KOÇ UNIVERSITY

Industrial Engineering Department
INDR 491 Industrial Engineering Design Project

Fall 2023

Design of an Analytical Framework for Data Center Efficient Energy Management

08.12.2023

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1. Brief system description

KoçSistem is a well-known company that was founded in 1945 and has its main office in Istanbul. It is part of a bigger group called Koç Bilgi Grubu AS. This company is known for providing services in the area of information technology. Over the years, KoçSistem has expanded its services and also provides network solutions to its customers. KoçSistem was earlier known by the name Koç-Unisys before it was renamed.

The company has expanded and offers more services in the field of information technology. Now, it provides consulting services and helps other companies integrate IT systems. It also creates software products for its customers. KoçSistem is not only known in Turkey but also in more than thirty other countries, especially in Azerbaijan, Malaysia, England, and China.

KoçSistem offers a wide range of services. Some of these services include solutions related to the Internet of Things (IoT), analytics to help businesses understand data better, business solutions for data centers, and cloud services for storing and managing data.

KoçSistem has its own data center in Üsküdar, Istanbul. It has two floors and consists of 12 different rooms that store server racks. There are multiple servers, 4 coolers, 3 chillers and 2 sensor temperatures in the KS10 room in KoçSistem Data Center. These sensors record data in the room for 5 minutes. The cold air entering the system from the coolers takes the heat of the system and goes out of the system. Likewise, the Chiller reduces the temperature of the system by adding cold water to the system. The fan speed in this system is not manual in the Data Center, but since the set parameters are set manually in this project, we will assume that the fan speed is also manual. Some of the rooms are customized to store servers dedicated to single servers, whereas other rooms consist of server racks for multiple servers. The layout of the rooms is not identical, and the building where their data center is located was built as a hospital.

2. Literature review and sector analysis

There have been various approaches to making data centers more efficient using both predictive and optimization tools. Prediction-based approaches mainly focus on predicting future efficiency metric values, most importantly Power Usage Efficiency (PUE), based on historical data provided by the physical sensors in the server room. Optimization-based approaches include linear and dynamic programming on both hardware and software aspects of data center frameworks.

2.1. Prediction-based Approaches

The first ground-breaking predictive method for data center efficiency was proposed by Gao (2014) from Google. His main goal was to create a model that predicts PUE from Google data centers' 2-year historical data using MLP (multilayer perceptron) with 5 hidden layers and 50 nodes in each hidden layer. The features of the neural network were as follows:

1. Total server IT load [kW]
2. Total Campus Core Network Room (CCNR) IT load [kW]
3. Total number of process water pumps (PWP) running
4. Mean PWP variable frequency drive (VFD) speed [%]
5. Total number of condenser water pumps (CWP) running
6. Mean CWP variable frequency drive (VFD) speed [%]

7. Total number of cooling towers running
8. Mean cooling tower leaving water temperature (LWT) setpoint [F]
9. Total number of chillers running
10. Total number of dry coolers running
11. Total number of chilled water injection pumps running
12. Mean chilled water injection pump setpoint temperature [F]
13. Mean heat exchanger approach temperature [F]
14. Outside air wet bulb (WB) temperature [F]
15. Outside air dry bulb (DB) temperature [F]
16. Outside air enthalpy [kJ/kg]
17. Outside air relative humidity (RH) [%]
18. Outdoor wind speed [mph]
19. Outdoor wind direction [deg]

Having such a robust and reliable model allowed Google to do sensitivity analysis and anomaly detection easily. Using controllable variables from the listed features, they analyzed their effects on PUE on several scenarios to decrease PUE.

$$PUE = \frac{P_{total}}{P_{IT}} = \frac{P_{cooling} + P_{IT} + P_{electricalLosses} + P_{misc}}{P_{IT}}$$

For an efficient data center, the power consumption for non-IT components should be as small as possible, i.e., PUE should be close to 1. In anomaly detection scenarios, they used the MLP model to catch erroneous readings of the individual sensors when actual PUE values were higher than predicted PUE values.

Shoukourian et al. (2017) proposed to model the Coefficient of Performance (COP) rather than PUE, as they discussed that COP indicates the power consumption of four cooling circuits, whereas PUE is the combination of COPs from all cooling elements in one number.

$$COP = \frac{Q_{CoolingCircuits}}{P_{CoolingCircuits}}$$

where $Q_{CoolingCircuits}$ is the aggregated amount of cold generated by four cooling circuits (in watts) and $P_{CoolingCircuits}$ is the aggregated amount of power generated by four cooling circuits (in watts).

They argued that using COPs, it is easier to observe the effects of various control variables on the overall efficiency. In their model, they used LSTM with two hidden layers and a final linear layer with the following features extracted from Leibniz Supercomputing Centre (LRZ):

1. Aggregated amount of cold generated by each cooling circuit
2. Aggregated amount of power consumed by the fans of each cooling tower
3. The number of active cooling towers
4. Wet bulb temperature
5. Inlet water temperature (to the distribution bar) from each cooling circuit
6. Return water temperature (to the distribution bar) to each cooling circuit

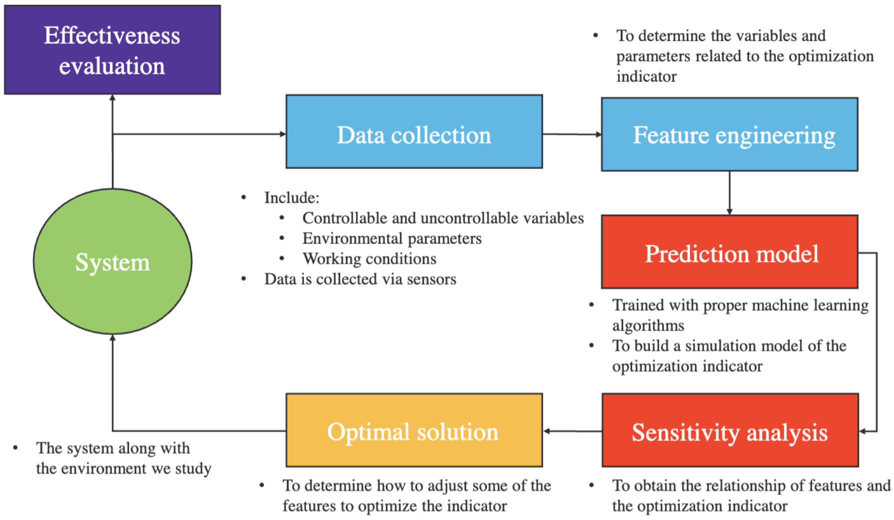

Figure 1: PUE optimization framework of Yang et. al (2021)

Yang et al. (2021) proposed another approach similar to Gao (2014) for the PUE optimization framework. First, they collected data from individual sensors in Tencent Tianjin Data Center building No. 4, containing 38 features, similar to the features Gao (2014) used, ranging from January 2018 until November 2019. After applying some feature engineering, they set up different prediction models, i.e., neural networks (NNs), light gradient boosting machine (LightGBM), random forest, and RNN. Finally, they conducted a sensitivity analysis within the constraints to optimize PUE.

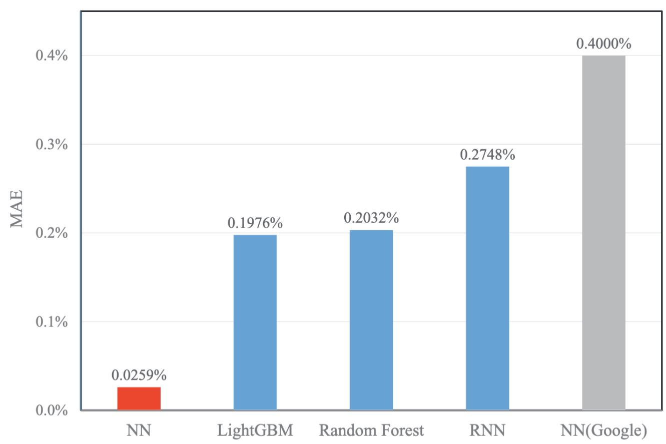

Figure 2: MAE of models Yang et al. (2021) and Gao (2014) used

They found out that the 10 most important features affecting PUE are total server IT load, condenser water flow of chillers, outside air enthalpy, chillers' current percentage, condenser water input temperature of chillers, chilled water output temperature of chillers, indoor air enthalpy, condenser water output temperature of cooling towers, chilled water of chillers and outside air wet bulb temperature. Among the controllable variables, the condenser water flow of chillers is the most important variable. They also outperformed Gao (2014) in the PUE prediction model and their best-performing model was a neural network with 3 hidden layers.

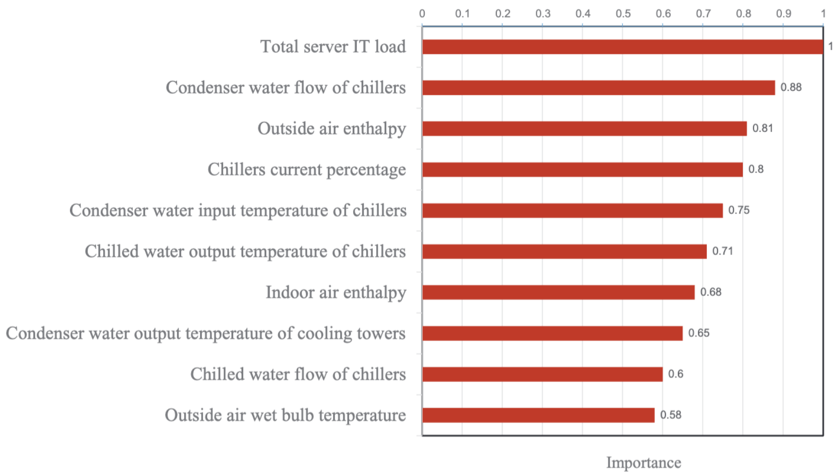

Figure 3: Top 10 most important features affecting PUE from Yang et al. (2021)

2.2. Optimization-based Approaches

Two optimization-based approaches that focus on different aspects of data center systems have previously been proposed. Stamatescu et. al (2018) came up with an approach in which they optimize the scheduling of virtual machines (VMs) in the data center servers with a mixed integer linear programming problem. The decision variables are the assignment of each virtual machine to each server at time t. The constraints mainly focus on the CPU and memory capacity of each server. The objective of the problem is to minimize the energy consumption caused by working servers, migration of VMs between different servers, and turning servers on/off in consecutive time steps.

COMMERCIAL ALGORITHM - ENERGY CONSUMPTION

Hour	1	2	3	4	5
Server 1	660	632	445	335	529
Server 2	160	166	158	146	135
Server 3	142	180	180	178	173
Server 4	10	174	269	8	0
Server 5	5	244	250	272	7
Server Consumption	977	1396	1302	939	844
Total IT Consumption of the Data Center: 5458 kWh/hour					

THE PROPOSED ALGORITHM - ENERGY CONSUMPTION

Hour	1	2	3	4	5
Server 1	628	740	645	0	0
Server 2	0	0	0	140	0
Server 3	0	0	0	0	0
Server 4	0	250	261	250	25
Server 5	258	270	261	270	265
Server Consumption	886	1260	1167	660	290
Total IT Consumption of the Data Center: 4263 kWh/hour					

Figure 4 and 5: Energy consumption comparison between commercial algorithm and Stamatescu et. al (2018)'s algorithm

In a comparison with a commercial algorithm, their approach decreased the total IT consumption by 22%, in a system with 5 servers and 5 types of application.

Lazic et al. (2018) came up with a linear optimization problem with a quadratic objective, by which they optimize the scheduling of air handling units (AHUs) to control the temperature and the airflow of the data center.

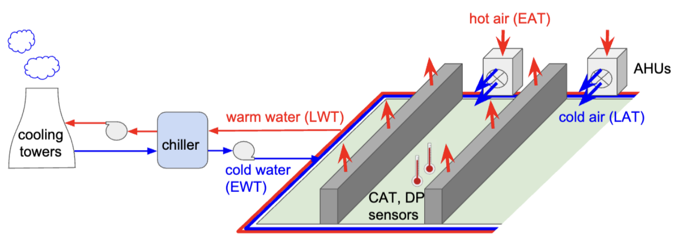

Figure 6: Data center cooling loop from Lazic et al. (2018)

They classified the variables of a data center system into three sections. “Control” variables (variables that can be manipulated) of their system were “fan speed” and “valve opening” for each AHU. “State” (variables that are predicted and regulated) variables were “differential air pressure” (DP), “cold-aisle temperature” (CAT), “entering air temperature” (EAT), and “leaving air temperature” (LAT). “Disturbance” variables were “server power usage” and “entering water temperature” of the chilled water at each AHU. Their optimization model had 1.2K variables along with a “large number” of linear and range constraints.

3. System Analysis

3.1. Problem Definition

KoçSistem is currently struggling with an inefficient cooling scheduling system across its data centers. This inefficiency is caused by running cooling systems that are more than sufficient. Therefore, the Power Usage Effectiveness (PUE) value, which depends on the change in total server IT load, temperature, humidity, and energy consumption of cooling systems, is higher than desired.

One of the biggest obstacles is the lack of predictability regarding server workload. This leads to manual and often imprecise cooling operations. The high PUE value proves inefficiency in energy consumption. The problem is that cooling operation arrangements are performed manually because there is a lack of predictability regarding server workload. This uncertainty causes strain on the server and disruption of operations. Consequently, this escalates the IT load on the data servers, reduces job performance, and potentially triggers customer dissatisfaction that could financially penalize KoçSistem through fines.

3.2. The Objectives and Scope of the Project

The primary objective of this project is to optimize the scheduling of the cooling system in KoçSistem's data centers. The project does not include any modifications to the existing physical air conditioning systems. Instead, it emphasizes the intelligent scheduling of cooling operations to reduce energy consumption and minimize cooling expenses.

Considering the symptoms and the problem explained in the problem definitions section, the main aim of this project is to create a mathematical model in order to help solve KoçSistem's high energy consumption and cut the cooling costs of their server rooms in the data centers.

Once the project is complete, we will improve server efficiency by stopping the CPUs from overheating and consequently reducing any customer job delays. We aim to develop a mathematical model to optimize the usage of cooling systems in the server rooms. With the developed model, we are planning to make employees effectively manage energy usage. The objective of this approach is to efficiently determine the most suitable cooling scheduling and times in response to the workload of servers, including both planned and unplanned server loads. The use of this dynamic technique provides optimal functioning for the data servers while minimizing energy usage.

A significant part of our project is sensitivity analysis. With sensitivity analysis, we will check the effect of parameters and how changing temperatures, like the amount of workload, changes in outside temperature, or how much a cooling system is being utilized, can affect energy use and the PUE value. Also, this will allow us to keep the server temperature within a certain range by observing the effects of such variables on the server temperature.

3.3. Data Analysis

For our data analysis, we started by looking at Excel files that were split into different sheets. We were provided with various data in different weeks, given what data was thought to be useful and our requests as our data analysis continued. We figured out that the common interval of the data provided by KoçSistem was from the beginning of April 2023 until the end of October 2023. Although this situation causes a lack of understanding of the system since it doesn't include winter months, we decided to use the data that is available to us rather than creating synthetic data.

We received data from rooms KS2, KS8, and KS10, but among them, the most promising room was KS10 because its data consisted of more features. We received daily and 5-minute data from KoçSistem. We decided to use only the 5-minute data to keep our merged data consistent with its timestamps, and the information provided by the daily data was not worth upsampling to 5-minute periods.

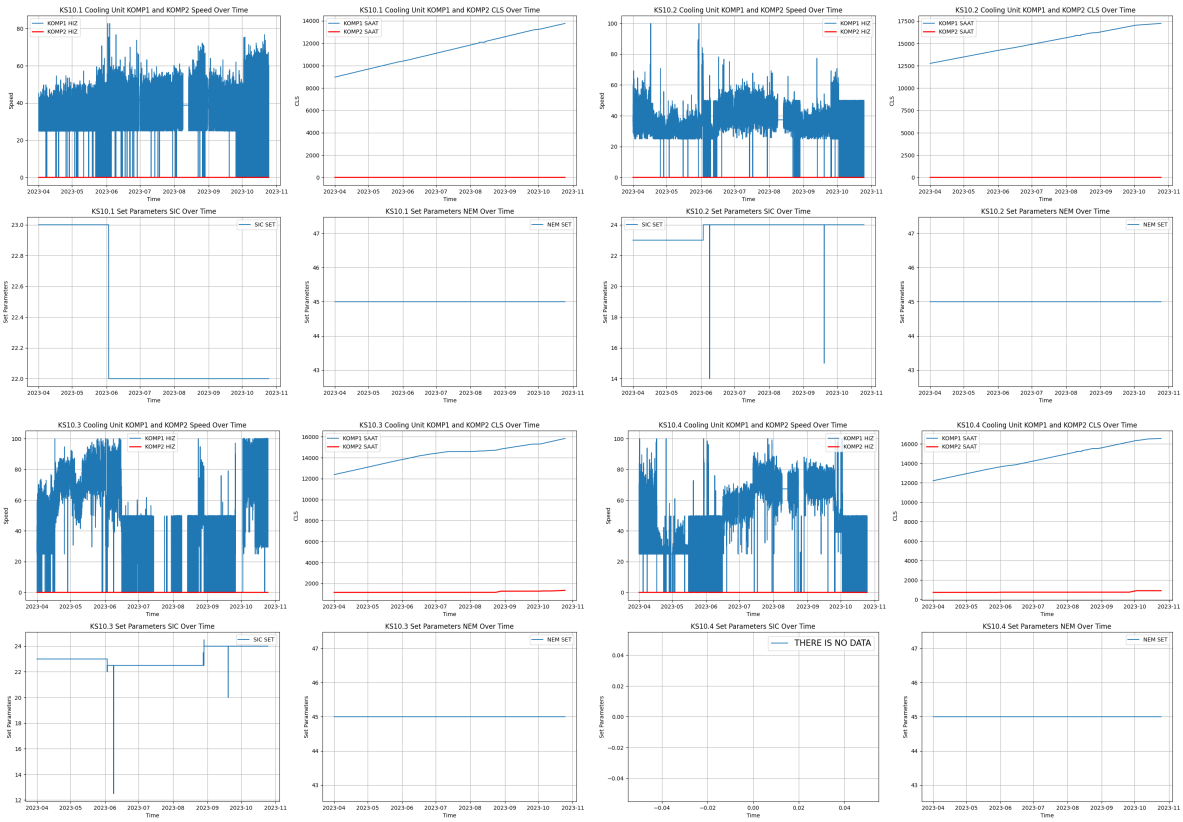

Figure 7: Cooling unit fan speeds, temperature and humidity set parameters for the servers in KS10.

We noticed that out of two cooling units on each server, only one of them had been utilized. Humidity set parameters for each server were held constant, and temperature set parameters were mostly kept the same. Clock values kept track of the total time each cooling unit was being utilized. Therefore, we only decided to include KOMP1 cooling unit speeds, as they are the only meaningful parameter among the server-related parameters. All of our findings above can be seen in Figure 7.

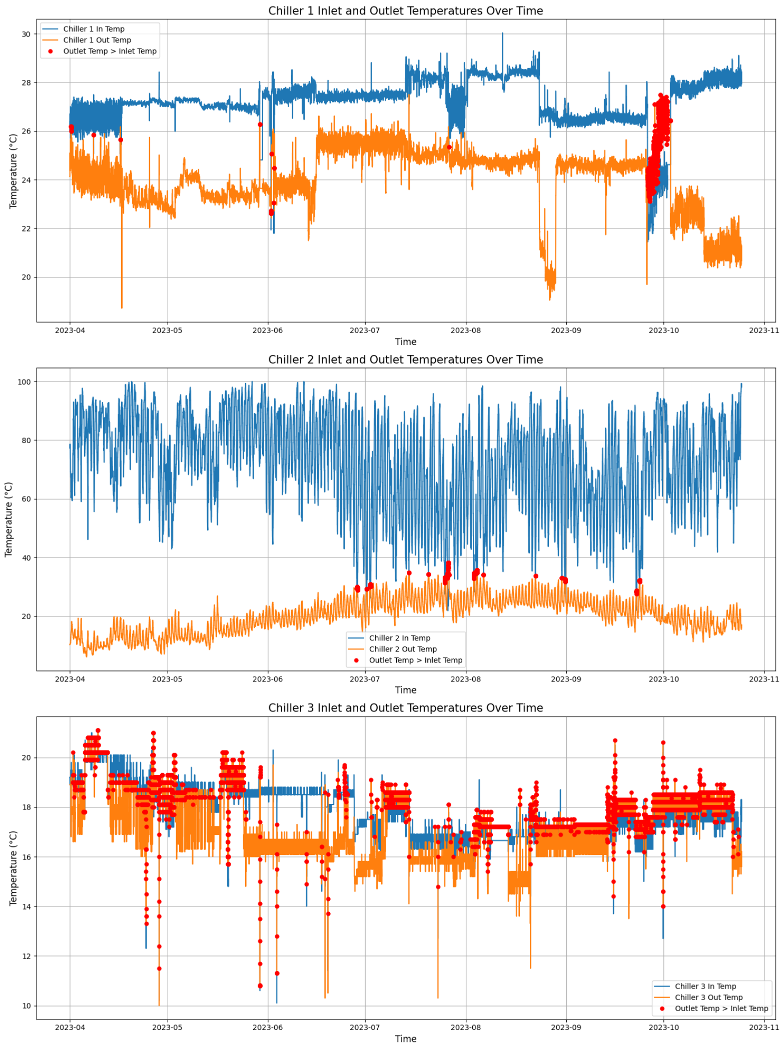

Figure 8: Chiller inlet and outlet water temperatures in the KS10 room.

As mentioned in the system description, chiller inlet temperature is the temperature of the water leaving the servers and en tering chillers, and the vice-versa for the chiller outlet temperature. However, as shown in Figure 8 with red dots, there are many data points at which the chiller inlet temperature is higher than the chiller outlet temperature. We interpret that at such timestamps, there is redundant cooling since chiller water is cooling down in the server room rather than heating up.

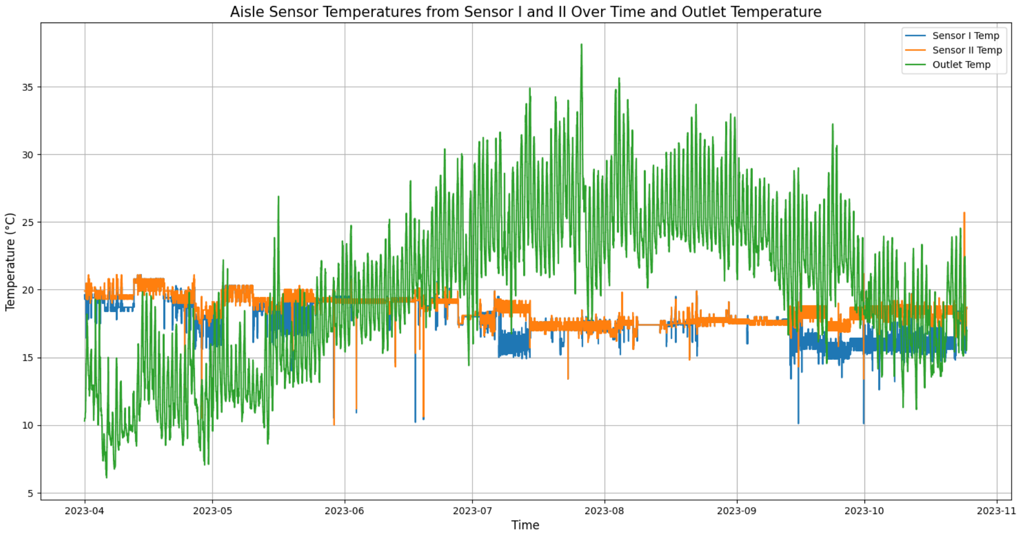

Figure 9: Sensor and outlet temperatures between April-November 2023 for KS10 room.

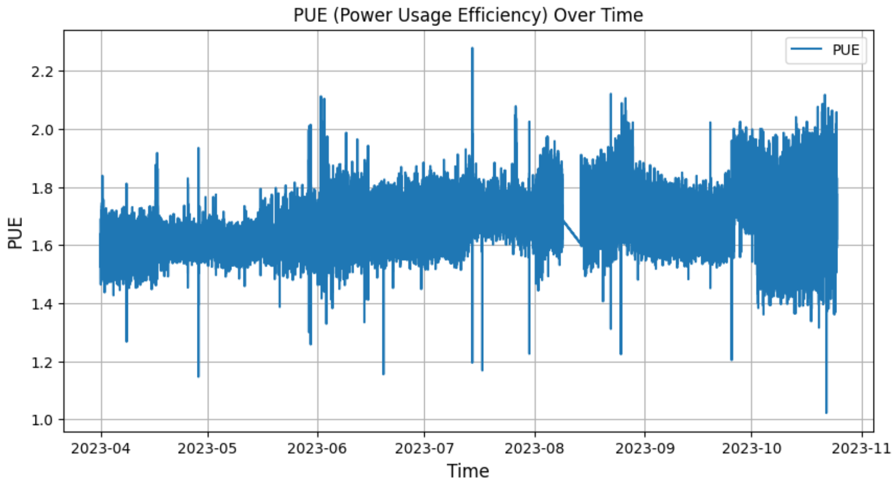

Figure 10: PUE between April-November 2023 of KS10 room.

Also, as seen in Figure 10, PUE of the KS10 room fluctuates mostly between 1.4 and 2.0. However, Google achieved a PUE of 1.1 in 2014, as Gao (2014) expresses. Even after 9 years, KS10 room couldn't achieve a stable PUE value close to 1.1. Therefore, we come to the conclusion that KS10 room's cooling scheduling can be improved significantly.

4. Proposed System

4.1. Inputs and Outputs

In the proposed system, the inputs include the speeds of four cooling units, which are monitored every five minutes; in and out water temperatures for three chillers; and room temperatures from two sensors. Additionally, the system acquires minute weather forecasts from online sources. These inputs are crucial for the system to determine the optimal operational speeds for the cooling units. The system makes decisions for the upcoming hour and provides an estimated PUE value and room temperature.

4.2. Major Components

Major components are categorized into data preprocessing, predictive modeling, model validation and selection, prediction model, and decision model.

4.2.1. Data Preprocessing

For data preprocessing, we incorporated raw data that was provided by KoçSistem. In our examination of the provided data, we realized that there are some NaN values at some timestamps for some features. We filled those gaps instead of removing the incomplete rows to preserve the 5-minute structure. We also replaced any extreme values that didn't fit the pattern by taking the average at the subsequent timestamps of such features. We added further dummies and lagged values of specific features to our data to improve the accuracy of the models that we are planning to train. The included dummies are days of the week, hours of the day, and months of the year. As we noticed that outlet temperature and humidity values are also important, we extracted those values using web scraping and incorporated them into our data. We also added a 1-day lagged value of PUE to be used in the PUE prediction model. After data preprocessing, our finalized data consists of 59342 data points and 53 features. Features include PUE, room aisle temperatures from 2 sensors, chiller inlet-outlet water temperatures, cooling unit fan speeds, outlet temperature and humidity values, dummies, and lagged features.

Before training and validating models, we split the data into training data, which is 80% of the whole data, and test data by random splitting.

4.2.2. Predictive Modeling and Model Validation

In predictive modeling, we implement several machine learning models, such as OLS, Random Forest, and Gradient Boosting, to predict PUE values and room temperature. While predicting the PUE values, all of the models take the features stated above (speed of the cooling units, in and out temperatures of the chillers, temperatures that are collected by the sensors in the KS10 room, outlet weather conditions, dummy, and lag variables). For room temperature forecasting, models take the features excluding PUE and sensor temperatures.

In the model validation and selection part, we investigated each trained machine learning model for both PUE and temperature prediction. RMSE and MAPE values are compared between models for train and test predictions. We also checked that residuals are normally distributed to ensure that our models predict properly without neglecting key assumptions.

After the validation part, we evaluated the candidate models for PUE and temperature prediction. The selected models will be used while exploring the possible solutions to the scheduling problem of cooling unit speeds. You can find the implementation of our predictive models and time series plots comparing true and predicted values for each model and predicted feature in the appendix.

Model	Parameters	Train MSE	Train RMSE	Train MAE	Train MAPE	Test MSE	Test RMSE	Test MAE	Test MAPE
OLS	None	0,0027	0,0519	0,0379	0,0225	0,0027	0,0524	0,0225	0,0226
Random Forest	max_features = 'sqrt'	**0,0002**	**0,0142**	**0,0101**	**0,0060**	0,0015	0,0387	0,0276	0,0164
Gradient Boosting	learning rate = 0.1 depth = 5	0,0011	0,0325	0,0238	0,0142	**0,0012**	**0,0360**	**0,0253**	**0,0151**
Lasso	alpha = 2e-5	0,0032	0,0566	0,0420	0,0249	0,0033	0,0571	0,0423	0,0250

Table 1: Error values for various predictive models of PUE

In PUE prediction, we have achieved a test MAPE of 1.51% in our best-performing model, gradient boosting. Therefore, we have chosen the gradient boosting algorithm for the prediction of PUE to be used in our decision model.

Model	Parameters	Train MSE	Train RMSE	Train MAE	Train MAPE	Test MSE	Test RMSE	Test MAE	Test MAPE
OLS	None	0,5008	0,7077	0,5447	0,0310	0,5015	0,7081	0,5435	0,0309
Random Forest	max_features = 'sqrt'	**0,0121**	**0,1102**	**0,0599**	**0,0034**	**0,0883**	**0,2973**	**0,1596**	**0,0092**
Gradient Boosting	learning rate = 0.1 depth = 5	0,1147	0,3387	0,2120	0,0121	0,1346	0,3669	0,2195	0,0126
Lasso	alpha = 2e-5	0,5642	0,7511	0,5730	0,0328	0,5660	0,7523	0,5731	0,0328

Table 2: Error values for various predictive models of Sensor I temperature

Model	Parameters	Train MSE	Train RMSE	Train MAE	Train MAPE	Test MSE	Test RMSE	Test MAE	Test MAPE
OLS	None	0,1580	0,3975	0,2142	0,0113	0,1523	0,3902	0,2136	0,0112
Random Forest	max_features = 'sqrt'	**0,0029**	**0,0541**	**0,0320**	**0,0017**	**0,0172**	**0,1315**	**0,0837**	**0,0045**
Gradient Boosting	learning rate = 0.1 depth = 5	0,0275	0,1659	0,1074	0,0057	0,0291	0,1708	0,1095	0,0058
Lasso	alpha = 2e-5	0,1717	0,4143	0,2373	0,0125	0,1650	0,4062	0,2367	0,0125

Table 3: Error values for various predictive models of Sensor II temperature

In sensor temperature prediction, we have achieved a test MAPE of 0.88% for sensor-I and 0.41% for sensor-II in our best-performing model, random forest. Therefore, we have chosen the random forest algorithm for the prediction of sensor temperatures to be used in our decision model.

4.2.3. Decision Model

Lastly, with the Decision Model, we will optimize the system by scheduling the speed of the cooling units for each 5 minutes to minimize the PUE value of the KS10 room while satisfying the desired range for room temperature. For the decision model, we will implement a nonlinear programming model to select the optimal speeds of cooling units for each 5-minute timestamp. With this decision model, we are planning to schedule cooling unit speed without sharp changes over subsequent periods, which results in more stable PUE values that are lower on average.

In terms of a mathematical model, our primitive model would be as follows:

$minimize \quad PUE$

$s.t.$

$$GradientBoosting(\{v_{t,1}, v_{t,2}, v_{t,3}, v_{t,4}\} \, U \, V_{t,1}) \; = \; PUE \qquad (1)$$

$$RandomForest1(\{v_{t,1}, v_{t,2}, v_{t,3}, v_{t,4}\} \, U \, V_{t,2}) \; \leq \; T_{set} \; + \; 3 \qquad (2)$$

$$RandomForest1(\{v_{t,1}, v_{t,2}, v_{t,3}, v_{t,4}\} \, U \, V_{t,2}) \; \geq \; T_{set} \; - \; 3 \qquad (3)$$

$$RandomForest2(\{v_{t,1}, v_{t,2}, v_{t,3}, v_{t,4}\} \, U \, V_{t,2}) \; \leq \; T_{set} \; + \; 3 \qquad (4)$$

$$RandomForest2(\{v_{t,1}, v_{t,2}, v_{t,3}, v_{t,4}\} \, U \, V_{t,2}) \; \geq \; T_{set} \; - \; 3 \qquad (5)$$

$$v_{t,i} \; - \; 0.1 \; * \; v_{(t-1),i} \; \leq \; v_{(t-1),i} \qquad for \; \forall i \in \{1, 2, 3, 4\} \qquad (6)$$

$$v_{t,i} \; + \; 0.1 \; * \; v_{(t-1),i} \; \geq \; v_{(t-1),i} \qquad for \; \forall i \in \{1, 2, 3, 4\} \qquad (7)$$

$$v_{t,i} \; \leq \; 100 \qquad for \; \forall i \in \{1, 2, 3, 4\} \qquad (8)$$

$$v_{t,i} \; \geq \; 0 \qquad for \; \forall i \in \{1, 2, 3, 4\} \qquad (9)$$

where;

- V_1 is the set of features to be used in PUE prediction model except cooling unit speeds, which are chiller inlet and outlet water temperatures, outlet temperature and humidity, room sensor temperatures, dummies and 1-day lagged value of PUE.

- V_2 is the set of features to be used in sensor temperature prediction models except cooling unit speeds, which are chiller inlet and outlet water temperatures, outlet temperature and humidity and dummies.

- $v_{t,1}$, $v_{t,2}$, $v_{t,3}$ and $v_{t,4}$ are the cooling unit speeds in servers 1, 2, 3 and 4 at time t. $v_{t,i}$ will be our decision variables, and we will have the information of the set $\{v_{s,i} \mid s < t\}$.

- Constraint 1 is the PUE prediction of our GB model trained previously. We will try to minimize the predicted PUE with changing values of $v_{t,i}$.

- Constraints 2-5 are the sensor temperature predictions of our Random Forest models trained previously. We will keep the room temperature within specified limits while changing the cooling unit speed.

- Constraints 6 and 7 ensure that we do not have a sharp decrease or increase in cooling unit speeds, which can cause redundant energy consumption and cooling unit malfunctioning.

- Constraints 8 and 9 ensure that cooling unit speeds lie between 0 and 100.

4.3. Flow Chart

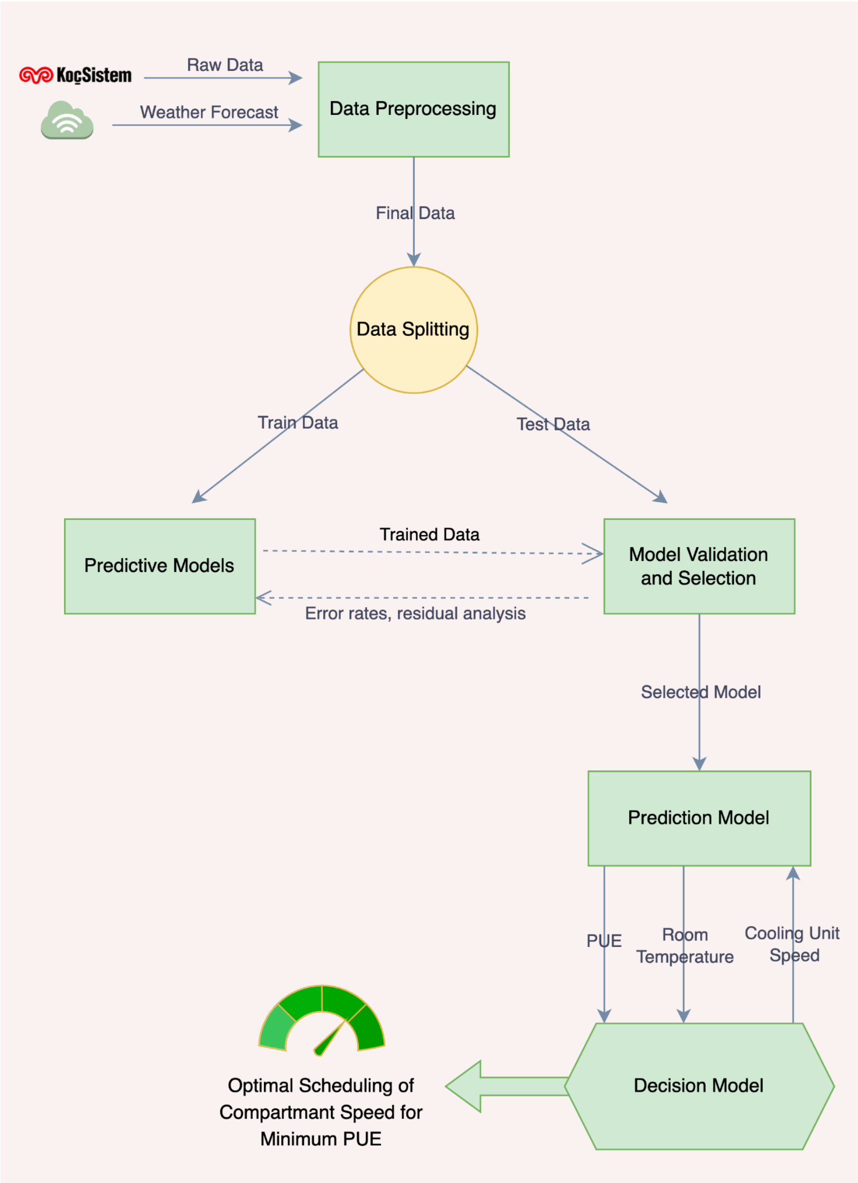

Figure 11: Flow chart for the KoçSistem cooling optimization framework.

4.4. Consideration of Alternatives

First of all, we will try to establish our decision-making model with nonlinear programming, but after observing the speed at which the model reaches the optimal result or whether the structure of the problem is suitable for nonlinear programming, we will decide whether to continue with this method or not. If we get negative results from these attempts, we will either replace Gradient Boosting and Random Forest algorithms with OLS to make our decision model linear or try to do the optimization with metaheuristic algorithms. The main algorithms we will try as metaheuristic algorithms will be simulated annealing, tabu search, and genetic algorithms. While trying to solve the problem with metaheuristic algorithms, we hope that the fitness function based on the pickle files that we created from trained prediction models will work very quickly and obtain a result close to optimal. Our main concern about using metaheuristic algorithms is deciding the stopping criteria for searching.

5. Project Plan

5.1. Current Accomplishments

The majority of the workloads are accomplished until today depending on the Gantt chart and the work packages that are provided in the project proposal document. The first work package was on the background research and analysis of the system. In that manner, the literature review is completed properly. The data center of KoçSistem in Ayazma is visited by several group members so that the system is observed in its original environment. The meeting involved an exchange of expertise with the professionals at the facility. They provided us with a comprehensive explanation of the system, followed by a guided tour of the server rooms.

The next work package was about data collection and preprocessing. Through extensive weekly meetings with our company-side supervisor, the principal operator of the data center, we identified the necessary data requirements. After obtaining cost, humidity, heat, and energy consumption data from the company, we determined the outliers, investigated the connections between features in the data, and found some patterns and correlations. In short, the first observations were made.

The scope of the third work package is data analysis and feature engineering. Accordingly, additional features, including days, seasons, and forecasted weather information published by meteorology, were incorporated, believing they could enhance the predictive capabilities of the models under development. We conducted a thorough analysis of feature importance to determine which features should be retained in the models. Finally, visualization of the data was completed, and exploratory data analysis was conducted.

In the work package four, we explored a range of predictive techniques, from basic approaches like linear regression and lasso regression and advanced machine learning models such as gradient boosting and random forest. We utilized several Python libraries to identify additional suitable models for our data, setting parameters and constraints and determining the division for training and testing. The development phase involved initiating the model's actual construction, with a focus on training, optimization, and the application of regularization techniques to address overfitting. We then evaluated the models' performance on training and testing datasets using metrics like RMSE and MAPE, interpreting each model's results to understand their strengths and weaknesses. In the model selection phase, we eliminated models based on their performance in the training and testing evaluations, streamlining our approach to ensure the most effective and efficient predictive capabilities. Finally, we decided to use gradient boosting for PUE forecasting and Random Forest for temperature forecasting.

In work package five, we conducted a sensitivity analysis of decision variables on PUE and sensor temperatures, both to validate our models and to extract the underlying effects of decision variables on PUE and room temperature.

5.2. Remaining Work Packages

Work package number	6	Start date or starting event:		**11.12.2023**	
Work package title	**Mathematical Modeling for Decision-Making**				
Participant number	**1**	**2**	**3**		
Participant name	Bora Aktaş	Serra Işık	Umur Berkay Karakaş		
Weeks per participant	3	4	4		

Objectives

- Formulate a mathematical model that represents the real world
- While considering constraints and objectives, implementing the mathematical model
- Analyzing the results of the model

Description of work

T6.1 (11.12.2023 – 01.01.2024) Developing the Model

The model is implemented in a Python environment, using Python libraries. Testing the developed model simultaneously and adjusting the model parameters accordingly.

T6.2 (01.01.2024 – 08.01.2024) Results and Decision Making

The model will be tested on the test data, and it will be compared with the results of the decisions already taken by the KoçSistem without considering the future. These outcomes will be analyzed, and key findings will be determined.

Deliverables

D6.1 (25.12.2023) A Mathematical Model implementation in Python
D6.2 (08.01.2024) Informed decisions and recommended changes for the current system

Milestones

M6.1 (18.12.2023) A reliable mathematical model, that considers all of the constraints, is developed for further use.
M6.2 (01.01.2024) Automated decision-making model

Work package number	7	Start date or starting event:	**16.10.2023**		
Work package title	**Reporting**				
Participant number	**1**	**2**	**3**	**4**	**5**
Participant name	Batuhan Gül	Bora Aktaş	Sena Karadağ	Serra Işık	Umur Berkay Karakaş
Weeks per participant	14	5	14	5	5

Objectives

- In a formal report, present our findings, insights, and recommendations
- Provide a comprehensive explanation of the project, including methodologies and results
- Communicate with the company

Description of work

T7.1 (30.10.2023 – 12.01.2024) Drafting the reports

Documentation of our findings, visualizations, and suggestions through the semester

T7.2 (13.01.2024 – 12.01.2024) Review and Final Report

Reviewing the draft for inconsistencies and finalizing the report according to the feedback from our advisor, company, and team members.

Deliverables

D7.1 (08.12.2023) Progress Report
D7.2 (12.01.2024) Final Poster
D7.3 (19.01.2024) Project Report

Milestones

M7.1 (12.01.2024) Finalization of the project
M7.2 (12.01.2024) Presentation of the project

6. References

1. Gao, J. (2014), “Machine learning applications for data center optimization”, Google.
2. Lazic, N.; Lu, T.; Boutilier, C.; Ryu, M.; Wong, E.; Roy, B. and Imwalle, G. (2018) “Data center cooling using model-predictive control”, Proceedings of the 32nd International Conference on Neural Information Processing Systems, 3818-3827.
3. Le, V. D. (2021). "Air free-cooled tropical data center: design, evaluation, and learned lessons". IEEE Transactions on Sustainable Computing.
4. Shoukourian, H.; Wilde, T.; Labrenz, D. and Bode, A. (2017), “Using machine learning for data center cooling infrastructure efficiency prediction”, 2017 IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW), 954-961.
5. Stamatescu, I.; Ploix, S.; Fagarasan, I.; and Stamatescu, G. (2018). “Data center server energy consumption optimization algorithm”. 2018 26th Mediterranean Conference on Control and Automation (MED).
6. Yang, Z.; Du, J.; Lin, Y.; Du, Z.; Xia, L.; Zhao, Q.; and Guan, X. (2021). “Increasing the energy efficiency of a data center based on machine learning”. Journal of Industrial Ecology, 26(1), 323–335.

7. Appendix

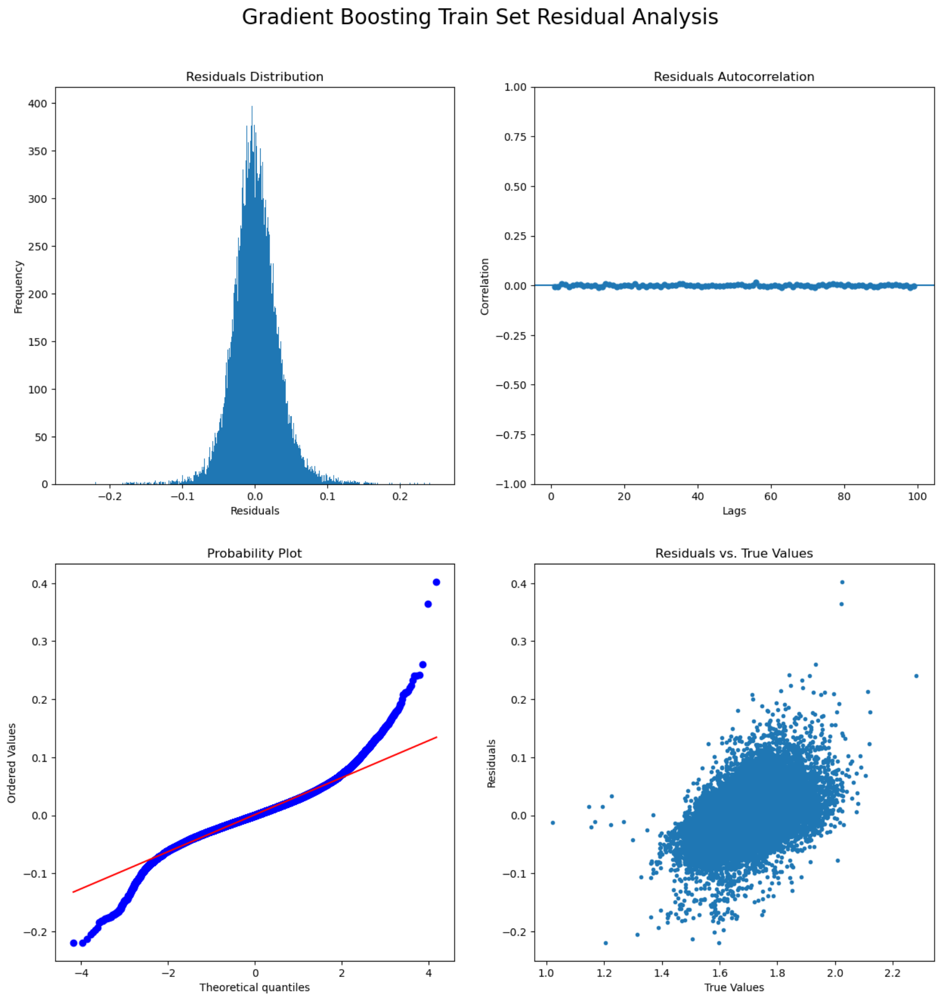

Figure 12: Residual analysis of gradient boosting model for PUE prediction on training set

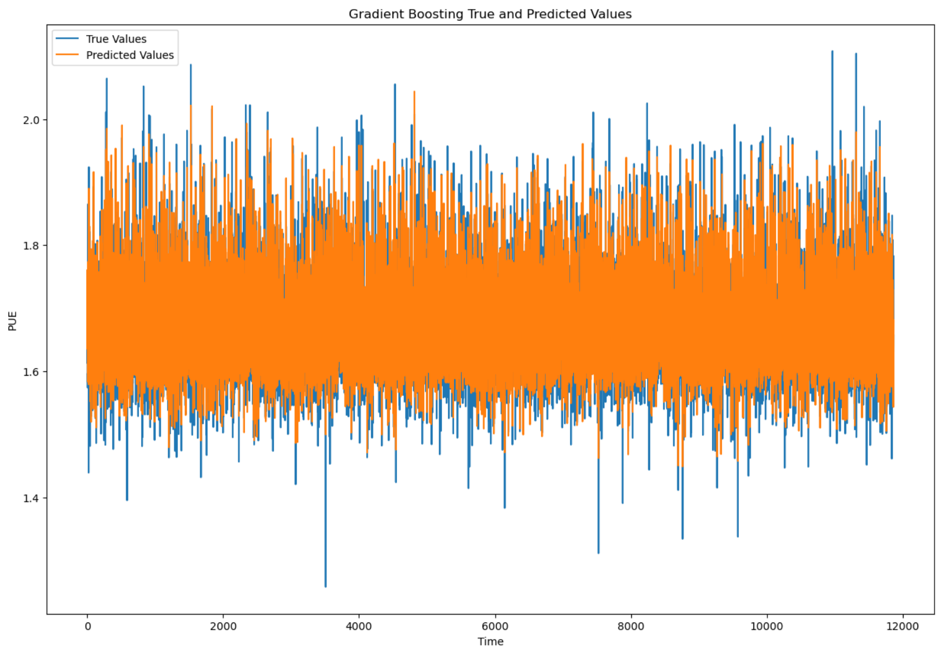

Figure 13: Predicted vs. actual PUE values in gradient boosting model for test set

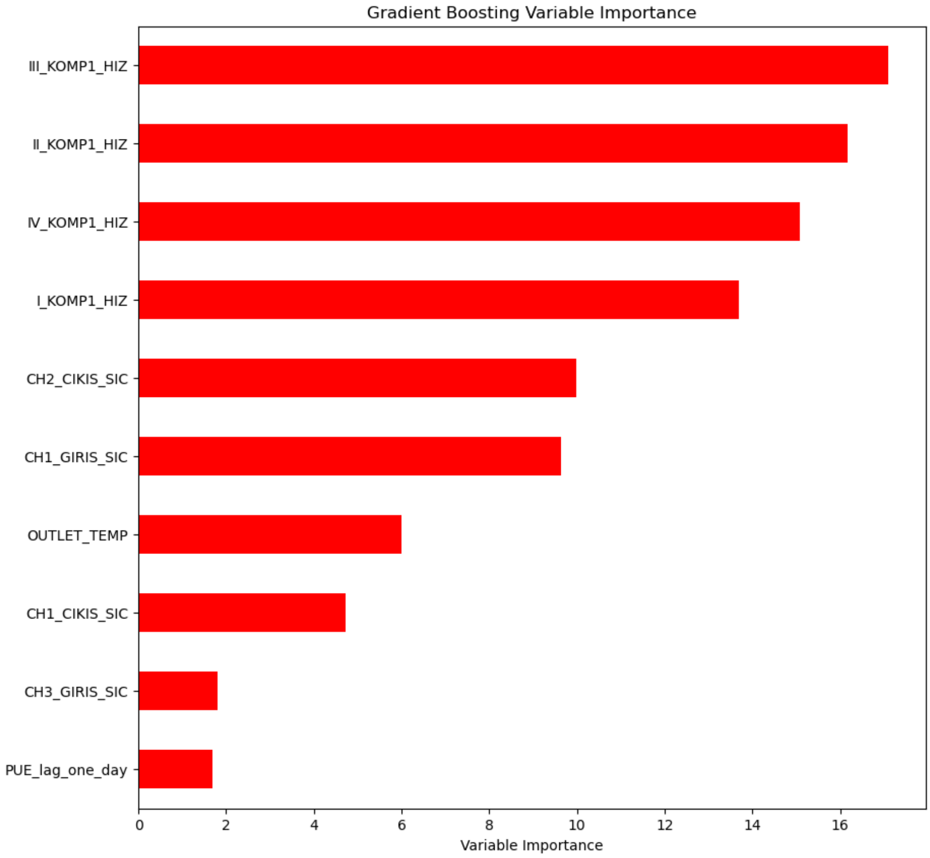

Figure 14: Top-10 most important variables in gradient boosting model for PUE prediction

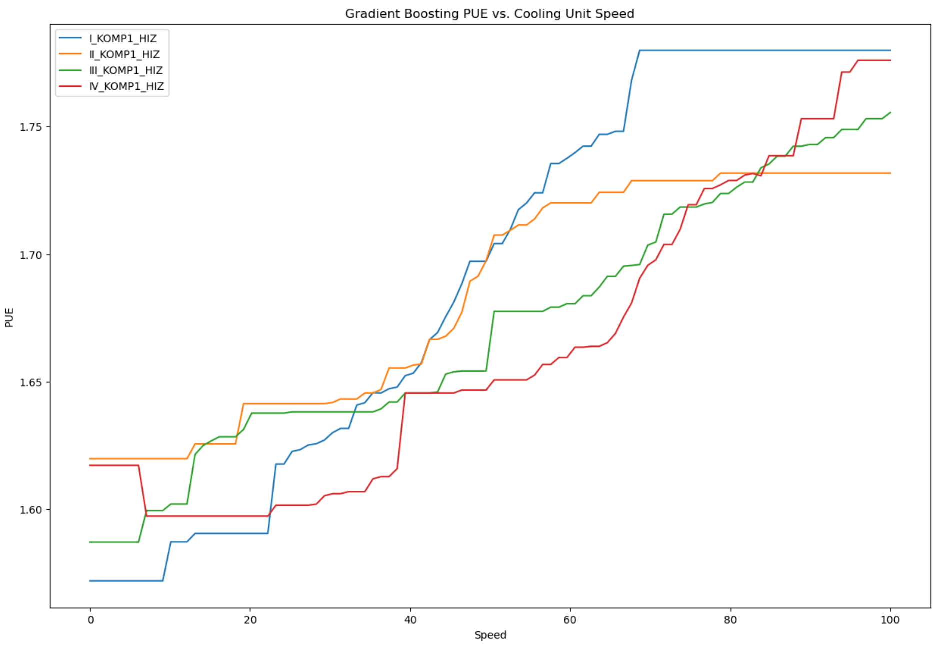

Figure 15: Sensitivity analysis for the effect of cooling unit speeds on PUE in gradient boosting model trained for PUE prediction

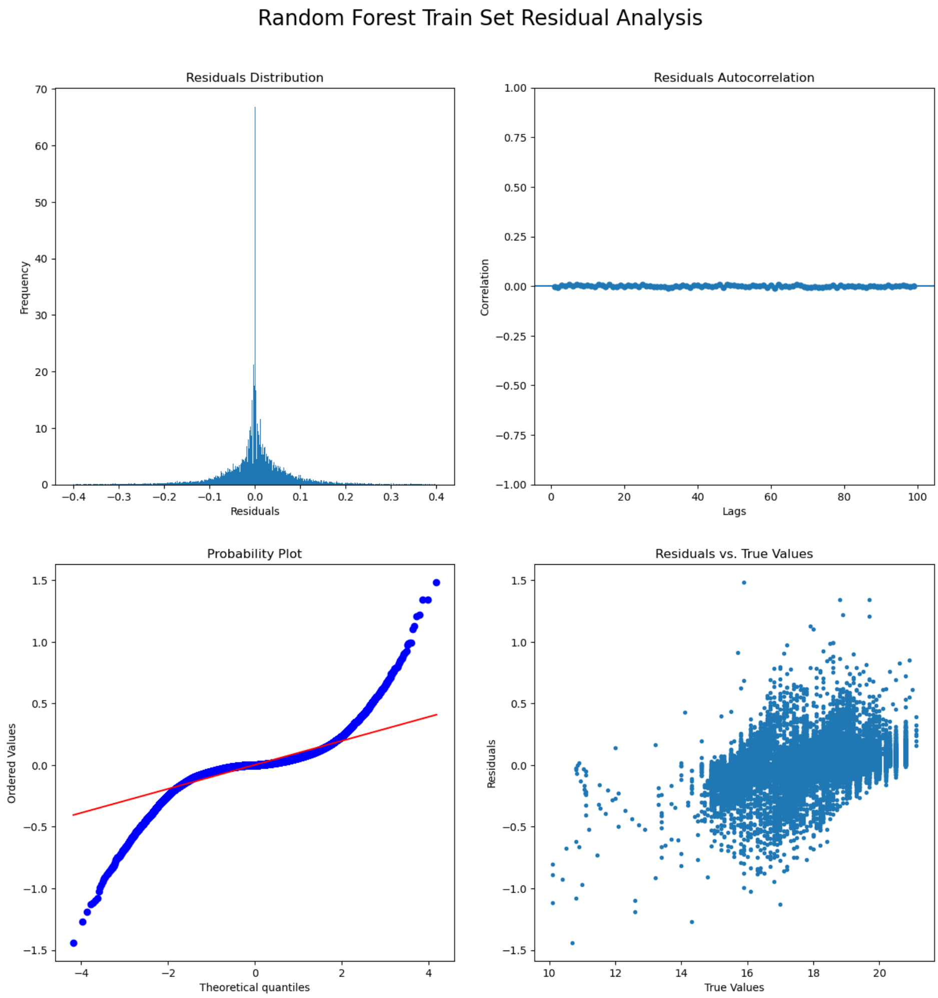

Figure 16: Residual analysis of random forest model for Sensor-I temperature prediction on training set

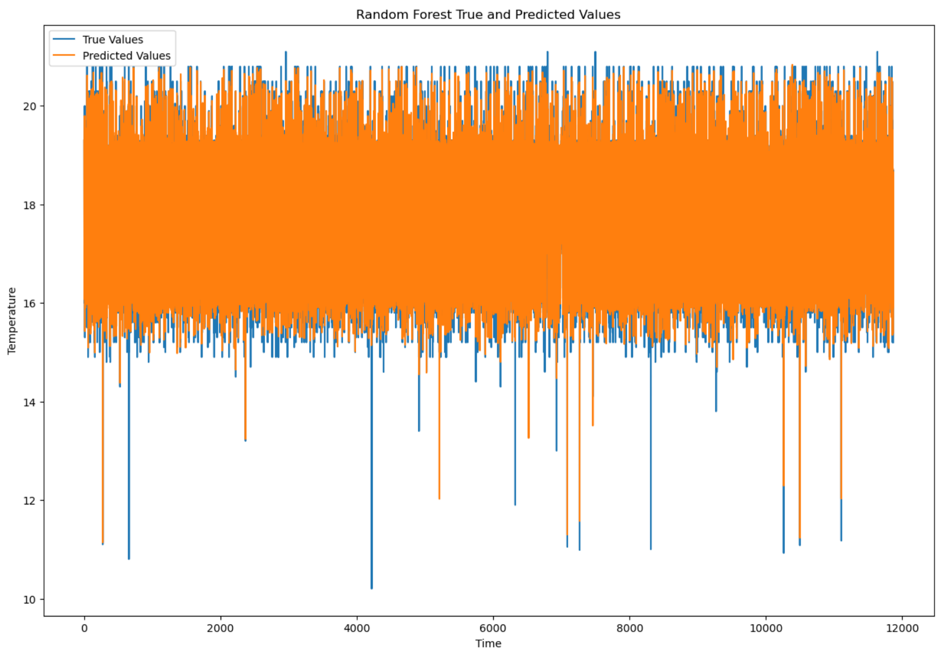

Figure 17: Predicted vs. actual Sensor-I temperature values in random forest model for test set

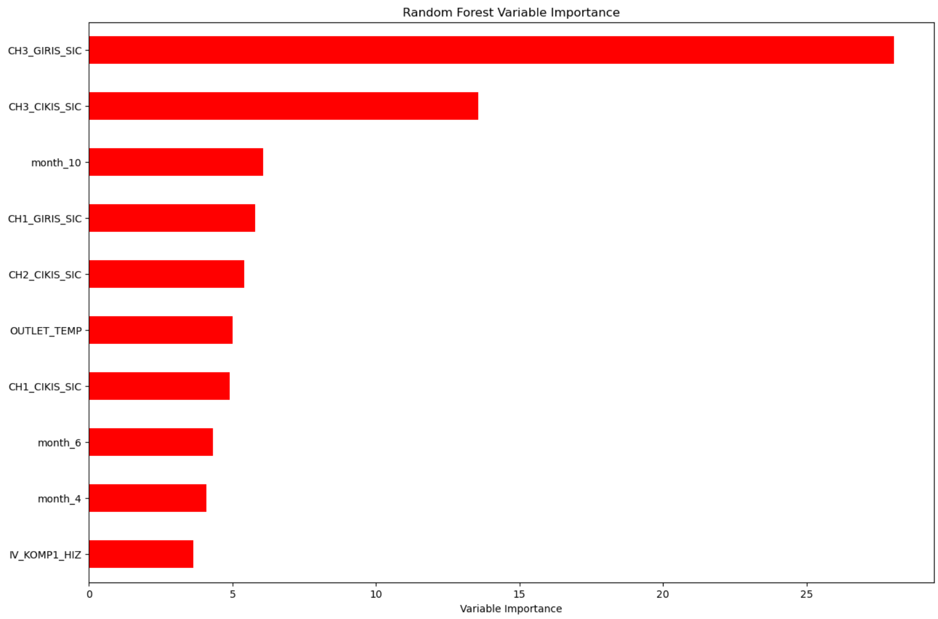

Figure 18: Top-10 most important variables in random forest model for Sensor-I temperature prediction

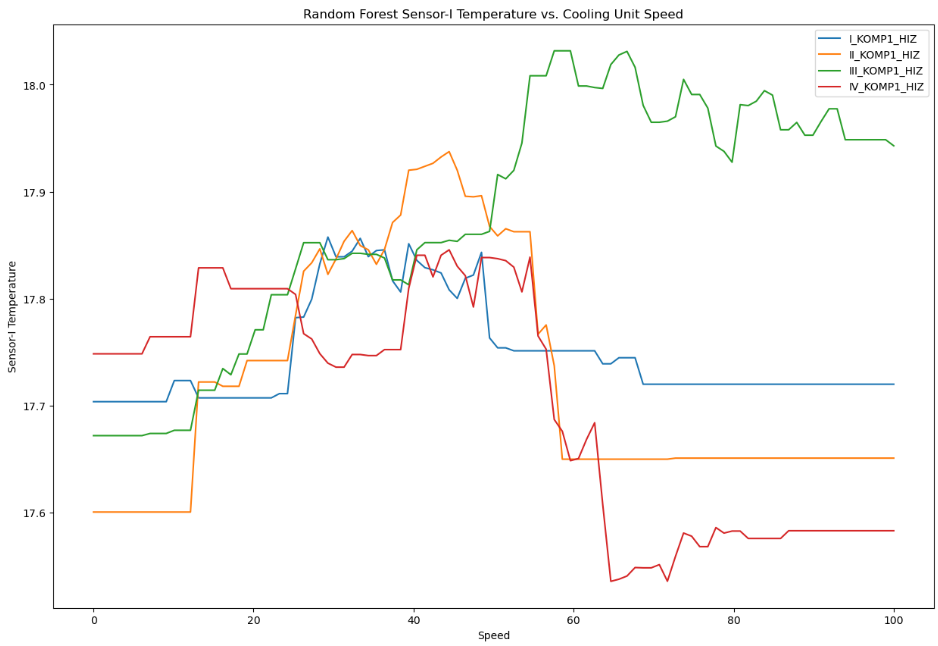

Figure 19: Sensitivity analysis for the effect of cooling unit speeds on Sensor-I temperature in random forest model trained for sensor-I temperature prediction

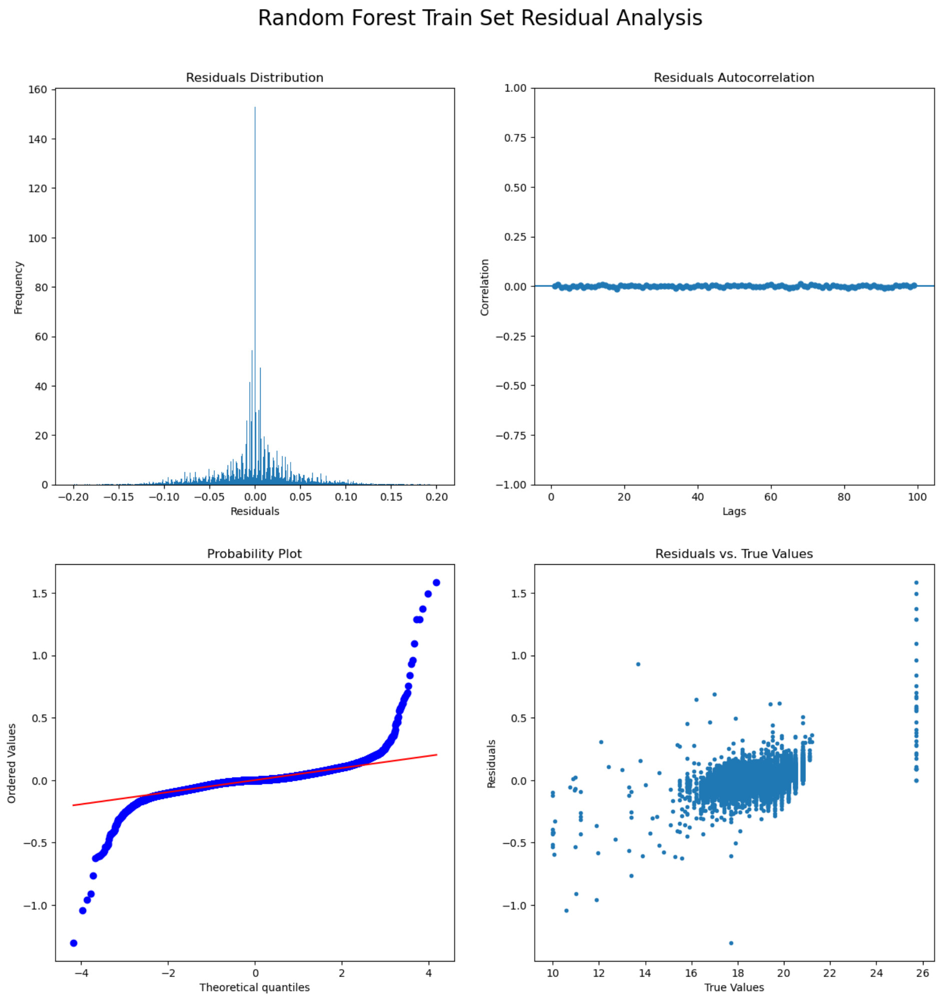

Figure 20: Residual analysis of random forest model for Sensor-II temperature prediction on training set

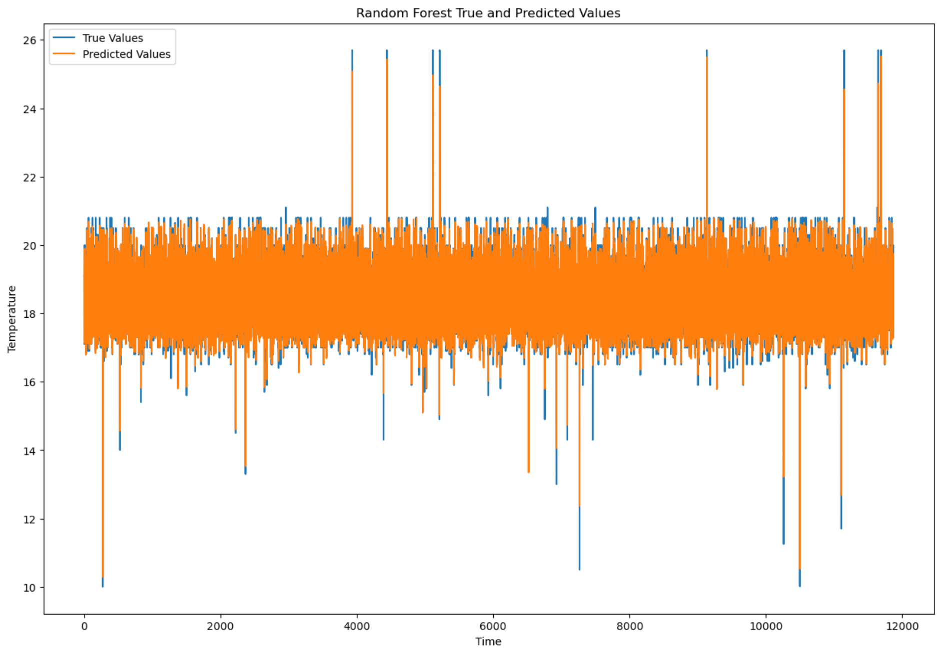

Figure 21: Predicted vs. actual Sensor-II temperature values in random forest model for test set

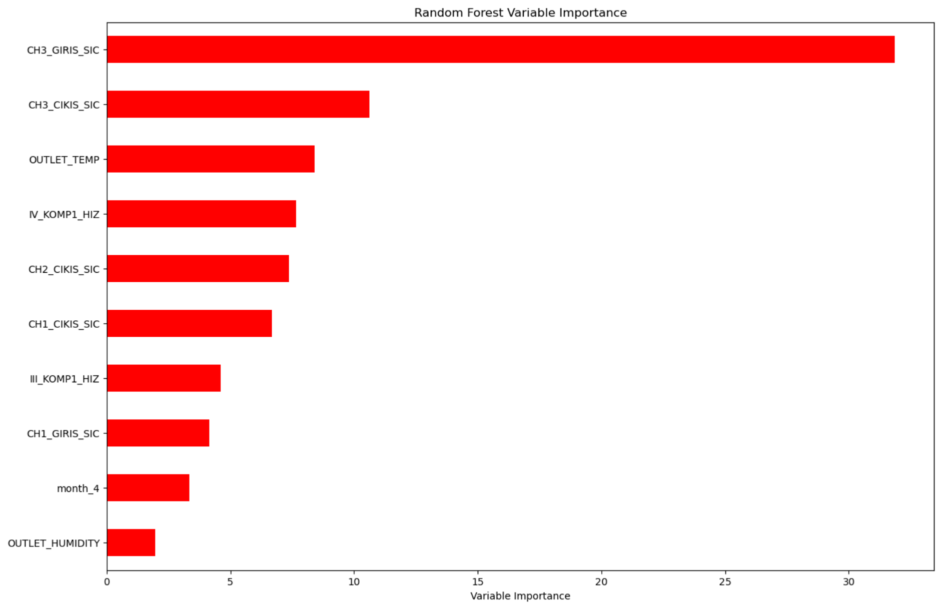

Figure 22: Top-10 most important variables in random forest model for Sensor-II temperature prediction

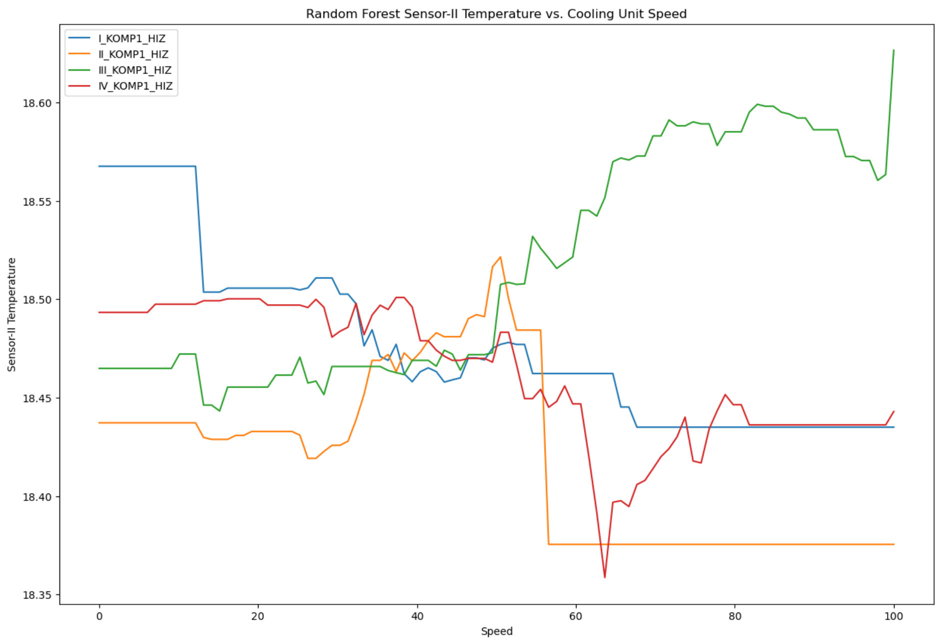

Figure 23: Sensitivity analysis for the effect of cooling unit speeds on Sensor-II temperature in random forest model trained for Sensor-II temperature prediction