different time intervals. Our results demonstrated that the random forest model and gradient boost model performed low RMSE and MSE values when predicting energy consumption at different time intervals. Our random forest model was the best model for getting the fewest possible errors in predicting server energy consumption with an RMSE value in minutes, hours, days, and weeks, respectively (0.018 [kWh], 0.017 [kWh], 0.04 [kWh], and 0.15 [kWh]).

By successfully implementing an accurate predictive model that has outstanding performance and gives predicted values that are similar to the actual values, many organizations can use this predictive model to optimize their energy consumption, reduce costs, and minimize their environmental footprint. Future studies might investigate the effectiveness of the predictive models across various server infrastructures in order to improve the models' generalizability and applicability and give reliable outcomes. Additionally, create a monitoring system that monitors and manages data-center energy consumption in real time. This system will use the data gathered to give suggestions and ideas for optimizing energy consumption, detecting energy-intensive processes, and adopting energy-saving initiatives. Finally, examine how effectively the forecasts generalize over various server locations as energy consumption rates could vary greatly.Consider how these models may be adapted for various system designs and workloads.

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