

Electricity Price Forecasting for Cloud Computing Using Machine Learning Model

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ABSTRACT- The information technology sector is being swiftly overtaken by cloud computing since it significantly simplifies computing without the need to purchase the actual gear required for computations; instead, these services are hosted by businesses that offer cloud services. These businesses depend on the availability of a reliable and affordable electrical power supply because they house numerous servers and computers whose primary power source is electricity. Cloud centers use a lot of energy. With recent increases in electricity costs, one of the primary issues in designing and efficiently placing data and scheduling nodes to offload or transfer storage are among some of the maintenance tasks of such centers is to minimize electricity use. We propose an Extreme Gradient Boosting (XGBoost) model in this project to offload or transfer storage, predict electricity prices, and so cut energy consumption expenses in data centers. On a dataset from the real world given by the Independent Electricity System Operator (IESO) in the Canadian province of Ontario, the effectiveness of this strategy is assessed in order to offload data storage in data centers and effectively reduce energy consumption. 70% of the data is used for training and 30% towards testing. With a r^2 _score of 91%, the XGBoost Regressor surpasses the Random Forest Regressor and Support Vector Regressor.

KEYWORDS- Data Storage, Energy Saving, Electricity Price Forecasting, XGBoost.

1. Introduction

As a storage platform, cloud computing is being used more and more frequently, which lessens hardware investments and procurement expenses. Data Centers (DCs) are in high demand due to the exponential growth in the demand for information. Data Centers (DCs) use 2% of the world's energy, which is a significant amount. It is anticipated to increase by 12% annually. A little over 39% of energy is utilized for cooling, 45% for powering IT infrastructure, and 13% for lighting. The cost of this level of consumption to the economy is high. In order to ensure reliability through replication, DC operators typically have a few DCs dispersed throughout different areas. Being near the clients will satisfy

the latency specifications. Distributed DCs, however, might result in cost unpredictability because power markets have fluctuating prices. These power markets have significant cost flexibility. As a result, DC manufacturers would construct DCs in regions with low temperatures and affordable electricity. Companies like Netflix employ content delivery networks (CDNs). To reduce the requirement for transmitting data over long distances and improve Quality of Service, they would place the data center closer to the clients. This approach might be used to transfer capacity from centralized DCs to hubs at the system's edge, enabling businesses to use less energy as a whole and cut expenses. Green environment and efficient energy usage have become a popular topic in recent decades due to its importance and dire need. For addressing the problems, several researchers have used both cutting-edge and conventional methods. Given that costs vary significantly from one geographic region to another, several academics advise conducting a market study for figuring out how much it would cost to put up servers in multiple places.

Similarly, numerous academics have concentrated on the various effects of machine learning methods on modelling, planning, and forecasting electricity prices, with a special emphasis on the worldwide market. Two machine learning algorithms usually get the job done, the first to forecast power prices and the second for energy systems.

The majority of prior research on power price prediction are still in their infancy and lack accuracy, computational overhead, or the ability to demonstrate results using real-time data. The front end, Python-Flask, is used for developing the user interface. The database is set up using MySQL, which is additionally utilized to store the details.

2. LITERATURE REVIEW

[1] S. Albahli et al.: Electricity Price Forecasting for Cloud Computing Using an Enhanced Machine Learning Model

The information technology sector is being swiftly overtaken by cloud computing since it significantly simplifies computing without the need to purchase the actual gear required for computations; instead, these services are hosted by businesses that offer cloud services. These businesses

depend on the availability of a reliable and affordable electrical power supply because they house numerous computers and servers whose primary power source is electricity. Cloud centers use a lot of energy. Minimizing data center power use and energy consumption is one of the key issues in developing and maintaining such centers in light of recent increases in electricity prices. Some of the key methods to address these issues are efficient data placement and node scheduling to unload or shift storage. In this paper, we suggest an Extreme Gradient Boosting (XGBoost) model to offload storage or shift it, forecast electricity prices, and as a result cut data center energy expense.

[2] IEEE TRANSACTIONS ON SMART GRID, VOL. 9, NO. 6, NOVEMBER 2018

The IEEE Transactions on Smart Grid is a cross disciplinary journal aimed at disseminating results of research on and development of the smart grid, which encompasses energy networks where prosumers, electric transportation, distributed energy resources, and communications are integral and interactive components, as in the case of micro grids and active distribution networks interfaced with transmission systems. The journal publishes original research on theories and principles of smart grid technologies and systems, used in demand response, Advance Metering Infrastructure, cyber-physical systems, multi-energy systems, transactive energy, data analytics, and EV integration. Surveys of existing work on the smart grid may also be considered for publication when they propose a new viewpoint on history and a challenging perspective on the future of intelligent and active grids.

[3] C. Canali, L. Chiaraviglio, R. Lancellotti, and M. Shojaifar, "Joint minimization of the energy costs from computing, data transmission, and migrations in cloud data centers," IEEE Trans. Green Commun. Netw., vol. 2, no. 2, pp. 580–595, Jun. 2018.

For the purpose of assigning Virtual Elements (VEs) in a Software-Defined Cloud Data Centre (SDDC) as efficiently as possible, we propose a novel paradigm termed JCDME. Further, we simulate the energy consumption by considering the computing expenses of the VEs on the real-world servers, the costs for transporting data across VEs, and the costs incurred for VE migration across the servers. A weight parameter is also added by JCDME to prevent a surplus of VE migrations. With an automated and adaptive calculation of the weight value for the VEs migration costs, we specifically suggest three potential solutions to the JCDME problem. We next compare the techniques under consideration over a range of situations, from a tiny SDDC up to a medium-sized SDDC made up of several hundred VEs and hundreds of servers. Our findings show that JCDME can conserve up to an additional 7% of energy compared to earlier energy-aware algorithms without substantially increasing the complexity of the solution.

2.1 Existing System

In existing system, models are build based on Multi-Layer Neural Network (MLNN) to estimate the load of electricity and its overall consumption. They also employed the Ensemble technique to discard the diverse errors and cancellation of noise and the technique lacks the robustness because of higher computational time.

Disadvantages

- Low Accuracy
- Time Consuming
- High Complexities
- Expensive

2.2 Proposed System

We propose this system to investigate a specific problem of whether it is valuable or not to use machine learning techniques to leverage a dramatic spike in electricity prices to offload data storage to minimize the energy consumption in cloud data centers using XGBoost Regressor, Random Forest Regressor and Support Vector Regressor.

Advantages

- High accuracy.
- Time Saving.
- Does not require highly trained staff.
- Inexpensive.
- Low complexities.

2.3 Architecture

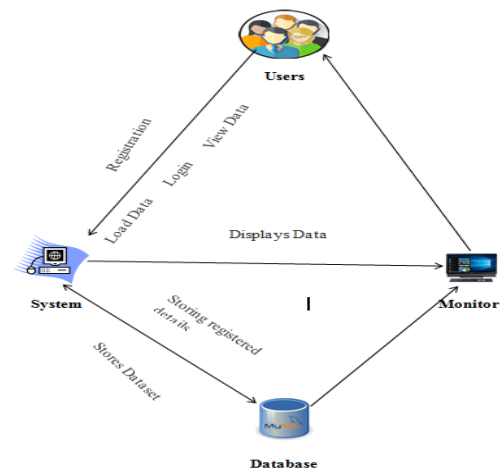


Figure 1. Architecture of Data Processing

2.4 Algorithm

System

Step1: System:

Step2: Login:

The system allows users to login to the system.

Step3: Store Dataset:

The System stores the dataset given by the user.

Step4: Model selection:

The system takes the data from the user and fed that data to the selected model.

Step5: Model Predictions:

The system takes the data given by the user and predict the output based on the given data.

User:

Step1: Registration:

Every user needs to register themselves in the system with a unique name and email.

Step2: Login:

Registered users can log in to the system.

Step3: View Modules:

After logging in successfully, the user can see the 4 modules.

Step4: Load Dataset:

The user can load the dataset he/she want to work on.

Step5: View Dataset:

The User can view the dataset by clicking the view dataset module.

Step6: Select model:

User can select the model provided by the system for accuracy.

Step7: Predictions:

User can enter random values for prediction.

Step8: Logout:

The user can log out of the system.

3. Results

After compiling we get a link to access after accessing that link the home page will be appear in that home page there will be three options. Home, registration and login.

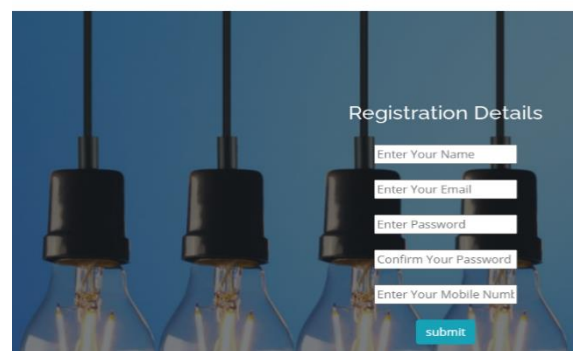
ELECTRICITY PRICE PREDICTION [Home](#) [Registration](#) [Login](#)



3.1 Home Page

After selecting "Register" on the home page, we will be given information, including our name, email address, password, and password confirmation. Finally, adding our phone number will create an account with our provided information.

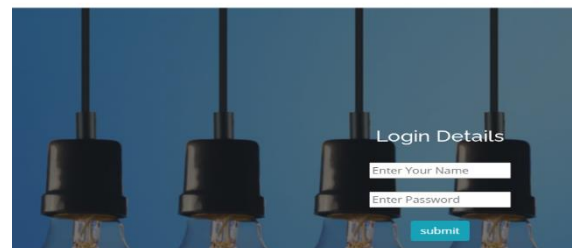
ELECTRICITY PRICE PREDICTION [Home](#) [Registration](#) [Login](#)



3.2 Registration Page

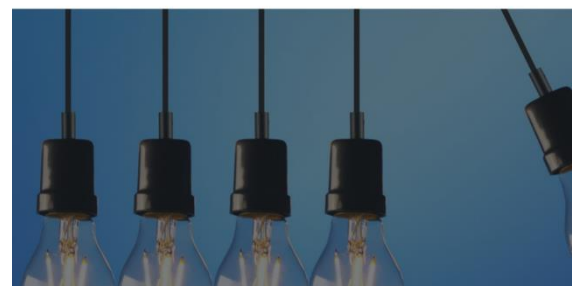
After entering our login information in the login page, we must click "Submit" to access a screen with options to load data, view data, select a model, make a prediction, and logout.

ELECTRICITY PRICE PREDICTION [Home](#) [Registration](#) [Login](#)



3.3 Login Page

ELECTRICITY PRICE PREDICTION [Home](#) [Load Data](#) [view data](#) [Select Model](#) [Prediction](#) [Logout](#)



3.4 After login page

When you pick the data set file from your computer and submit it, a data set will open in the website when you click the load data button to bring up the data load tab.

In the next page we can view the data.

ELECTRICITY PRICE PREDICTION [Home](#) [Load Data](#) [view data](#) [Select Model](#) [Prediction](#) [Logout](#)



3.5 Load data set

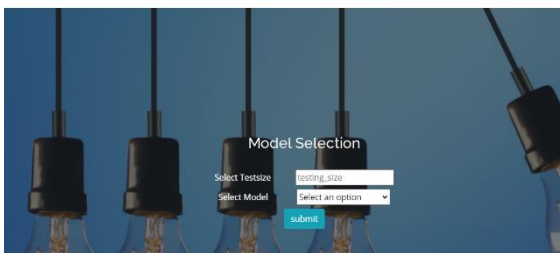
ELECTRICITY PRICE PREDICTION [Home](#) [Load Data](#) [view data](#) [Select Model](#) [Prediction](#) [Logout](#)

S/N	generation fossil gas	generation fossil hard coal	generation hydro pumped storage consumption	generation hydro water reservoir	generation other renewable	generation waste	total load forecast	total load actual	Time	price actual
1	4844.0	4821.0	863.0	1899.0	73.0	196.0	26118.0	25385.0	0.0	65.41
2	5196.0	4755.0	920.0	1658.0	71.0	195.0	24934.0	24382.0	1.0	64.92
3	4857.0	4581.0	1164.0	1371.0	73.0	196.0	23515.0	22734.0	2.0	64.48
4	4314.0	4131.0	1503.0	779.0	73.0	191.0	22642.0	21286.0	3.0	59.32
5	4130.0	3840.0	1836.0	720.0	74.0	189.0	21785.0	20564.0	4.0	56.04
6	4235.0	3590.0	2109.0	713.0	74.0	188.0	21441.0	19965.0	5.0	53.63
7	4040.0	3388.0	2109.0	886.0	74.0	186.0	21285.0	20810.0	6.0	51.73
8	4030.0	3208.0	2031.0	1012.0	72.0	189.0	21545.0	20377.0	7.0	51.43
9	4052.0	3228.0	2119.0	1019.0	73.0	196.0	21443.0	20094.0	8.0	48.98
10	4137.0	3437.0	2192.0	1357.0	74.0	198.0	21560.0	20637.0	9.0	54.2
11	4059.0	3516.0	2030.0	1817.0	72.0	204.0	22824.0	22250.0	10.0	58.94
12	3931.0	3845.0	1183.0	1516.0	73.0	206.0	23720.0	23547.8	11.0	59.86
13	3764.0	4230.0	972.0	1304.0	75.0	209.0	24180.0	24133.0	12.0	60.17
14	3754.0	4064.0	922.0	1286.0	74.0	210.0	24797.0	24713.0	13.0	62.05

3.6 Data Viewing

Here, we have to select the mode and test size. We have to give below 30 in the size of the testing and click on the submit button which is appeared in the page after submitting will open a prediction page.

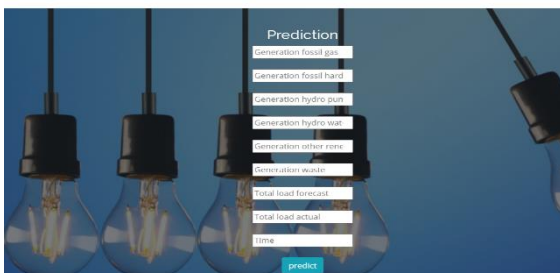
ELECTRICITY PRICE PREDICTION [Home](#) [Load Data](#) [view data](#) [Select Model](#) [Prediction](#) [Logout](#)



3.7 Model Selection

This is the prediction page in this after filling the details will get a prediction price of the Electricity.

ELECTRICITY PRICE PREDICTION [Home](#) [Load Data](#) [view data](#) [Select Model](#) [Prediction](#) [Logout](#)



3.8 Electricity Price Prediction

4. Conclusion

In this effort, we've succeeded in creating ML models to lower data center pricing spikes. This was created in an intuitive environment utilizing Python programming and Flask. With a $r2_score$ of 91%, the XGBoost Regressor excels over the Random Forest Regressor and Support Vector Regressor. This approach predicts electricity prices while using the least amount of time and effort possible and minimizing price spike variations. By adding new hyperparameters and constraints, this system can be expanded to increase the models' accuracy. Furthermore, clustering may assist in determining a spike's lower error so that we may calculate the forecast's missing or undesirable spike error.

5. REFERENCES

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