Analyzing Facility Servers Using Random Forest and XGBoost for Optimized Job Allocation

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Abstract: Computer systems consume huge amount of energy causing higher levels of carbon emissions thus polluting the environment. This study addresses the issue by developing machine learning algorithms to conserve resources across datacentres. The machine learning models have been developed to predict a higher level accuracy focusing job level scheduling. The Random Forest used for job scheduling may result in enhancing performance of green data centres by reducing the energy consumption. Our future research tries to improve the existing resource management solutions focusing on job level characteristics.

1 INTRODUCTION

It is mind-boggling in the way data centers are regularly linked to contemporary computing, they massively contribute to carbon footprint due to the enormous energy used in supporting servers, storage, as well as networking systems (Selin, 2024). This high electricity demand is generally produced from fossil fuels hence partnering large amounts of carbon dioxide (CO2). Also, the devices that help to keep equipment at an appropriate temperature to operate, worsens energy utilization, thereby making the power of the facility high.

Diesel generators that are used during black out also release CO2 further stressing the importance of clean up practices. The misuse of resources is viewed to worsen the environmental effects hence inefficient utilization of resources, energy and other resources get wasted.

Flexible resource management will improve the use of resources, minimise any likelihood of resource wastage, and closely monitor energy consumption. Others are scope 3 emissions which include emissions from the following infrastructure, the equipment of data center and other related equipment. This research can be related to several Sustainable Development Goals, namely, SDG 3 on clean air quality, SDG 4 through integrating sustainability into education curricula and materials, SDG 7 for affordable and clean energy through green jobs and innovations in the Cloud technology, as well as SDG 8 and 9 through creation of green jobs and technological innovations respectively. It also helps in achieving of sustainable development goal 11 (Sustainable cities and communities), SDG12 (Responsible consumption and production),SDG13 (Climate action), SDG15(Life on land) through the efficiency of resources and minimizing emissions. In addition, SDG-17 (Partnerships for the Goals) implementation is backed by cooperation with industry and academia. It advances the work by utilizing XGBoost and Random Forest regression algorithms for efficient job allocation depending on rack sensor information. it aims at reducing energy consumption; reducing carbon footprint; and enhancing resource allocation efficiency in data center using machine learning methods. This strategy looks into several concerns in the environment and opens doors to improve the sustainability processes for cloud computing platforms.

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2 LITERATURE SURVEY

This survey focuses upon some of the current developments in green computing and many energy-efficient technologies in different areas with emphasis on innovative techniques for resource optimization and reduced environmental impact. The paper gives a thorough survey of fourteen-cryptography-relevant studies dealing with the opportunities and challenges in the fields of data mining, cloud services, and high-performance computing. They point out that adaptable algorithms and frameworks are essential in meeting the varying demands of heterogeneous computer environments, which in themselves call for sustainability.

2.1 Related Work

Guo et al. (Guo et al., 2023) undertook initial research on HPC, which exploited sensor data from large-scale networks to analyze the workload distribution on energy efficiency, using two techniques- workload optimization and dynamic core allocation- to minimize energy and enhance system utilization. However, these methodologies have problems regarding multibody systems with diverse temperature and energy management requirements.

Abbas et al. (Abbas et al., 2023), like Guo et al., propose an energy-efficient architecture that depends on renewable energy sources and consequently one that favors green computing. Their approach intends to optimize resource consumption and encourage sustainable energy use in computing environments. However, it was deemed, indeed, that creating robust algorithms that can adapt dynamically to diverse energy sources is essential for accomplishing sustainability as well as optimal performance.

Ahmad et al. (Ahmad et al., 2021) carried out an encompassing literature review in order to find out the practices and challenges brought by adopting green cloud computing, but from a client-centric point. According to their findings, sustainable practices have to be incorporated in cloud computing to help lessen the impacts of energy consumption, environmental responsibility, and reliability of the services. The creation of complete frameworks considering the sustainability of hybrid cloud services, including qualitative studies to consider their environmental influence, together with validation of proposed green techniques, remains open.

Within the field of mobile cloud computing, Skourletopoulos et al. (Skourletopoulos et al., 2018) introduce a model of elasticity debt analytics that aims to optimize resource provisioning, employing a game- theoretic approach to reduce elasticity debt. These techniques remain a real challenge in adapting the model to changing conditions and integrating ML technologies for enhanced resource utilization.

Raja (Raja, 2021) explains how green computing can reduce energy waste in the IT sector and further other approaches to minimize carbon footprints, such as through energy-efficient data centers and renewable energy sources. He discusses the potential of greening initiatives with respect to environmental sustainability for the IT sector, while flexible management and control over varied energy demands will specifically require adaptive solutions.

Qiu et al. (Qiu et al., 2018) discuses on exploration of how Cloud Service Brokers might provide new avenues toward energy efficiency and quality of service through optimized demand allocation and pricing strategies. While the work by these authors shows some improvement over that by others, they still face challenges with real-world deployment and scalability issues.

Qiu et al. (Qiu et al., 2015) also give an insight into PCM optimization in Green Cloud Computing using genetic algorithms aimed at improving memory usage and efficient resource allocation.

Tuli et al. (Beloglazov and Buyya, 2014) proposed an energy-aware combinatorial virtual machine allocation model for minimizing the power consumption in data centers. This model works well in static circumstances but the architecture is hemmed in by open issues regarding the management of workloads for real-time contexts and requires adaptive algorithms to scale up with emerging technologies such as edge computing and IoT.

Alarifi et al. (Xiao and Li, 2018) suggest an Energy-Effective Hybrid framework for cloud data centers that differently consolidate and utilize servers. However, optimization of migration algorithms and transition to sustainable energy sources are some open issues still facing researchers in this area.

Chiaraviglio et al. (Chiaraviglio et al., 2014) put forth a dynamic methodology for online power and load computation, whereby the server's power states can be dynamically altered. This will result in a very high saving in energy needs. However, many open problems relating to scalability and multi-objective optimization remain open.

Kulkarni et al. (Kulkarni et al., 2024) continue with innovation and creation of cloud-based mood-driven music recommendation system combining personalized recommendations from user profiles, collaborative filtering, and machine learning. The system, with its scalable architecture is an apt recommendation-on-demand, where contextual information and listening habits are indigenously considered while making recommendations. Future research will focus on enhancing the system's responsiveness to evolving user preferences and fine-tuning recommendation algorithms for different user categories.

Reddy et al. (Reddy et al., 2023) present the challenge of predicting flight delays, especially those induced by bad weather. Having trained various machine learning algorithms on an integrated dataset of weather and flight results from JFK airport, they determined that XGBoost performed best, achieving an RMSE with a severity of 0.81. The current obstacles remain improving the model's responsiveness to real-time data and addressing other factors influencing flight delays.

Pecheti et al. (Pecheti et al., 2024) present the Drug Information and Recommendation System that draws on Amazon Web Services (AWS) to support drug review opinions. Their work shows a design approach involving data collection, preprocessing, and prediction on drugs ultimately leading to the deployment of the Sentiment AI platform. The system ensures both scalability and software security by utilizing services provided by AWS such as EC2 and S3 and IAM. Future improvements are intended to lead an expansion of data sources regarding the system and improvement of analytical capacity within the real-world environment.

Reddy et al. (Reddy et al., 2024), proposed a sentiment analysis model based on Long Short-Term Memory (LSTM) and natural language processing algorithms for evaluating user reactions to YouTube content. Trained on the IMDB dataset alongside AWS, the model provides an avenue for further enhancements to widen the dataset for better generalization whilst working on the interactive dashboard to aid forward an even deeper user insight.

Selvi, S. et al. (Selvi and Manimegalai, 2024) Proposed new optimization techniques [Multiverse Optimization (MVO)], which enhances the efficiency for task scheduling taking advantage of neighborhood structures. This approach brings several benefits, including significantly reduced energy consumption and degradation of makespan as it can be verified through laboratory testbed results with improved performance metrics in contrast to other scheduling approaches, which we have outlined above. This study demonstrates that the proposed scheduler will be able, through experimental evaluation, to schedule tasks appropriately resulting in minimization of operational costs for a green cloud computing environment. Although the results are impressive, more research is needed to solve these scalability challenges. There is much more work to do in this area and there are no clear answers yet on how effective resource management should be for the future of cloud computing.

2.2 Research Gap

An integrated approach shows a huge research gap in pressure, temperature, and water flow sensors' behavior among racks in data centers while they are in operation. Even though behavior of individual sensors is researched on its own, the application of machine learning models in supporting prediction and understanding of the collective behavior of multi-sensor usage in dynamic and intense workload environments is not clear. Also, another question to be answered is the training of machine learning algorithms for analyzing anomalies or inefficiencies across different sensors, which are revealed through discrepancies from normal behavior. Of course, these projects will make data center operations better, resource usage optimization, and real-time monitoring more accurate.

3 METHODOLOGY

This paper presents a clear framework for the systematic creation of predictive models from sensor data. It is the data transformation, developing machine learning models, benchmarking and fine tuning of the models and the solutions ready for implementation. It goes through the steps of data acquisition, data preparation, data transformation and feature extraction, model building, model assessment and, model refinement, and concerns of model deployment. Here's a detailed breakdown of the steps involved.

3.1 Data Acquisition and Analysis

The raw data consists of data measured by sensors, and includes data from 20 racks where each rack had seventy-two servers. In every server employed, job execution finds 24 cores at its behest. The dataset includes readings from eleven sensors for each rack, monitoring various parameters: The following is a list of links status, rackcdu liquid level, rackcdu pressure, facility pressure, facility water flow, rackcdu leak detection, heat load (sampling rate of 60s),facility water temperature supply, facility water temperature return, server liquid temperature supply, and server liquid temperature return. Some of the recognized attributes include; Device, Sensor, Time, Value, and Units where measurements include pressure, temperature, and Water flow parameters.

3.2 Preprocessing

This means that preprocessing helps with the quality of the data that will be fed into a machine learning algorithm as well as how consistent that data is. The units are normalized against each other in accordance with each sensor's specific type, where each type is assigned its index. It is in this normalization that uniformities as well as accurate training models are made possible. The case when a have missing or inconsistent values of data points is a typical problem of preprocessing; such methods as interpolation or data imputation are applied to complete the gaps as well as to manage outliers, thus preparing a suitable data set for the model.

3.3 Feature Selection

Feature engineering is more important, where all these features are chosen and structured or formatted in such a way that would take good results on the predictive models. In this regard, the analysis of the sensor data leads to the mapping of the values to particular labels including the facility water flow or server liquid temperature of the system which serves as the features in the training model phase.
Feature selection is performed according to the measures' importance and relevance to the target variable, for example, for heat load or water temperature prediction. There is no doubt that having domain knowledge is very important in selecting the most significant features. Furthermore, there could be literals conducted to achieve new features that are more suitable for revealing the interdependencies inside the data to improve the model's predictability.
In this study, two features were selected. They are:
• Units: The Type of Measurement of sensors in the datacentres for a particular period of time.
• Value: The Result of measurement of sensors in the datacentres for a particular period of time.

3.4 Model Training and Evaluation

For the predictive modeling step, the machine learning algorithms are used, such as regression models: Random Forest and XGBoost. Both algorithms are a kind of learning algorithms that are used to forecast target variable based on the input of characteristic sensors. Hyperparameter tuning is then done in each model for better results, all of them have been trained on the pre-processed and the features that were engineered.
Before defining the hyperparameters, they have to be tuned properly by using the grid search or randomized search, which ensures higher accuracy and model generalization. Case of Random Forest, other parameters like number of estimators and tree depth are tuned while for XGBoost the boosting parameters such as learning rate and maximum tree depth are tuned.
The effectiveness of the models is estimated using Mean Squared Error (MSE), Root Mean Squared

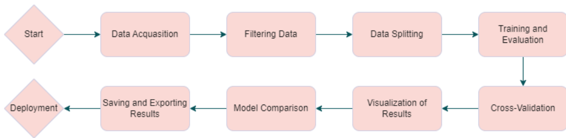


Figure 1: Model Architecture

Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R2). These are information on the performance of the model and it capability in predicting on unseen data.
Cross-validation is used to overcome the problem of overfitting so that inherited property prediction is made with high reliability. It attempts to divide the data into the training and the validation part many times, with each new model acting on a different division. This approach offers a complete evaluation of the different model performance on different data samples and the necessary adjustments are made.
Optimization of a model goes further from the given training to improve the prediction capability and reduce computation time. Algorithm-specific optimizations are the following ones: for example, in case of Random Forest, the importance of features is used to prune less important features. In the case of XGBoost, there are tuning parameters like the number of iterations boosting the model, learning rate, and maximum depth are set in detail to optimize the model's efficiency.

3.5 Overview

The below Fig. 1 outlines a comprehensive machine learning workflow, starting with Data Acquisition to gather relevant data, followed by Filtering Data to clean and preprocess it. The process continues with Data Splitting to create training and testing sets, then moves to Training and Evaluation of models, often incorporating Cross-Validation to optimize performance. After training, Visualization of Results provides insights through graphical representation, followed by Model Comparison to identify the best-performing model. The results are then Saved and Exported, and the workflow concludes with Deployment, where the refined model is implemented for real-world use.

4 RESULTS AND ANALYSIS

Table 1 also demonstrates the performance of the model Random Forest Regressor using Mean Absolute Error (MAE),Mean Squared Error (MSE) Root Mean Squared Error (RMSE) and R-squared (R2) of twenty different racks. Both 70/30 and 80/20 splits are provided also with/without cross-validation. This is demonstrating how cross-validation affects the prediction by having some cases with increased R2 than others with a worse performance when cross-validation is applied. Rear observations are high R2 values-the values literally near or more than 0.95 for most racks without cross validating and cross validating has shown much less values that can be good indicators of overfitting racks. Moreover, improvements are noticed when cross-validation is incorporated in some racks especially Rack 16 whose R2 rises to as high as 0.445 in the loop.

Table 1: Rack Wise Results for RF Regressor only for Numeric Values

Rack no.	Split	CV	MAE	MSE	R2
Rack 1	70/30	No	58.621	64189.336	0.996
	70/30	Yes	2917.325	2756325.59	-0.836
	80/20	No	58.472	64661.218	0.996
	80/20	Yes	2917.325	2756325.59	-0.836
Rack 2	70/30	No	56.3	48833.29	0.994
	70/30	Yes	560.939	1273912.904	0.948
	80/20	No	56.39	49663.522	0.993
	80/20	Yes	560.939	1273912.904	0.948
Rack 3	70/30	No	35.682	25434.312	0.989
	70/30	Yes	699.939	3608070.746	0.69
	80/20	No	34.947	23347.428	0.99
	80/20	Yes	699.939	3608070.746	0.69
Rack 4	70/30	No	65.503	111249.705	0.973
	70/30	Yes	865.975	4039189.745	0.73
	80/20	No	62.672	110123.774	0.974
	80/20	Yes	865.975	4039189.745	0.73
Rack 5	70/30	No	150.078	439327.808	0.875
	70/30	Yes	1656.948	18500900.81	-0.16
	80/20	No	49.89	42524.393	0.997
	80/20	Yes	1656.948	18500900.81	-0.16
Rack 6	70/30	No	49.423	38197.812	0.992
	70/30	Yes	1371.369	5677594.478	-0.143
	80/20	No	49.065	38118.672	0.992
	80/20	Yes	1371.369	5677594.478	-0.143
Rack 7	70/30	No	33.622	39029.145	0.952
	70/30	Yes	1394.243	7975824.019	0.018
	80/20	No	34.002	16941.352	0.998
	80/20	Yes	1394.243	7975824.019	0.018
Rack 8	70/30	No	35.233	20647.193	0.997
	70/30	Yes	1394.243	7975824.019	0.018
	80/20	No	34.002	16941.352	0.998
	80/20	Yes	1394.243	7975824.019	0.018
Rack 9	70/30	No	113.636	260977.59	0.982
	70/30	Yes	1611.013	17412938.19	-0.18
	80/20	No	114.719	268206.437	0.982
	80/20	Yes	1611.013	17412938.19	-0.18
Rack 10	70/30	No	190.414	433605.361	0.943
	70/30	Yes	1719.228	8069397.218	-0.141
	80/20	No	185.795	423796.024	0.878
	80/20	Yes	1719.228	8069397.218	-0.141

Table 2 illustrates the performance of the XG-Boost Regressor model on 20 different racks with numeric test data based on MAE, MSE, RMSE, and R2. We report results for four splits 70/30 and 80/20 with and without CV. In general, the R2 values are high (above 0.9) though it does not apply cross-validation but when applying cross-validation, the vast racks such as Rack 1 that originally had an R2 of 0.147, drastically drop hugely to an R2 if -1.643. Even more, some racks, namely Rack 5 and Rack 6, also demonstrate the decrease in the value of R2 after the cross validation, which also points to the overtraining of models. However, some racks, for instance, Rack 16 have a positive R2 of 0.992 without cross-validation but a negative value with cross-validation. The results emerge in terms of the inconsistency of utilising cross-validation in the XGBoost model, where the variation of R2 values and errors is large among different racks.

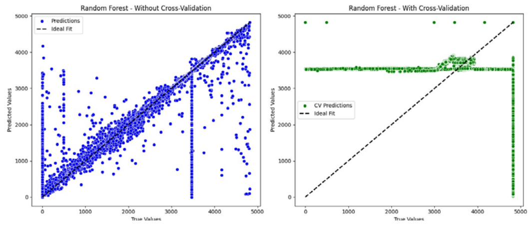
Table 2: Rack Wise Results using XGBoost Regressor for Numeric Values Test Data 10 Racks

Rack No.	Split	CV	MAE	MSE	R2
Rack 1	70/30	No	66.783	82676.425	0.994
	70/30	Yes	3536.528	39687716.82	-1.643
	80/20	No	66.891	86840.584	0.994
	80/20	Yes	3536.528	39687716.82	-1.643
Rack 2	70/30	No	70.161	102338.714	0.995
	70/30	Yes	576.594	1422092.694	0.943
	80/20	No	69.154	98179.045	0.995
	80/20	Yes	576.594	1422092.694	0.943
Rack 3	70/30	No	63.298	106335.139	0.991
	70/30	Yes	698.085	3545491.34	0.691
	80/20	No	62.871	107386.452	0.991
	80/20	Yes	698.085	3545491.34	0.691
Rack 4	70/30	No	70.562	157762.494	0.99
	70/30	Yes	890.744	14535632.96	-0.607
	80/20	No	127.833	1638371.263	0.928

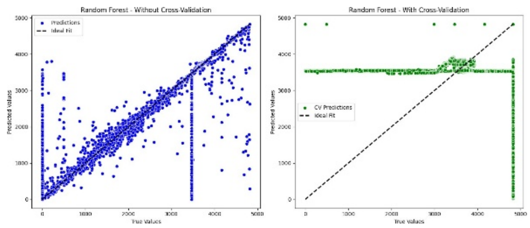
	80/20	Yes	1530.762	2014891.83	-0.212
Rack 5	70/30	No	72.424	104194.679	0.993
	70/30	Yes	1655.008	18499826.64	-0.16
	80/20	No	71.682	102993.421	0.994
	80/20	Yes	1655.008	18499826.64	-0.16
Rack 6	70/30	No	60.03	75719.105	0.985
	70/30	Yes	1705.83	8809078.817	0.069
	80/20	No	257.811	414063.18	0.93
	80/20	Yes	1653.531	9372708.78	0.079
Rack 7	70/30	No	46.446	62130.995	0.986
	70/30	Yes	1885.324	16551543.82	-1.038
	80/20	No	46.645	55290.557	0.993
	80/20	Yes	1885.324	16551543.82	-1.038
Rack 8	70/30	No	70.711	148246.431	0.992
	70/30	Yes	2133.422	26405897.6	-0.515
	80/20	No	70.766	149922.959	0.992
	80/20	Yes	2133.422	26405897.6	-0.515
Rack 9	70/30	No	134.751	408264.553	0.976
	70/30	Yes	1639.415	17501719.73	-0.186
	80/20	No	136.184	4068378.53	0.976
	80/20	Yes	1639.415	17501719.73	-0.186
Rack 10	70/30	No	117.404	308557.061	0.987
	70/30	Yes	1540.57	18859281.3	-0.141
	80/20	No	115.255	303458.405	0.982
	80/20	Yes	1540.57	18859281.3	-0.141

Comparison of Table 1 and Table 2 show that the RF Regressor has effectively learned from the data and consistently performs well across rakes and data splits, as evidenced by the higher R^2 values, often approaching or exceeding 0.9; thereby confirming a strong correlation between predicted and actual values. For example, in Rack 1 with a 70/30 split and no cross-validation, the RF Regressor records 0.996 R^2, while XGBoost gets 0.994. As against the performance of the RF Regressor, the XGBoost Regressor shows massive variability in performance-and wades through the data it learns awfully even under similar conditions. Many of the R^2 values are negative or very close to 0-in particular, for the 80/20 splits-suggesting that XGBoost does not capture the underlying patterns well. For example, Rack 10's R^2 was -0.141 at an 80/20 split with cross-validation for XGBoost, while the same scenario for RF Regressor resulted in 0.968.

The two graphs shown in Fig. 2 (a), (b) presents the predicted vs. true values of a Random Forest model, its performance with and without cross- validation is highlighted. In the first graph Points are blue and scattered but their corresponding points seem to lie near the ideal fit line but not completely perfect as some of them are a little farther, this is because of overfitting but not a serious one. In comparison, the second graph where the residuals were corrected with cross-validation presents green points away from the ideal fit line more often and specially at higher values, which suggests lower reliability and stochasticity in the validation folds.

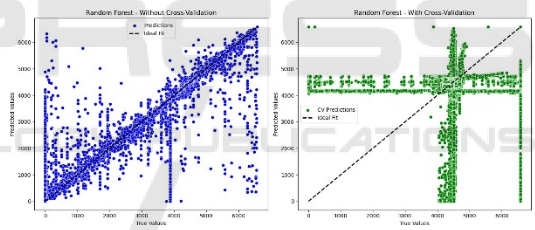


(a) Rack 4 in 70:30 Split ratio

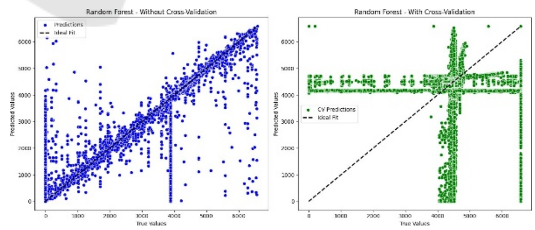


(b) Rack 4 in 80:20 split Ratio

Figure 2: Scatter Plot between True Values and Predicted Values in Random Forest Regressor for Rack 4



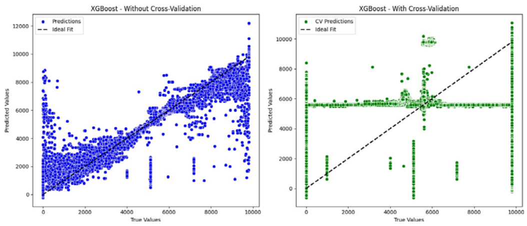
(a) Rack 10 in 70:30 Split ratio



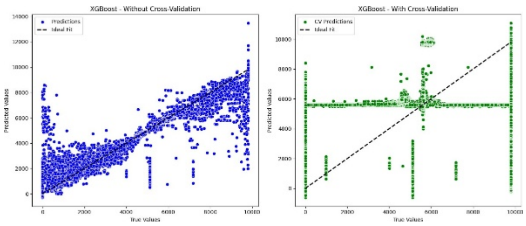
(b) Rack 10 in 80:20 split Ratio

Figure 3: Scatter Plot between True Values and Predicted Values in Random Forest Regressor for Rack 10

This comparison shows the model's performance to cross-validation and the difficulty of maintaining a stable level of predictive accuracy across different data splits.

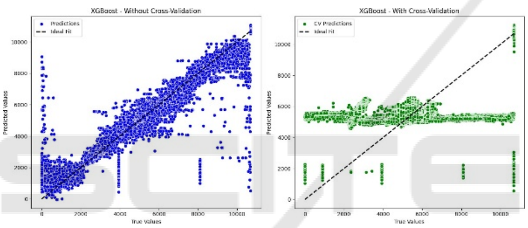


(a) Rack 3 in 70:30 Split ratio

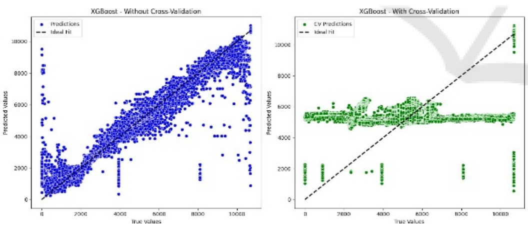


Rack 3 in 80:20 split Ratio

Figure 4: Scatter Plot between True Values and Predicted Values in XGBoost Regressor for Rack 3



Rack 6 in 70:30 Split ratio



Rack 6 in 80:20 split Ratio

Figure 5: Scatter Plot between True Values and Predicted Values in XGBoost Regressor for Rack 6

The two plots above Fig. 5 (a), (b) illustrates the comparison between the XGBoost model performance with the model which include the cross Validation for Rack 6. The left plot shows the results when cross-validation is not done while the predictions are depicted using blue circles. The correct plot includes cross-validation check, and predictions are marked in green dots. PredPol: In both the plots above, the dotted line line indicates the Which indicates the true positive or perfect fit line that equates the true values to the predicted values. Also, when making predictions without using cross-validation they seem to be distributed farther and are a less accurate representation of the ideal line because of this, the line on the right shows how predictions with cross-validation look like and demonstrate how cross-validation affects the consistency and ability to generalize when making predictions. This comparative analysis discusses the effect of cross-validation on the result of the model, in terms of accuracy and behavior.

5 CONCLUSIONS

This research shows how a Random Forest and XG-Boost can be used to identify outliers in a data centres. From regression tasks in these models, meaning- ful information regarding the performance of different types of racks was obtained. More work in the future will be towards the analysis and prediction of patterns of job assignments using the sensors. Moreover, the use of these models to create simulation environments should be the focus of future research because it will allow better control over data center management.

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