PREDICTIVE MODEL TO FORECAST THE ENERGY CONSUMPTION OF AIR-COOLED CHILLER BASED ON AMBIENT TEMPERATURE & LOAD PROFILE

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Abstract

In the commercial buildings, HVAC systems account for approximately 40-50% of total power consumption, out of which 60-66% is utilized in the plant itself. 75-80% of the plant room power consumption is used in HVAC systems.

Due to the global energy surge, even a minuscule drop in input power, can largely affect the energy patterns of the premises. Therefore, there is a pressing need to explore various cutting-edge technologies that include artificial intelligence and machine learning vis-à-vis this increasing need.

Currently, the existing solutions rely majorly on rule-based control systems that are based on defined setpoints as set by the operator (Kim et al., 2019). As a result, they lack adaptability to varying conditions and lack understanding of the complex relationships between the various parameters.
The existing solutions use limited training data and preprocessing techniques which directly affect the robustness and the generalization capabilities of the AI models implemented. While some solutions use a single model approach with an absence of a comparative study that evaluates different models including hybrid architectures, the others pose challenges in integrating into the existing control systems.

This research presents a comprehensive experimentation with a large array of algorithms which is aimed at building a predictive model that forecasts and optimizes power consumption of air-cooled chillers.
Analysis of load profile and outdoor temperature data enables precise forecasting and efficient chiller control, leading to substantial energy savings and environmental benefits. The findings from this research have broad implications for the cooling systems industry, providing valuable insights for policymakers, engineers, and facility managers seeking to enhance energy efficiency and sustainability in their operations.

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1. Introduction

1.1 Background

HVAC systems, particularly chillers are used in various applications including manufacturing, residential buildings, commercial buildings, and data centres. Chillers are a crucial component of the HVAC system whose focus is thermal fluid generation for heating or cooling applications.

Along with maintaining significant operations, these systems account for a major portion of the building energy consumption which is close to 25 to 40% of the total energy (Wei et al., 2014; Nisa and Kuan, 2021). With the increasing energy surge, it becomes a challenge to achieve optimal energy efficiency without affecting the operational needs. Therefore, there is a need to leverage the use of cutting-edge technologies such as artificial intelligence. To address this challenge and the need, this research proposal focuses on the development of a predictive model that uses artificial intelligence to forecast and optimize the power consumption of air-cooled chillers.

Being the most energy extensive system, Chillers possess a tremendous opportunity for achieving substantial energy savings. Optimized and efficient chiller operations not only reduce the wear and tear of the equipment itself but also reduce the operational costs along with significantly contributing to the global drive towards sustainability and reduced carbon footprint. By optimizing the energy consumption of the chillers, this research shall make a profound contribution across the industries, towards achieving the environmental and financial goals.

Traditional chiller operations rely majorly on rule-based control systems where the logics are pre-programmed based on pre-defined conditions and thresholds. While these logics provide a basic control strategy for the chillers, they fail to adapt to the dynamic ambient conditions and load profile. These limitations can lead to substandard energy consumption and operational costs. Furthermore, existing AI-based solutions which use ANN models, have shown promise but they also exhibit limitations. These models have been built on limited datasets and minimal preprocessing techniques, potentially affecting their accuracy and generalizability. Additionally, a significant gap exists in terms of a comparative study that compares the potential of different machine learning algorithms including the hybrid ones. This gap hinders the understanding of which algorithms are best suited for the optimization of the energy consumption of air-cooled chillers.

The primary aim of the research is to build novel AI algorithms that could effectively predict and optimize the energy consumption of the air-cooled chillers based on various factors that include the ambient temperature, chilled water flow, chiller water temperature etc. By integrating these variables into the model, the model will be able to adapt to the varying conditions in real time and will be able to make accurate predictions that can further help in efficient chiller control. This research proposes a comprehensive study of different models and addresses the limitations of the existing solutions.

The research methodology encompasses data collection, model development, and validation using real-world operational data from an air-cooled chiller.

In conclusion, this research contributes to the development of a robust and accurate predictive model for optimizing the energy consumption of air-cooled chillers. The integration of ambient temperature and load profile data enables precise forecasting and efficient chiller control, leading to substantial energy savings and environmental benefits. The findings from this study have broad implications for the cooling systems industry, providing valuable insights for policymakers, engineers, and facility managers seeking to enhance energy efficiency and sustainability in their operations.

1.2 Problem Statement

The energy consumption of air-cooled chillers is a significant operational concern due to its environmental and economic implications. However, existing approaches lack comprehensive predictive models that consider the dynamic interplay between ambient temperature and load profiles. This research aims to address this gap by developing a predictive model that accurately forecasts energy consumption in air-cooled chiller systems, taking into account the influence of ambient temperature variations and load profiles.

The absence of a comprehensive predictive model hampers the ability to optimize energy efficiency in air-cooled chiller systems. By bridging this gap, the research seeks to empower industries with a tool that not only forecasts energy consumption but also enables proactive measures to optimize efficiency.

The economic implications of inadequate energy consumption forecasts are felt in the form of increased operational costs. By providing an accurate predictive model, this research aims to assist industries in implementing cost-effective measures.

Furthermore, incomplete predictive models may lead to suboptimal chiller operation, causing unnecessary wear and tear on equipment. By accurately considering ambient temperature variations and load profiles, the proposed model can mitigate excessive strain on the chiller system, prolonging equipment life and reducing maintenance costs.

1.3 Aim and Objectives

The main aim of the study is to develop an advanced predictive model that effectively forecasts and optimizes the energy consumption of air-cooled chillers by leveraging critical parameters such as ambient temperature and load profile.

The research objectives are as follows:

- To analyse the different techniques used in modeling and forecasting the energy consumption of an air-cooled chiller.
- To develop a predictive model for air-cooled chillers' energy consumption.
- To compare between the various predictive models including SVM, random forests and deep learning algorithms such as RNN and other hybrid models. Each algorithm has its strengths and weaknesses, and this comparison aims to identify which model or combination of models performs best for the given task.
- To evaluate the performance of the model through rigorous testing using the various evaluation metrices.
- To facilitate informed decision-making for facility managers and engineers by providing actionable recommendations to enhance the energy efficiency of their chiller system using innovative AI-based strategies.

1.4 Research Questions

The following research questions are suggested for each of the research objective as highlighted as follows.

- What are the key parameters and variables that influence the energy consumption in air-cooled chiller systems?
- How effectively does the predictive model account for seasonal variations and extreme weather conditions in predicting air-cooled chiller energy consumption and identifying opportunities for energy savings?

- How machine learning techniques, such as neural networks or deep learning models, outperform traditional regression methods in predicting and optimizing air-cooled chiller energy consumption?
- How does the incorporation of the proposed predictive model into existing chiller control systems affect overall energy consumption, cost savings, and environmental impact on a long-term basis?

1.5 Scope of the Study

This research covers the below scope of the study.

- Analysis of type of chillers and application:
    - The research focuses specifically on air-cooled chiller used in commercial and industrial applications.
    - It excludes other types of cooling systems such as water-cooled chillers or specialized cooling technologies.
- Data Collection and Analysis:
    - The study involves collecting 02 years historical operational data (between January 2021 to December 2022) for an air-cooled chiller feeding an office building in Dubai, United Arab Emirates.
    - The analysis includes ambient temperature data, load profiles, and chiller operational parameters.
- Predictive Modeling:
    - The primary focus is on developing a predictive model that optimizes energy consumption based on ambient temperature and load profiles.
    - The model incorporates machine learning techniques and multiple regression analysis.
- Validation Metrics:
    - The study uses standard evaluation metrics such as R-squared, mean squared error (MSE) and mean absolute error (MAE).
- Preparing Report and Dissertation:
    - The scope includes preparing a detailed research report and dissertation document following academic guidelines and standards.

1.6 Significance of the Study

The research study is supposed to be significant in many ways. Key points are mentioned below:

- Offers a proactive approach to optimize energy consumption in air-cooled chillers, a key contributor to overall energy usage in commercial and industrial sectors. This approach contrasts with traditional reactive methods, providing a forward-thinking strategy to enhance energy efficiency.
- Provides a tailored predictive model that dynamically adjusts chiller operation on integration with building automation system, leading to substantial energy savings without compromising cooling efficiency. This customization ensures a more accurate and efficient adaptation to the unique operational requirements of different facilities, contributing to the versatility and applicability of the proposed model.
- Demonstrates practical strategies for facility managers and engineers to reduce energy bills and operational costs. By integrating the predictive models with the building automation system via cloud deployment or on Edge devices, the equipment can be made to run at a sweet spot that reduces the overall energy consumption of the chiller without compromising with the comfort of the building occupants.
- Implementing the proposed strategies not only reduces operational costs but also enhances the competitiveness of industries. Companies adopting energy-efficient practices can position themselves as leaders in sustainability, appealing to environmentally conscious consumers and stakeholders. This dual benefit of cost reduction and improved corporate social responsibility further underscores the significance of the study.
- In many regions, there is an increasing focus on environmental regulations and energy efficiency standards. The study's recommendations can assist industries in aligning with and even exceeding these regulations, ensuring compliance, and avoiding potential penalties. This proactive approach to regulatory adherence enhances the resilience of businesses in a dynamic and evolving regulatory landscape.
- Equips stakeholders with accurate energy consumption forecasts, enabling them to make informed decisions about energy usage and demand response strategies.

1.7 Structure of the Study

This research is structured to unfold systematically, addressing key aspects pertinent to the building of predictive models for energy consumption in air-cooled chillers. Chapter 1 initiates the exploration, delving into the background of the study, articulating the problem statement, defining the study's aim and objectives, and formulating research questions. It delineates the scope of the research, highlighting the significance of the study within the context of sustainable HVAC solutions. The subsequent chapter, Chapter 2, ventures into the extensive landscape of existing knowledge, delving into energy consumption challenges, traditional control methods, and the application of Artificial Intelligence (AI) in Heating, Ventilation, and Air Conditioning (HVAC) systems. It offers an overview of related research and meticulously identifies research gaps, providing the foundation for the contributions.

Chapter 3, the focus of this research methodology chapter, lays out the approach that was employed to investigate and address the identified gaps. The chapter embarks on a journey of data, beginning with data collection and a comprehensive description of the dataset. The data preprocessing and feature selection stages ensure the data's readiness for modeling, while model development encompasses a diverse array of traditional Machine Learning models, advanced Deep Learning architectures, and innovative hybrid models. In the chapter's culmination, model validation techniques are examined. This meticulous structure guides the research endeavours towards creating efficient, predictive models for optimizing air-cooled chiller systems, contributing to the advancement of sustainable and cost-effective HVAC solutions.

Chapter 4 begins with an introduction and proceeds to an in-depth exploratory data analysis (EDA). It covers various aspects, including an overview of the dataset, summary statistics, univariate and bivariate analyses, and outlier detection and treatment. The tools and technologies utilized, such as Python, Jupyter Notebook, TensorFlow/Keras, Scikit Learn, and visualization libraries, are discussed. The section culminates with a summary of the analysis and design strategies employed.

The Results and Discussions chapter commences with an introduction, followed by an evaluation of the results obtained from different models. Each model's performance, measured by R2-score, Mean Squared Error (MSE), and Mean Absolute Error (MAE), is comprehensively analysed. The section concludes with a summary of the findings.

The final chapter begins with an introduction, summarizing the challenges faced and considerations taken into account during the research. Future recommendations are presented, outlining potential areas for improvement and expansion. The chapter concludes by summarizing the contributions made to knowledge through the study.

2. Literature Review

2.1 Introduction

Air-cooled chillers are essential components of HVAC (Heating, Ventilation, and Air Conditioning) systems widely used in various applications to provide cooling. They play a crucial role in maintaining comfortable indoor temperatures in commercial buildings, industrial facilities, data centres, and more.

Figure 1: Air Cooled Chiller

Basically, air-cooled chillers are a type of refrigeration system designed to remove heat from a specific space or process. They work by absorbing heat from the environment and then rejecting it outside. This cooling effect is achieved through the circulation of chilled water or refrigerant. Air-cooled chillers are commonly used in various applications, including:

Commercial Buildings: They provide climate control in offices, shopping malls, hospitals, hotels, and other commercial spaces.

Industrial Processes: Industries such as manufacturing, food processing, and chemical production rely on air-cooled chillers for process cooling.

Data Centres: Air-cooled chillers help regulate temperatures in data centres to prevent overheating and ensure the reliable operation of servers and equipment.

Typical components of an air-cooled chiller system include the chiller unit itself, which contains a compressor, evaporator, condenser, and expansion valve. Additionally, there are cooling towers, pumps, and distribution systems for chilled water.

Air-cooled chillers operate on the principles of the refrigeration cycle. They circulate a refrigerant through the system to absorb heat from the indoor space or process. This heat is then expelled to the outdoor environment, cooling the chilled water or refrigerant for recirculation.

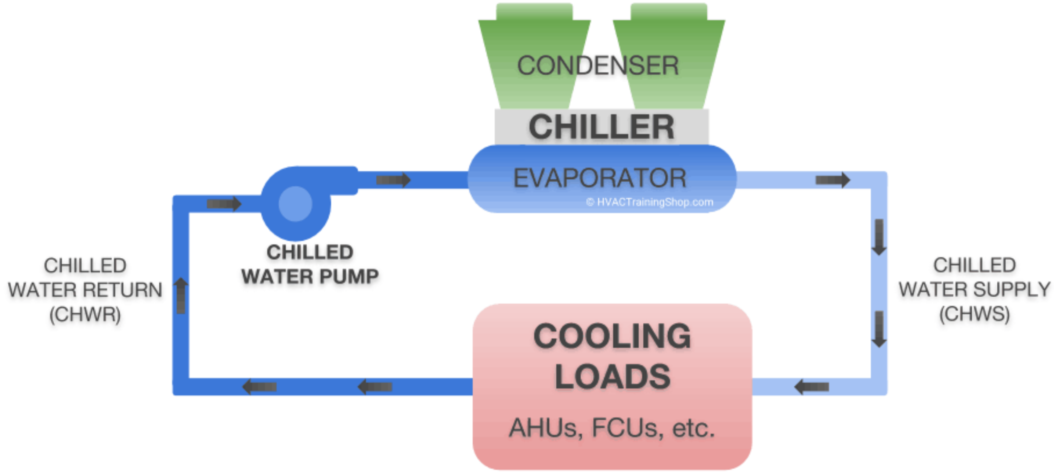


Figure 2: Air Cooled Chiller Plant Schematic

Air-cooled chillers are known for their significant energy consumption. They often account for a substantial portion of a building's total electricity usage. As a result, optimizing the operation of air-cooled chillers is essential for reducing energy costs and minimizing environmental impact.

2.2 Energy Consumption Challenges:

Air-cooled chillers, while indispensable in many industries, pose significant energy consumption challenges:

Operational Costs: Energy costs associated with operating air-cooled chillers can be substantial, particularly in large-scale facilities. This expense often constitutes a major portion of a building's overall operational budget.

Environmental Impact: The energy consumption of air-cooled chillers contributes to greenhouse gas emissions, which have adverse environmental effects, including climate change and increased carbon footprint.

Efficiency Variability: The efficiency of air-cooled chillers can vary depending on factors such as load demand, outdoor temperature, and maintenance status. This variability requires dynamic and adaptive control strategies to optimize performance.

Load Fluctuations: Cooling load requirements in buildings and industrial processes can fluctuate throughout the day and across seasons. Traditional chiller control methods may struggle to adapt to these variations efficiently.

2.3 Existing Control Methods:

Traditional control methods for air-cooled chillers include:

Setpoint Adjustments: Adjusting temperature setpoints for the chiller system to match the cooling demands of a building or process. While effective to some extent, this approach may not be optimal for energy savings.

Rule-Based Control: Using predefined rules and logic to determine chiller operation based on factors like outdoor temperature or time of day. These rules may lack adaptability to changing conditions.

Manual Intervention: In some cases, chiller operation is manually controlled by operators who adjust settings based on their judgment. This method can be effective but relies on human decision-making.

2.4 Application of AI in HVAC:

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly applied in HVAC systems, including air-cooled chiller plants:

Predictive Modeling: AI and ML algorithms are used to create predictive models that anticipate cooling load requirements and energy consumption based on historical data, weather forecasts, and other variables.

Fault Detection: AI can be employed to detect and diagnose faults in chiller systems, helping maintenance teams address issues promptly to avoid energy inefficiencies.

Optimization: AI-driven optimization algorithms dynamically adjust chiller operation based on real-time data, including load profiles and ambient temperature, to minimize energy consumption while meeting cooling demands.

Data-Driven Insights: Machine learning techniques analyze vast amounts of data from chiller systems to provide insights into performance, efficiency, and opportunities for energy savings.

Integration: AI can be integrated with building automation systems to create smart HVAC solutions that respond intelligently to changing conditions, improving overall energy efficiency.

2.5 Related Research

In the pursuit of optimizing energy consumption in HVAC systems, several research endeavours have explored the potential of machine learning and deep learning techniques. These studies have ventured into diverse aspects of chiller energy prediction, offering unique approaches and insights.

The paper by (Kanewala et al., 2021) addresses the imperative to enhance building energy efficiency by focusing on prominent machine learning and deep learning techniques such as random forests and neural networks. The study employs various techniques to prevent overfitting and optimize model hyperparameters, while acknowledging the potential for expanding predictions beyond chiller energy consumption using broader building data.

The study by (Kim et al., 2019) optimized chiller energy prediction using ANN by varying input variables, training data, and neurons. High prediction accuracy was achieved with 8 input variables, 60% training data, and 12 neurons, yielding only a 0.9% error compared to actual energy consumption.

To predict subway station chiller electricity consumption, the paper by (Yin et al., 2023) used different models, showing feasibility and effectiveness based on RMSE and MAPE assessment. For different refrigeration scenarios, relative errors for BPNN, CCNN, and SVR are all below 8%, indicating improved accuracy compared to existing literature.

The study by (Nassif, 2014) uses Artificial intelligence to enhance HVAC control through neural networks. These models can be integrated into the EMCS, supporting energy management and optimal control optimizing the system for potential cooling energy savings of 11%.

Data mining and optimization techniques used in the paper by (Kusiak et al., 2013) reduced air handling unit energy use. Predictive models and nonlinear optimization lowered chiller consumption, increasing pump and fan energy for a 23% reduction in total AHU system energy.

The study by (Kusiak et al., 2010) develops a very effective way of energy optimisation. Optimal control settings are updated hourly, leading to a 7.66% total energy savings despite increases in specific components.

The study by (Kim et al., 2020) utilizes artificial neural network (ANN) prediction models to forecast energy consumption of HVAC equipment. The performance of these models is assessed based on various indicators during the training and testing periods, revealing satisfactory results that meet ASHRAE guidelines.

The study by (Jia and Zhao, 2019) concludes that the chiller power consumption modeling method presented is feasible. The proposed ENN model achieves accurate predictions (RE < 3%) for most test data sets within a short training time (under 3 seconds).

The prediction model by (Nisa and Kuan, 2021), using thermodynamic and MLP algorithms, predicts chiller power in the same period, while the time-series forecasting model, utilizing MLP, 1D-CNN, and LSTM, forecasts power for the next minute. MLP performs well in prediction, while LSTM excels in time-series forecasting.

The proposed optimization model by (Wei et al., 2014) demonstrates 14% energy savings on two different days. The efficient two-level intelligent algorithm completes computations within 1 min, making it feasible for real-time optimal control of chiller plants.

2.6 Research Gaps

While the existing research offers valuable insights into predicting chiller energy consumption using machine learning and deep learning techniques, several research gaps warrant attention.

2.6.1 Focus on Chiller-Specific Predictions:

While the current body of research employs machine learning and deep learning techniques to predict overall building energy consumption, there is a conspicuous gap in focusing specifically on chiller energy predictions. Chillers often stand out as the most energy-intensive equipment in industrial plants, making their individual analysis imperative for a comprehensive understanding of energy usage. Exploring predictions solely in the context of chillers can uncover specific optimization strategies tailored to these critical components.

2.6.2 Data Accessibility and Quality:

A notable research gap lies in the accessibility and quality of data used for training and validating predictive models. Many studies may not explicitly address issues related to the availability of high-quality data, including historical energy consumption data, ambient conditions, and system parameters. Ensuring the reliability and representativeness of the data is crucial for the accuracy and generalizability of the developed models.

2.6.3 Longer-Term Assessments in Dynamic Scenarios:

Despite impressive results in some studies, there is a notable gap in the literature concerning longer-term assessments and analyses of model performance in dynamic, real-world scenarios. Many existing studies rely on short-term training data, and there is a need to explore how predictive models maintain their efficacy over extended periods. Real-world scenarios introduce unique challenges that may evolve over time, and understanding the long-term performance of these models is critical for their practical application and reliability.

2.6.4 User Adoption and Implementation Challenges:

There is a gap in understanding the challenges associated with user adoption and implementation of predictive models in real-world settings. Factors such as the cost of implementation, ease of integration into existing systems, and user acceptance are critical aspects that can influence the practical success of these energy optimization strategies.

2.7 Summary

The compilation of various research works presented in this section offers a multifaceted exploration of energy optimization in HVAC systems. These studies employ machine learning and deep learning techniques, and they span topics from chiller energy consumption to broader building energy management. Collectively, they provide insights into diverse methodologies, performance indicators, and potential avenues for enhancing energy efficiency.

3. Research Methodology

3.1 Introduction

The research methodology outlined herein is designed to investigate and model the energy consumption of air-cooled chiller with a keen focus on real-world applicability. The approach hinges on rigorous data preprocessing, thoughtful feature selection, diverse model development, and meticulous model evaluation. By harnessing the power of data-driven insights and advanced machine learning techniques, the aim will be to establish predictive models that can make informed decisions in real-time to optimize energy usage while meeting cooling demands efficiently.

In the following sections, the intricacies of this research methodology are delved into. The methodology begins with "Data Preprocessing," where the integrity and quality of the dataset is ensured by employing cleaning, scaling, and normalization techniques. Subsequently, "Feature Selection" becomes the focal point, where the most influential parameters are discerned in predicting power consumption accurately. The heart of the study lies in "Model Development," where a gamut of machine learning approaches, ranging from traditional models to advanced deep learning architectures and innovative hybrid models, are put to the test.

To culminate the research, these models are rigorously evaluated using an array of metrics, such as Mean Absolute Error, Root Mean Squared Error, and Cross-Validation, to gauge their performance, robustness, and ability to generalize. Through this comprehensive methodology, this research not only contributes to the body of knowledge in HVAC system optimization but also to offer practical solutions for making air-cooled chiller systems more sustainable, cost-effective, and environmentally friendly.

With the research methodology set forth, a significant stride is taken towards addressing the critical energy challenges faced by modern building systems while simultaneously advancing the frontier of predictive modeling and optimization in the realm of HVAC.

3.2 Data Collection

The data utilized in this research was sourced from an air-cooled chiller system servicing an office building in Dubai, United Arab Emirates. The dataset encompassed a diverse range of parameters critical to chiller system operation and energy consumption analysis. These included ambient temperature, entering chilled water temperature, leaving chilled water temperature, active capacity of the chiller, time stamp chiller power consumption, and the active chilled water setpoint of the chiller.

Over a comprehensive collection period spanning two years, from January 1, 2021, to December 30, 2022, data was recorded at precise 1-minute intervals. To facilitate seamless data retrieval and monitoring, the chiller was seamlessly connected to a cloud platform via a remote monitoring service provided by the chiller manufacturer, and data retrieval was executed from this platform. This comprehensive dataset served as the foundation for the research's predictive modeling and optimization efforts, offering a real-world perspective on chiller system performance.

Table 1: Data Description

Variable	Unit	Description
Setpoint (setpoint)	°C	Leaving chilled water temperature setpoint which the chiller tries to maintain.
Outside Temperature (outside_temp)	°C	Outside air temperature monitored via temperature sensor.
Return Temperature (return_temp)	°C	Return chilled water temperature coming from the building, monitored via temperature sensor
Supply Temperature (supply_temp)	°C	Supply chilled water temperature going to the building, monitored via temperature sensor
Building Load (building_load)	kW	Actual cooling capacity of the chiller, also considered as the building load since there is only 01 chiller in the plant
Power Input (power_input)	kW	Electrical power consumed by the chiller
Time (time)	yyyy-mm-dd hh:mm:ss	Time stamp

3.3 Data Description

The dataset employed in this study comprises a comprehensive set of parameters (table 1) essential for the analysis of energy consumption in an air-cooled chiller system. It encompasses

a total of seven parameters, each contributing valuable insights into chiller system performance. These parameters consist of ambient temperature, entering chilled water temperature, leaving chilled water temperature, active capacity of the chiller (which also indicates the building load at the given point since there is only one chiller in the premises), power consumption, the active setpoint of the chiller and the time stamp. With a substantial dataset collected over a period of two years, totalling 1,048,572 instances, the focus of this research centres on modeling and optimizing power consumption, the primary target variable. This rich and extensive dataset offers a robust foundation for developing predictive models and conducting optimization procedures that aim to enhance the energy efficiency of air-cooled chiller systems in real-world applications. Below is the description of the different columns in the data:
Furthermore, table 2 shows the design parameters of the air cooled chiller selected for this thesis:

Table 2: Design Parameters

Variable	Unit
Chiller Cooling Capacity	334.2 kW
Design Return Temperature	14.5 °C
Design Supply Temperature	5.5 °C
Design Power Input	134.5 kW
Design Outside Temperature	46.0 °C

3.4 Data Preprocessing

Data preprocessing is a critical step in ensuring the quality and reliability of the dataset. Given the complexity of chiller system data, several preprocessing tasks were undertaken:

Data Cleaning: The data cleaning part involved several steps to ensure the dataset is in a suitable form for analysis and modeling. Here's an explanation of each step carried out:

- The 'time' column was initially stored as a string. To facilitate time-based analysis, it was converted to a datetime datatype. This allows for easy extraction of month and day information.
- Outliers can significantly impact the analysis and model performance. In this case, observations with extreme values in the 'power_input' column were identified and

removed. This step ensured that the subsequent analysis is not unduly influenced by these extreme values.

- Rows where the 'building_load' was zero are excluded. This decision was made because the instances where the building load was zero were not relevant or meaningful for the analysis or modeling task.

Figure 3 below shows a snapshot of how the data looks like.

	setpoint	outside_temp	return_temp	supply_temp	power_input	time	building_load
0	7.0	22.3764	8.21838	7.02139	16.0	2021-01-01 00:00:00	78.537
1	7.0	22.3764	8.21838	7.02139	16.0	2021-01-01 00:01:00	78.537
2	7.0	22.3764	8.21838	7.02139	16.0	2021-01-01 00:02:00	78.537
3	7.0	22.3764	8.21838	7.02139	16.0	2021-01-01 00:03:00	78.537
4	7.0	22.3764	8.21838	7.02139	16.0	2021-01-01 00:04:00	78.537

Figure 3: Preview of Dataset

Derived Metrics: From the 'time' column, new features such as 'day' and 'month' were created. These derived metrics were helpful in providing insights into the monthly and daily patterns in the data. For example, they would help enable the analysis of how power consumption of the chiller varies across different months and days. Later on, these categorical columns - 'month' and 'day', were converted into dummy variables. This was done to represent the categorical data in a format suitable for machine learning models. The original categorical columns were then dropped.

Scaling and Normalization: The dataset contained parameters with varying scales. Scaling and normalization techniques, such as Min-Max scaling and Standard scaling were applied to ensure that all features contribute equally to the modeling process.

3.5 Data Visualization

Data visualization served as a powerful tool in the exploratory phase of the analysis, enabling to gain insights into the underlying patterns, trends, and distributions within the dataset. This visual exploration is paramount for understanding the inherent structure of the data, identifying potential outliers, and informing subsequent modeling decisions.

3.5.1 Univariate Analysis:

In the exploration of individual variables, various visualization techniques were employed such as histograms and distribution plots. These visualizations allowed to comprehend the distributional characteristics of key features, including 'outside_temp,' 'return_temp,' 'supply_temp,' 'power_input,' and 'building_load.' By examining the shape and spread of these distributions, central tendencies were identified, and potential skewness were detected.

3.5.2 Derived Metrics Visualization:

Furthermore, meaningful metrics were derived from the original timestamp data, creating 'month' and 'day' variables. Visualization of these derived metrics provided insights into temporal patterns, revealing how power consumption varied across different months and days. The bar plots for monthly and daily energy consumption showcased discernible trends, aiding in the identification of potential seasonality and day-of-week effects.

3.5.3 Bivariate Analysis:

Bivariate analysis, conducted through scatter plots and pair plots, allowed to explore relationships between continuous variables. These visualizations provided a holistic view of how variables such as 'outside_temp,' 'return_temp,' and 'setpoint' correlated with the target variable 'power_input.' Notably, scatter plots illustrated potential linear or nonlinear associations, guiding the understanding of variable interdependencies.

3.5.4 Categorical Variable Analysis:

The analysis of categorical variables, such as 'month' and 'day,' involved bar plots to visualize variations in power consumption across different months and days of the week. These visual representations offered insights into monthly trends and highlighted distinctions in energy consumption patterns between weekdays and weekends.

3.6 Model Development

Further to data visualization, the thesis delved into the construction and refinement of predictive models. Leveraging the insights gained from the exploratory data analysis, various machine learning and deep learning techniques were employed to capture and elucidate the intricate relationships within the dataset.

The objective was to develop robust models that accurately predict power consumption based on the given features, ultimately enhancing the understanding of the underlying dynamics.

Traditional ML Models: Several traditional machine learning models, including Multivariate Linear Regression, Decision Trees, Random Forest, Support Vector Machines, and Gradient Boosting, were implemented to establish baseline performance. Below is the detailed methodology carried out for each algorithm:

Deep Learning Models: Advanced deep learning architectures, such as Neural Networks (NNs) and Long Short-Term Memory networks (LSTMs), were explored to capture complex relationships within the data. Below is the detailed methodology carried out for each algorithm:

Hybrid Models: Hybrid models, combining the strengths of both traditional ML and deep learning, were proposed, and tested. These include ensemble methods such as Gradient Boosting and Random Forests with Neural Networks, Autoencoder with Regression Head, Ensemble of Neural Networks and Attention Mechanism with Regression models. Below is the detailed methodology carried out for each algorithm:

3.7 Training and Hyperparameter Tuning

Models are trained using appropriate training datasets, with hyperparameters tuned to enhance performance. This involves adjusting learning rates, batch sizes, and other parameters to strike a balance between underfitting and overfitting. To systematically explore the architectural space, a grid search approach was employed. This involved defining a range of possible values for key hyperparameters and systematically training models with all possible combinations. The grid search not only allowed for a comprehensive exploration of architectural configurations but also facilitated the identification of optimal hyperparameter values for each model.

3.8 Model Validation

Evaluation metrics play a pivotal role in assessing the performance of predictive models. Given the nature of the problem (i.e., regression problem) , the following metrics were considered:

Mean Absolute Error (MAE): Measures the average absolute difference between predicted and actual power consumption, providing insights into the model's accuracy.

Mean Squared Error (MSE): Similar to MAE but emphasizes larger errors, making it sensitive to outliers.

Coefficient of Determination (R-squared): Evaluates the proportion of variance in power consumption explained by the model, indicating goodness of fit.

3.9 Summary

Through meticulous data preprocessing, feature selection, and diverse model development, predictive models capable of real-time energy optimization shall be developed.

The extensive evaluation process will ensure robustness and model generalization, setting the stage for a comprehensive investigation that offers practical solutions for enhancing the sustainability and cost-effectiveness of building climate control systems.

In this pursuit, the methodology is not only a research framework but a practical pathway to efficient and eco-friendly HVAC solutions.

4. Analysis and Design

4.1 Introduction

In the pursuit of developing effective regression models, a series of experiments were conducted, exploring the various machine learning models, deep learning models and also hybrid approaches that combine traditional machine learning techniques with advanced neural network architectures. This section outlines the models implemented, tools used, the development process, and a detailed analysis of the simulation strategies employed throughout the experimentation.

4.2 Exploratory Data Analysis

Exploratory Data Analysis is a crucial phase in understanding the characteristics of the dataset, identifying patterns, and informing decisions during model development. This section elaborates on the EDA process undertaken in the context of the various regression models that were conducted as part of this thesis.

4.2.1 Data Overview and Summary Statistics

The initial step involves obtaining a comprehensive overview of the dataset. Descriptive statistics, including mean, median, standard deviation, and quartiles, offer insights into the central tendency and variability of the data. Visualizations such as histograms and box plots provide a visual summary of the data distribution and help identify potential outliers.

	setpoint	outside_temp	return_temp	supply_temp	power_input	building_load
count	1.048571e+06	1.048571e+06	1.048571e+06	1.048571e+06	1.048571e+06	1.048571e+06
mean	8.229395e+00	3.088360e+01	9.809552e+00	8.993532e+00	1.922986e+01	7.530343e+01
std	1.523097e+00	7.113727e+00	2.385754e+00	2.654490e+00	1.648687e+01	5.976936e+01
min	4.000000e+00	1.240050e+01	5.676610e+00	4.092480e+00	0.000000e+00	0.000000e+00
25%	7.000000e+00	2.514290e+01	8.471890e+00	7.106170e+00	0.000000e+00	0.000000e+00
50%	7.301170e+00	3.095400e+01	9.148990e+00	8.121730e+00	1.850000e+01	8.355000e+01
75%	1.000000e+01	3.803080e+01	1.092620e+01	1.027625e+01	3.581250e+01	1.253250e+02
max	1.200000e+01	4.903490e+01	3.424220e+01	3.417450e+01	2.048032e+03	3.342000e+02

Figure 4: Summary Statistics

The **setpoint** variable has a mean value of 8.23, indicating the average target level. With a standard deviation of 1.52, there is relatively low variability around the mean. The minimum setpoint is 4.0, and 25% of the data falls below 7.0, while 75% falls below 10.0. The maximum setpoint is 12.0. The **outside temperature** has a mean of 30.88, with a standard deviation of 7.11, indicating moderate variability. The minimum temperature is 12.4, and the 25th percentile is 25.14, while the 75th percentile is 38.03. The maximum temperature is 49.03.

The **return temperature** has a mean of 9.81, and a standard deviation of 2.39. The minimum return temperature is 5.68, and 25% of the data falls below 8.47, while 75% falls below 10.93. The maximum return temperature is 34.24.

The **supply temperature** has a mean of 8.99, and a standard deviation of 2.65. The minimum supply temperature is 4.09, and 25% of the data falls below 7.11, while 75% falls below 10.28. The maximum supply temperature is 34.17.

The **power input** has a mean of 19.23, with a standard deviation of 16.49. The minimum power input is 0.0, and 25% of the data has a power input of 0.0. The median power input is 18.5, and 75% of the data falls below 35.81. The maximum power input is 2048.03.

The **building load** has a mean of 75.30, with a standard deviation of 59.77. The minimum building load is 0.0, and 25% of the data has a building load of 0.0. The median building load is 83.55, and 75% of the data falls below 125.33. The maximum building load is 334.2.

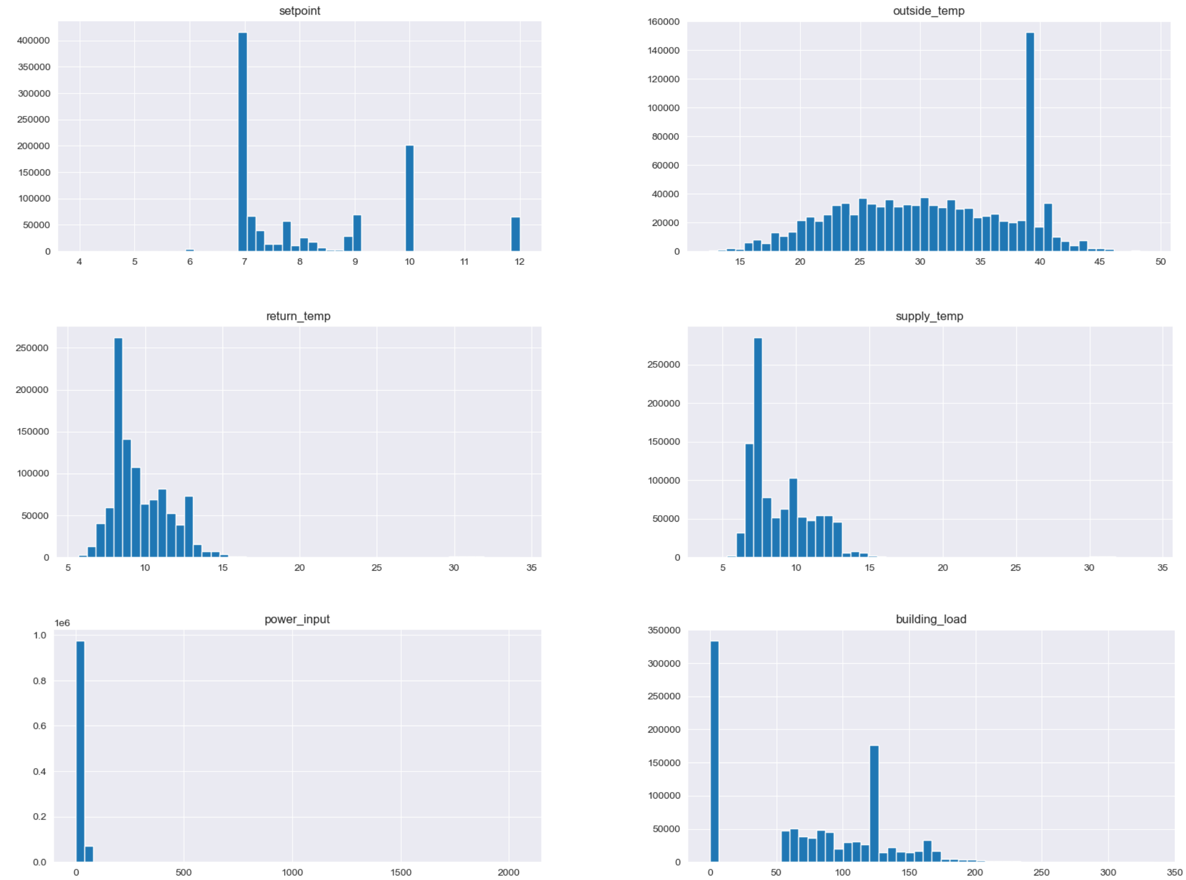


Figure 5: Univariate Analysis

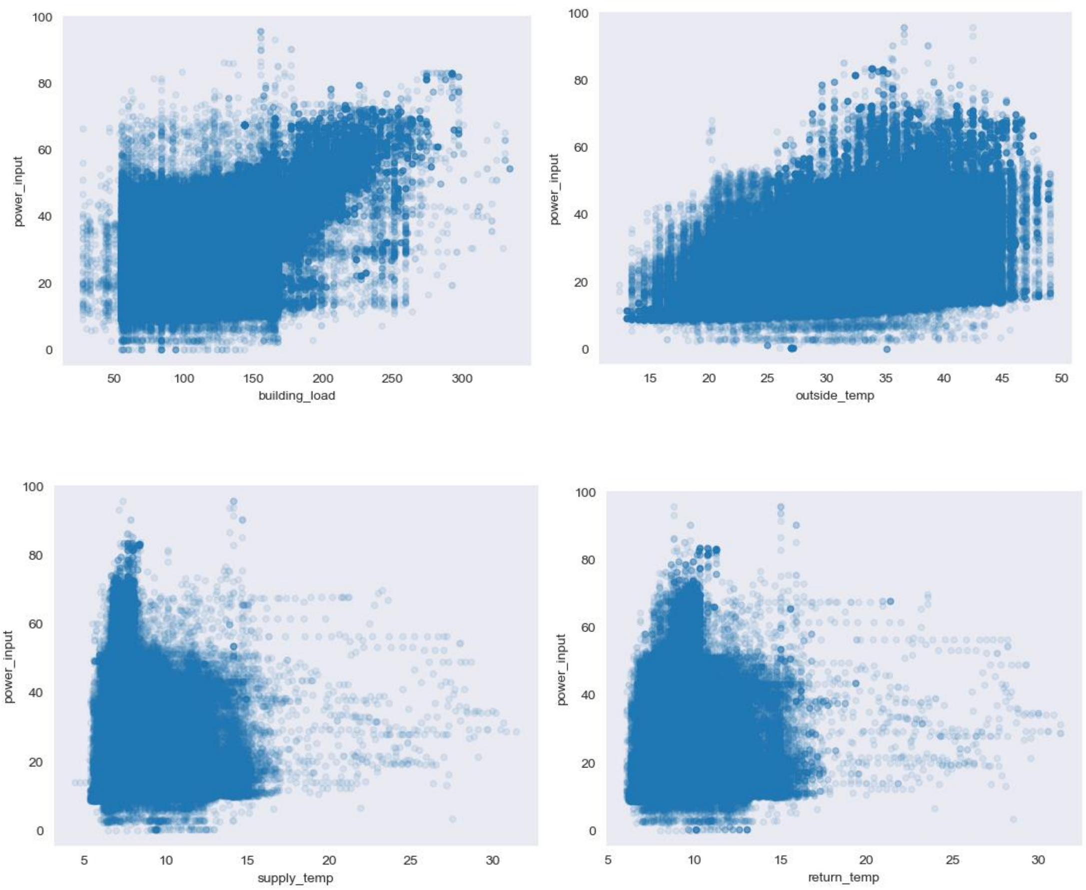
4.2.2 Univariate Analysis

Understanding the distribution and characteristics of individual features is crucial. Feature histograms (refer to figure 5) played a crucial role in understanding individual variables and their characteristics.

Univariate analysis helped identify patterns or trends within individual variables and by examining the summary statistics, histograms, and distribution plots for each variable, it made it possible to observe the central tendency, spread, and shape of the data.

4.2.3 Bivariate Analysis

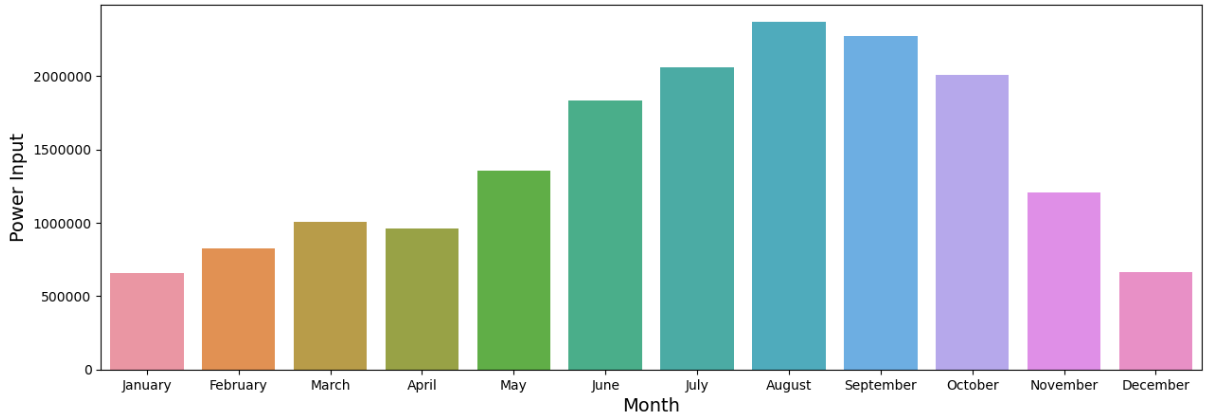
Bivariate analysis played a crucial role in exploring connections between different pairs of variables (refer to figure 6). Scatter plots highlighted potential associations of each independent variable with the target variable, guiding feature selection and engineering decisions.



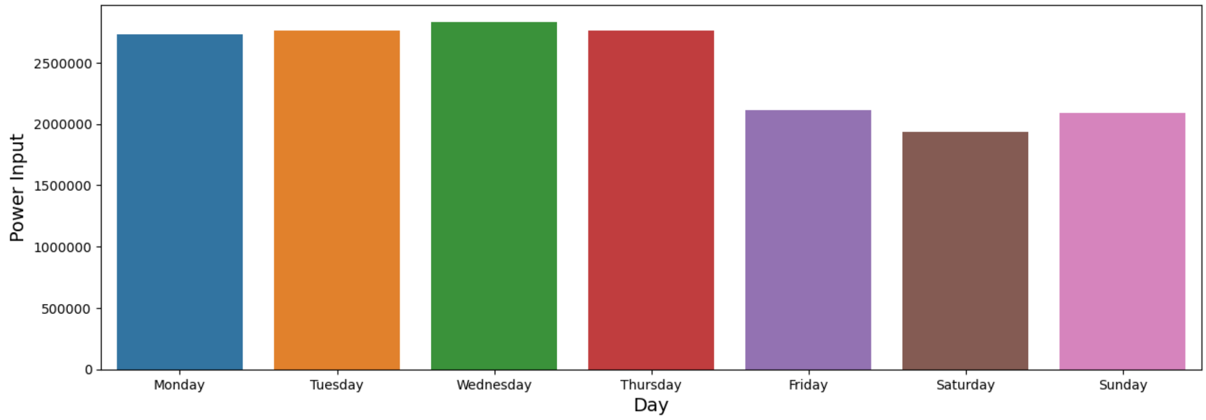
<u>Figure 6:</u> Bivariate Analysis

Figure 7 was created to understand the monthly trend of the power consumption of chiller. So basically, the plot shows that the highest energy consumption takes place in the month of August, followed by September and then October and July and the rest.

January and December have the least amount of energy consumption, maybe due to the fact that most of the people are on vacations around this time and also the ambient temperature is quite low as compared to the rest of the months.



<u>Figure 7:</u> Monthly trend of power consumption

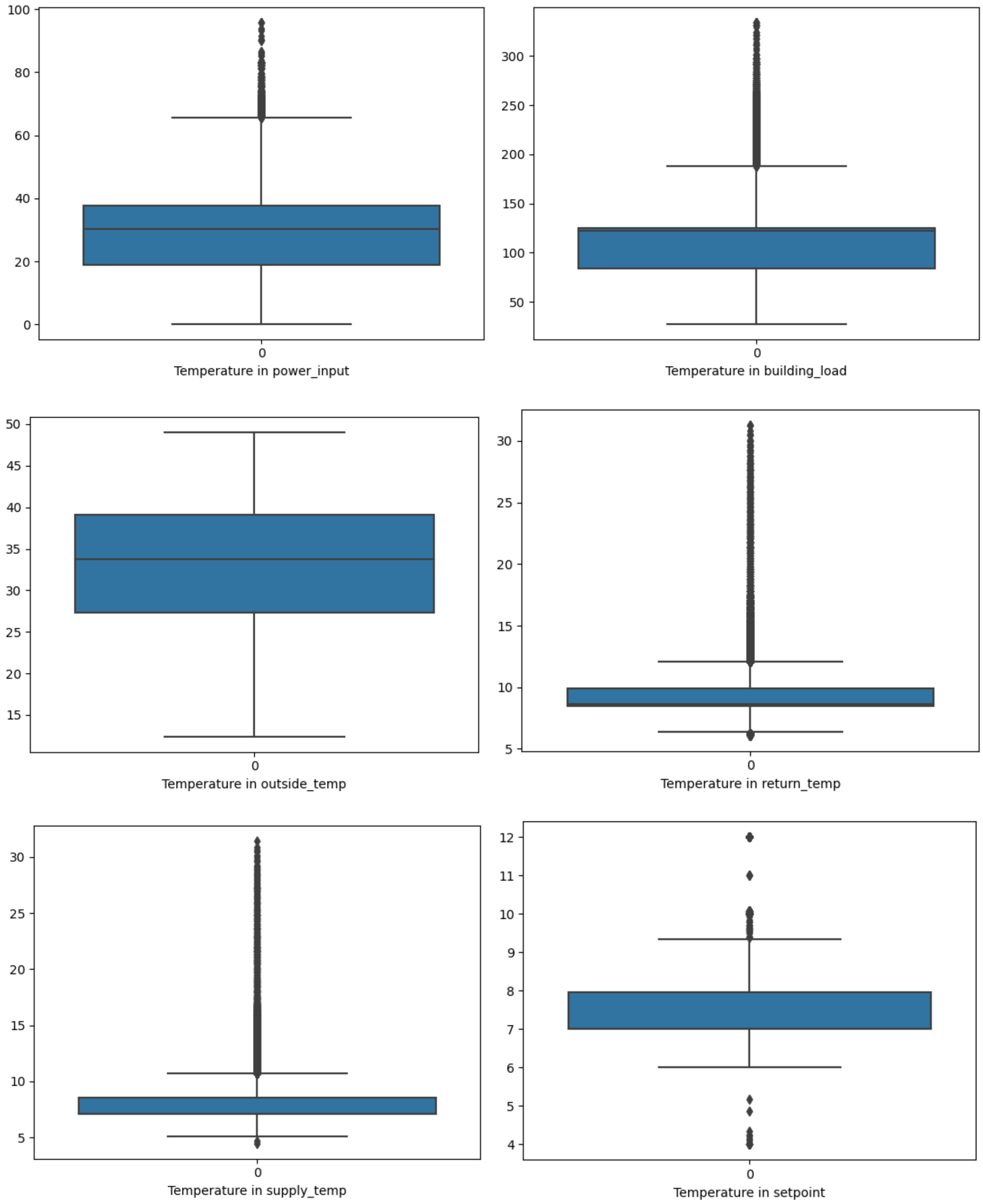


<u>Figure 8:</u> Daily trend of power consumption

The highest energy consumptions are on the weekdays as weekends are less occupied in the office. Saturday is the lowest while Friday and Sunday are at the same level due to the reason that in 2021, the weekends were Friday and Saturday while in 2022, the weekends in Dubai were changed to Saturday and Sunday.

4.2.4 Outlier Detection and Treatment

Identification and handling of outliers are critical for model robustness. Box plots were created to identify outliers. Depending on the nature of the outliers, strategies such as trimming, transformation, or removal might be applied to ensure the model is not unduly influenced by extreme values. In the column 'power_input', as seen from the summary statistics and box plots, there were some outlier values. The maximum value is 2048; however, the design power input of the chiller itself is 134.9 kw which means that any value which is more than this value is potentially an outlier. Hence, an outlier threshold of 135 was defined for the power_input column which means that any data point with an absolute value of power_input greater than 135 is considered an outlier.



<u>Figure 9:</u> Outlier Analysis

4.3 Tools and Technologies

The implementation of the various machine/deep learning models and even hybrid models was facilitated by a suite of tools and technologies, each playing a crucial role in the development and evaluation process. The primary tools included:

4.3.1 Python and Jupyter Notebook

The experimentation heavily relied on the Python programming language, with Jupyter Notebook as the IDE used for data preprocessing, model development, data visualisation and model evaluation.

4.3.2 TensorFlow/Keras

TensorFlow (version 2.15.0) and Keras (version 2.15.0) served as the primary deep learning frameworks. TensorFlow provides a flexible and comprehensive platform for building and training neural network models. Its ease of use and extensive documentation make it a preferred choice for deep learning experiments.

As a high-level neural networks API running on top of TensorFlow, Keras simplifies the model-building process, enabling rapid prototyping and experimentation.

4.3.3 Scikit-Learn

Scikit-Learn (version 1.2.1) was instrumental in implementing traditional machine learning models such as linear regression, decision trees, random forests, support vector regressor and gradient boosting. Its diverse set of tools for data preprocessing, model selection, and evaluation were useful in building the models and also in the hyperparameter tuning using Grid Search cross validation techniques.

4.3.4 Matplotlib and Seaborn

Matplotlib (version 3.7.0) and Seaborn (version 0.12.2) were employed for data visualization, offering a versatile toolkit for creating insightful plots and graphs including histograms, distribution plots, box plots, scatter plots, pair plots etc. These were pivotal in conveying the results visually, aiding in the interpretation of model performance.

4.4 Model Implementation & Experimentation

The core of the experimentation lies in the implementation of diverse hybrid models. Each model is meticulously designed to leverage the strengths of both classical machine learning algorithms and neural networks. The models include:

4.4.1 Multivariate Linear Regression

Linear Regression is a foundational tool in statistical modeling, providing a straightforward framework for understanding and predicting the relationship between two or more variables. While more complex relationships may require advanced techniques, linear regression served as a valuable starting point in data analysis and modeling.

Below were the different steps carried out in the modeling process:

4.4.1.1 Feature Selection using RFE method:

To identify the most significant predictor variables, Recursive Feature Elimination (RFE) was employed. The linear regression model was initially fitted on the training set, and RFE was applied to select the top 15 features based on their significance (included the derived metrics).

4.4.1.2 Creating the Model:

The selected features were used to create a new training set (X_train_rfe). A linear regression model was then formulated using the Ordinary Least Squares (OLS) method from the statsmodels library. The model's statistical summary was examined to understand the coefficients, p-values, and overall goodness of fit.

4.4.1.3 Model Refinement:

To ensure model interpretability, the constant term was removed, and the Variance Inflation Factor (VIF) was calculated for each feature. This step helped identify and mitigate multicollinearity.

4.4.1.4 Residual Analysis:

Two key assumptions of linear regression were validated:

1. **Normal distribution of error terms:** A distribution plot of the residuals confirmed their normal distribution with a mean value close to zero.

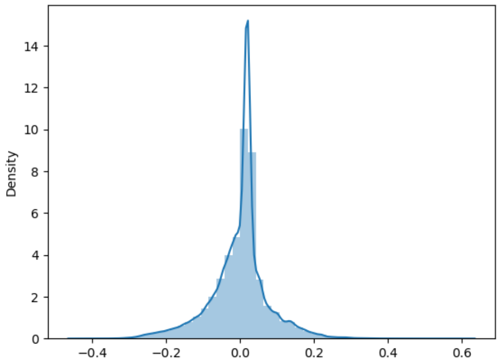


Figure 10: Assumption-1: Normal distribution of error terms

2. **Homoscedasticity of error terms:** A scatter plot between residuals and the target variable (y_train) ensured constant variance, validating the assumption.

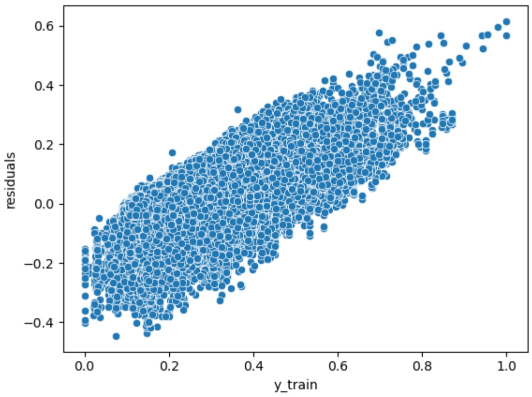


Figure 11: Assumption-2: Homoscedasticity of error terms

4.4.1.5 Model Evaluation:

In the end, the model was evaluated on both the training and test sets. Predictions were made on the test set, and their accuracy was assessed using visualizations. Metrics such as R-squared, Mean Absolute Error (MAE), and Mean Squared Error (MSE) were computed for both the training and test sets, providing a comprehensive evaluation of the model's performance.

4.4.2 Decision Trees

The Decision Tree Regression methodology began with the selection of a Decision Tree Regressor as the base model.

4.4.2.1 Hyperparameter Tuning:

Hyperparameter tuning was conducted through a grid search over crucial parameters:
max_depth: This parameter determines the maximum depth of the decision tree. Range of values considered was - [None, 5, 10, 15]
min_samples_split: It signifies the minimum number of samples required to split an internal node. Range of values considered was - [2, 5, 10]
min_samples_leaf: This parameter sets the minimum number of samples required to be at a leaf node. Range of values considered was - [1, 2, 4]

GridSearchCV was employed for cross-validated hyperparameter tuning, utilizing negative mean squared error as the optimization metric.
The outcome of the grid search revealed the optimal hyperparameters, providing insights into the configuration that maximizes predictive performance. The best hyperparameters came out to be {'max_depth': 15, 'min_samples_leaf': 4, 'min_samples_split': 10}

4.4.2.2 Model Training and Evaluation:

The best model was instantiated with the identified hyperparameters and trained on the training dataset. The subsequent predictions on both the training and test sets enabled a comprehensive evaluation.
Metrics such as R-squared, Mean Absolute Error (MAE), and Mean Squared Error (MSE) were computed for both the training and test sets, providing a comprehensive evaluation of the model's performance.

4.4.3 Random Forests

Random Forest Regression is an ensemble learning technique that constructs multiple decision trees during training and outputs the mean prediction of the individual trees for regression tasks. It excels in capturing complex relationships within the data and is less prone to overfitting compared to individual decision trees.

The hyperparameters, such as the number of trees (n_estimators), maximum depth of trees (max_depth), minimum samples required to split an internal node (min_samples_split), and minimum samples required to be a leaf node (min_samples_leaf), play a crucial role in shaping the Random Forest model.

4.4.3.1 Model Creation:

A Random Forest regressor was instantiated initially without specifying hyperparameters.
Hyperparameter tuning was conducted through a grid search over crucial parameters. A hyperparameter grid was defined, encompassing values for 'n_estimators', 'max_depth', 'min_samples_split', and 'min_samples_leaf'.
Range of values considered was:
'n_estimators': [100, 150, 200, 250, 300],
'max_depth': [None, 5, 10, 15],
'min_samples_split': [2, 5, 10],
'min_samples_leaf': [1, 2, 4]

GridSearchCV was employed to perform a systematic search across the hyperparameter space, utilizing cross-validation to evaluate each combination's performance.
The best hyperparameters were determined based on the results of the grid search. The optimal hyperparameters were - 'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 10 and 'n_estimators': 300.
A new Random Forest regression model was created using the identified optimal hyperparameters. The model was trained on the provided training dataset, allowing it to learn the underlying patterns.

4.4.3.2 Evaluation:

Predictions were generated for both the training and test sets using the trained Random Forest model. Performance metrics, including R-squared (R2) score, mean squared error (MSE), and mean absolute error (MAE) were computed for both the training and test sets.
These metrics provided insights into the model's accuracy, generalization ability, and suitability for predicting 'power_input.'

4.4.4 Support Vector Machines

Support Vector Machines (SVM) regression is a versatile technique employed for regression tasks, capable of capturing both linear and nonlinear patterns in the data. It operates by identifying a hyperplane that best represents the relationship between input features and the target variable, 'power_input' in this context. SVM offered flexibility through different kernel functions, such as the radial basis function (RBF) and linear kernels, allowing adaptation to diverse data structures.

4.4.4.1 Model Creation:

The best model was instantiated with different types of kernels – ‘rbf’ and ‘linear’.

1. **Kernel 'rbf' Model:**
   - The SVM regression model with an RBF kernel was instantiated with hyperparameters C=1.0 and epsilon=0.1.
   - The training set was used to fit the model, enabling it to learn the underlying patterns in the data.
   - Predictions were generated for both the training and test sets, reflecting the model's ability to generalize to new data.

2. **Kernel 'linear' Model:**
   - An additional SVM regression model with a linear kernel was created, employing hyperparameters C=1.0 and epsilon=0.2.
   - Similar to the RBF model, this linear model was trained on the dataset, and predictions were made for both training and test sets.

4.4.4.2 Model Evaluation:

Performance metrics, including R-squared (R2) score, mean squared error (MSE), and mean absolute error (MAE), were computed for both the models on both training and test sets.
These metrics provided insights into the model's accuracy, goodness of fit, and ability to generalize to unseen data.

4.4.5 Gradient Boosting

Gradient Boosting Regression is an ensemble learning method that builds a sequence of weak learners, typically decision trees, and combines their predictions to create a strong predictive model. It operates in an iterative fashion, with each new tree focusing on correcting the errors of the combined ensemble. Key hyperparameters, such as the number of trees (n_estimators) and the learning rate, play a crucial role in shaping the Gradient Boosting model. The higher the number of trees, the more complex the model becomes, while the learning rate controls the contribution of each tree to the overall prediction.

4.4.5.1 Model Creation:

A Gradient Boosting regressor was instantiated initially without specifying hyperparameters. Hyperparameter tuning was conducted through a grid search over crucial parameters. A hyperparameter grid was defined, including values for 'n_estimators' and 'learning_rate'.
Range of values considered was:
'n_estimators': [50, 100, 150, 200, 300]
'learning_rate': [0.001, 0.01, 0.1, 0.2, 0.3, 0.4, 0.5]

GridSearchCV was utilized to perform a systematic search across the hyperparameter space, using cross-validation to assess each combination's performance.
The best hyperparameters were identified based on the results of the grid search. The optimal hyperparameters were - 'n_estimators': 300 and 'learning_rate': 0.5

A new Gradient Boosting regression model was created using the identified optimal hyperparameters. The model was then trained on the provided training dataset, enabling it to learn and improve its predictions through multiple iterations.

4.4.5.2 Model Evaluation:

Predictions were generated for both the training and test sets using the trained Gradient Boosting model. Performance metrics, including R-squared (R2) score, mean squared error (MSE), and mean absolute error (MAE) were computed for both the training and test sets.
These metrics offered insights into the model's accuracy, generalization ability, and suitability for predicting 'power_input.'

4.4.6 Neural Networks

Neural Networks (NN) are a class of machine learning models inspired by the human brain's architecture. They consist of layers of interconnected nodes, or neurons, contributing to the learning process. Multiple NN models were explored for predicting 'power_input' based on specific architectural configurations.

4.4.6.1 Model-1 (NN_m1):

Architecture:

- The first neural network model adopted a relatively simple architecture.
- It began with an input layer consisting of 64 neurons, each activated by the Rectified Linear Unit (ReLU) activation function.
- A hidden layer with 32 neurons and ReLU activation function followed.
- The output layer comprised a single neuron using a linear activation function.

Compilation:

- The model was compiled using the Mean Absolute Error (MAE) loss function.
- The Adam optimizer was employed with a learning rate of 0.001.
- Evaluation metrics included MAE and Mean Squared Error (MSE).

Training:

- The model was trained for 50 epochs with a batch size of 32.
- A validation split of 0.1 was applied during training.

Evaluation:

- Performance metrics, including MAE, MSE, and the R-squared (R2) score, were computed on the test set.
- The R2 score helped assess the proportion of variance in the dependent variable that the model captured.

4.4.6.2 Model-2 (NN_m2):

Architecture:

- An enhanced architecture was introduced with increased complexity.
- The input layer featured 100 neurons with ReLU activation.
- Three hidden layers each comprised 100 neurons with ReLU activation, and the final hidden layer had no activation.

- The output layer was a dense layer with a single neuron.

Compilation:

- The model was compiled using the Mean Absolute Error (MAE) loss function.
- The Adam optimizer was employed with a learning rate of 0.001.
- Evaluation metrics included MAE and Mean Squared Error (MSE).

Training:

- The model was trained for 50 epochs with a batch size of 32.
- A validation split of 0.1 was applied during training.

Evaluation:

- Performance metrics, including MAE, MSE, and the R-squared (R2) score, were computed on the test set.
- The R2 score helped assess the proportion of variance in the dependent variable that the model captured.

4.4.6.3 Model-3 (NN_m3):

Architecture:

- This model incorporated Batch Normalization and Dropout to improve generalization.
- It featured an input layer with 100 neurons, followed by Batch Normalization and Dropout (20%).
- Three hidden layers, each with 100 neurons, Batch Normalization, Dropout (20%), and ReLU activation.
- The output layer was a dense layer with one neuron.

Compilation:

- The model was compiled using the Mean Absolute Error (MAE) loss function.
- The Adam optimizer was employed with a learning rate of 0.001.
- Evaluation metrics included MAE and Mean Squared Error (MSE).

Training:

- The model was trained for 50 epochs with a batch size of 32.
- A validation split of 0.1 was applied during training.

Evaluation:

- Performance metrics, including MAE, MSE, and the R-squared (R2) score, were computed on the test set.

- The R2 score helped assess the proportion of variance in the dependent variable that the model captured.

4.4.6.4 Model-4 (NN_m4):

Architecture:

- A more extended architecture was explored to further increase model complexity.
- The input layer had 100 neurons with ReLU activation.
- Four hidden layers, each with 100 neurons, incorporated Batch Normalization, Dropout (20%), and ReLU activation.
- The output layer remained a dense layer with a single neuron.

Compilation:

- The model was compiled using the Mean Absolute Error (MAE) loss function.
- The Adam optimizer was employed with a learning rate of 0.001.
- Evaluation metrics included MAE and Mean Squared Error (MSE).

Training:

- The model was trained for 50 epochs with a batch size of 32.
- A validation split of 0.1 was applied during training.

Evaluation:

- Performance metrics, including MAE, MSE, and the R-squared (R2) score, were computed on the test set.
- The R2 score helped assess the proportion of variance in the dependent variable that the model captured.

4.4.7 Long Short-Term Memory Networks (LSTMs)

LSTMs belong to the family of recurrent neural networks and are particularly well-suited for time-series prediction tasks where understanding and capturing long-term dependencies are paramount. In the realm of predicting power input for HVAC equipment, the use of Long Short-Term Memory (LSTM) networks proves to be instrumental.

4.4.7.1 Model-1 (LSTM_m1):

Architecture:

- The LSTM model was constructed with one LSTM layer having 50 neurons and a ReLU activation function.
- The output layer was a Dense layer with a single neuron.
- The Mean Squared Error (MSE) was used as the loss function, and the Adam optimizer was employed.

Training and Evaluation:

- The model was trained for 50 epochs with a batch size of 32.
- Evaluation metrics, including MAE, MSE, and R2 Score, were computed on the test set.
- The predictions were inverted to the original scale for better interpretability.
- The true and predicted values were visualized using a plot.

4.4.7.2 Model-2 (LSTM_m2):

Architecture:

- An extended architecture was explored by adding more LSTM layers.
- The model included three LSTM layers with 50 neurons each and a ReLU activation function.
- A Dense layer with one neuron followed the LSTM layers.

Compilation, Training, and Evaluation:

- The model was compiled similarly to Model 1.
- Training was performed for 100 epochs with a batch size of 32, incorporating early stopping to prevent overfitting.
- The training loss and validation loss were visualized over epochs.

4.4.8 Gradient Boosting with Neural Networks (Hybrid_m1)

The Model-9 hybrid approach combined the strengths of Gradient Boosting and Neural Networks to enhance the predictive capabilities for power input in chiller. By training a Gradient Boosting model on original features and utilizing its predictions as features for a Neural Network, this hybrid model aimed to capture intricate patterns and dependencies, leveraging the advantages of both algorithms.

4.4.8.1 Architecture:

- Gradient Boosting Model:
  - A Gradient Boosting Regressor with 100 estimators was trained on the original features, considering 'outside_temp,' 'return_temp,' and 'building_load.'
- Neural Network Model:
  - A Sequential Neural Network was constructed with one input layer, two hidden layers (64 and 32 neurons, respectively) using the ReLU activation function, and one output layer with a linear activation function.
  - The Neural Network was compiled with the Adam optimizer and Mean Absolute Error (MAE) and Mean Squared Error (MSE) as loss functions.

4.4.8.2 Training Process:

- The Neural Network was trained using the predictions from the Gradient Boosting model as features.
- Training was conducted for 50 epochs with a batch size of 32, and a validation split of 10% was employed.

4.4.8.3 Evaluation:

Performance Metrics:

- The hybrid model's performance was evaluated using Mean Squared Error (MSE) and Mean Absolute Error (MAE) metrics.

4.4.8.4 Visualization:

- A scatter plot was generated to visually assess the predictions against true values. The red dashed line represents an ideal alignment, and the scatter plot illustrates the alignment between true and predicted values.

4.4.9 Autoencoder with Regression (Hybrid_m2)

The hybrid model presented here combines an Autoencoder with a Regression Head. The Autoencoder was employed for unsupervised feature learning and dimensionality reduction, while the Regression Head was responsible for predicting the target variable based on the encoded features. This architecture aimed to capture essential information from the input data using the Autoencoder and leveraged these learned features for accurate regression predictions.

4.4.9.1 Architecture:

- Autoencoder:

  The Autoencoder was composed of an encoder and a decoder. The encoder part consisted of two hidden layers with 128 and 64 neurons, respectively, using ReLU activation functions. The encoded layer had three neurons, determining the dimensionality of the learned features.

  The decoder mirrors the encoder architecture, with two hidden layers and an output layer with a linear activation function. The Autoencoder was trained to minimize Mean Squared Error (MSE) between the input and output.

- Regression Head:

  The Regression Head was a separate neural network built on top of the encoded features produced by the Autoencoder. It comprised three layers with 64, 32, and 1 neuron(s), respectively, using ReLU and linear activation functions. The model was trained to predict the target variable, optimizing both Mean Squared Error (MSE) and Mean Absolute Error (MAE).

4.4.9.2 Training Process:

- Autoencoder Training:

  The Autoencoder was trained using the input data with the objective of reconstructing the input at the output layer. This process resulted in an encoder that learns a compact representation of the input data, reducing it to a lower-dimensional space.

- Feature Extraction:

  The encoder was extracted from the trained Autoencoder and used to transform both the training and test datasets. The encoded features represented a compressed and informative version of the original data.

- Regression Head Training:

  The Regression Head was then trained on the encoded features to predict the target variable. This two-step process ensured that the model learns meaningful representations from the Autoencoder and uses them effectively for regression.

4.4.9.3 Evaluation:

The hybrid model's performance was evaluated using two primary metrics:

- Mean Squared Error (MSE)
- Mean Absolute Error (MAE)

4.4.9.4 Visualization

To visually assess the model's performance, a scatter plot was created. The plot compared the true target values against the predictions made by the hybrid model. A reference line was included in the plot, representing a perfect alignment of predicted and true values.

4.4.10 Random Forest with Neural Network Features (Hybrid_m3)

The hybrid model presented here is a combination of a Neural Network (NN) and a Random Forest (RF). This hybrid architecture aimed to capitalize on the NN's ability to extract intricate features from the data and the RF's strength in making accurate predictions based on these features.

4.4.10.1 Architecture:

- Neural Network (NN):

  The first part of the hybrid model involved a Neural Network with three layers. The input layer had 64 neurons and used the ReLU activation function, followed by a hidden layer with 32 neurons also using ReLU activation. The output layer had one neuron with a linear activation function, suitable for regression tasks. This NN was designed to learn and capture essential features from the input data.
- Random Forest (RF):

  The second part of the hybrid model was a Random Forest. After training the NN, the features it extracted from the input data were used as inputs to the Random Forest model. A Random Forest was an ensemble learning method that built a multitude of decision trees during training. For regression, the predictions from individual trees were averaged to obtain the final predictions.

4.4.10.2 Training Process:

- Neural Network Training:
  The NN was trained using Mean Squared Error (MSE) and Mean Absolute Error (MAE) as loss functions. It took the preprocessed and normalized training data as input and learnt to extract relevant features. The use of two loss functions provided a balance between accuracy and robustness.
- Feature Extraction:
  Once the NN was trained, it was employed to extract features from both the training and test datasets. These features served as a condensed representation of the original data.
- Random Forest Training:
  The Random Forest model was trained using the features extracted by the pre-trained NN and the corresponding ground truth target values. This step ensured that the Random Forest learnt to make predictions based on the meaningful features captured by the NN.

4.4.10.3 Evaluation:

The performance of the hybrid model was then evaluated using two key metrics:

- Mean Squared Error (MSE)
- Mean Absolute Error (MAE)

4.4.10.4 Visualization:

To visually assess the model's performance, a scatter plot was created. The plot compared the true target values against the predictions made by the hybrid model. Additionally, a reference line was included in the plot, representing a perfect alignment of predicted and true values.

4.4.11 Ensemble of Neural Networks (Hybrid_m4)

The ensemble model, constructed by combining multiple neural networks, leverages the diversity of individual models to improve overall predictive performance. This approach aimed to capture a broader range of patterns within the data and enhance the model's robustness.

4.4.11.1 Architecture:

The architecture comprised a specified number of neural networks, each consisting of densely connected layers. Each individual neural network was trained independently on the preprocessed and normalized data. The ensemble model combined predictions from these individual models by averaging their outputs to generate a more stable and generalized prediction.

4.4.11.2 Training Process:

Multiple neural networks were built and trained on the same dataset using Mean Squared Error (MSE) as the loss function and the Adam optimizer. The training process for each network involved updating the model parameters to minimize the difference between predicted and actual values. This process was repeated for the specified number of epochs and batch size.

4.4.11.3 Evaluation:

The ensemble model's performance was assessed using the Mean Squared Error (MSE), providing a quantitative measure of the model's accuracy in predicting the target variable. This metric reflected the collective predictive strength of the ensemble, considering the diverse insights contributed by individual neural networks.

4.4.11.4 Visualization:

A scatter plot was then generated to visualize the relationship between true and predicted values. The plot included a reference line for comparison, aiding in the assessment of the ensemble model's predictive accuracy. This visualization offered an intuitive understanding of how well the ensemble model aligned with the actual data points, showcasing the effectiveness of combining diverse neural network predictions.

4.4.12 Attention Mechanism with Regression (Hybrid_m5)

The attention hybrid model with regression integrates attention mechanisms into a regression model. This model aimed to enhance the understanding of intricate patterns within the input data, providing a robust foundation for predicting the target variable.

4.4.12.1 Architecture Details:

The architecture consisted of an attention mechanism incorporated into a regression model. The attention layer dynamically weighed input features, allowing the model to focus on the most relevant information. The regression head processed the attended features to generate predictions. The model was trained using Mean Squared Error (MSE) as the loss function and optimized with the Adam optimizer.

4.4.12.2 Training Process:

The training process involved feeding the preprocessed and normalized data into the attention hybrid model. The attention mechanism adapted to the input patterns during the training epochs, and the regression head refined the learned features. The training parameters, such as the number of epochs and batch size, were set to optimize the model's performance.

4.4.12.3 Evaluation:

The model's performance was evaluated using the Mean Squared Error (MSE), which quantified the squared difference between predicted and actual values. This metric provided insights into the accuracy of the attention hybrid model in capturing the variance within the target variable.

4.4.12.4 Visualization:

To assess the model's predictive capabilities, a scatter plot was generated to visualize the relationship between true and predicted values. The plot helped in understanding how well the attention hybrid model aligned with the actual data points. The visualization included a reference line, aiding in the interpretation of the model's predictive accuracy.

4.5 Summary

In conclusion, the journey through model experimentation has been a comprehensive exploration of diverse strategies to enhance regression modeling. From a detailed exploration of the dataset through Exploratory Data Analysis (EDA) to the implementation of a variety of hybrid models, this chapter has sought to push the boundaries of regression modeling. The tools and technologies employed, including Python and Jupyter Notebook, have served as robust foundations for this exploration. The iterative process of trying various architectures and hyperparameter tuning has provided valuable insights into the intricate interplay between traditional machine learning techniques and advanced neural network architectures. The results and analysis presented in the subsequent chapter shed light on the performance of these models under different conditions.

5. Results and Discussions

5.1 Introduction

The Results and Discussions chapter embarks on a thorough examination of the performance metrics derived from each regression model implemented during the experimentation phase. This section delves into the R2-score, Mean Squared Error (MSE), and Mean Absolute Error (MAE) to gauge the efficacy of each model. The primary aim is to draw insights into how well the models capture the underlying patterns in the dataset and to identify the models that outperform others in terms of predictive accuracy.

5.2 Evaluation of Results

This subsection critically evaluates the performance of each regression model, dissecting the key metrics, namely R2-score, MSE, and MAE. The Linear Regression model serves as a baseline, and subsequent models, including Decision Trees, Random Forests, Support Vector Machines (SVM) with radial basis function (rbf) and linear kernels, Gradient Boosting, Neural Networks (NN), Long Short-Term Memory networks (LSTM), and various Hybrid models, are scrutinized. The analysis includes an exploration of the strengths and weaknesses of each model, shedding light on their ability to capture complex relationships within the dataset.

Table 3: Evaluation Metrices

S.No.	Model	R2-score	MSE	MAE
1	Linear Regression	0.58365	0.00615	0.05439
2	Decision Trees	0.71606	0.00419	0.03716
3	Random Forests	0.74668	0.00374	0.03357
4	SVM_rbf	0.53009	0.00694	0.06801
5	SVM_linear	0.40392	0.0088	0.08005
6	Gradient Boosting	0.67925	0.00473	0.0429
7	NN_m1	0.60573	0.00582	0.04537
8	NN_m2	0.61789	0.00564	0.04458
9	NN_m3	0.58551	0.00612	0.04783
10	NN_m4	0.5989	0.00592	0.04706
11	LSTM_m1	0.61173	0.00564	0.04454
12	LSTM_m2	0.61895	0.0056	0.0448
13	Hybrid_m1	0.62691	0.00552	0.04599
14	Hybrid_m2	0.63648	0.00538	0.04652
15	Hybrid_m3	0.67651	0.00479	0.04652
16	Hybrid_m4	0.63669	0.00538	0.04652
17	Hybrid_m5	0.56228	0.00648	0.04652

The evaluation of the regression models provides valuable insights into their respective performances. Starting with Linear Regression, its moderate R2-score of 0.58365 suggests a reasonable fit, but limitations in capturing non-linear relationships may be hindering its predictive capabilities. Decision Trees exhibit improved performance (R2-score: 0.71606), showcasing their ability to model complex relationships. However, the black-box nature of Decision Trees could lead to overfitting, especially with intricate datasets.

Random Forests, an ensemble of Decision Trees, further refines predictions (R2-score: 0.74668), mitigating overfitting to some extent. Support Vector Machines with an RBF kernel demonstrate adaptability to non-linear patterns, but the linear kernel performs suboptimally, emphasizing the importance of choosing appropriate kernel functions. Gradient Boosting, another ensemble method, achieves a competitive R2-score of 0.67925, highlighting its ability to capture subtle nuances.

Moving to Neural Networks (NN), the diverse performance across various architectures (NN_m1 to NN_m4) underscores the sensitivity of NN models to hyperparameters and architecture choices. Long Short-Term Memory (LSTM) models (LSTM_m1 and LSTM_m2) perform well, leveraging their ability to capture temporal dependencies in time-series data.

Hybrid models (Hybrid_m1 to Hybrid_m5) present a blend of traditional and neural network approaches. While some configurations demonstrate promising results, the variability in performance indicates the need for careful selection of features and architectures. Potential challenges in the models could stem from insufficient data, noisy features, or suboptimal hyperparameters.

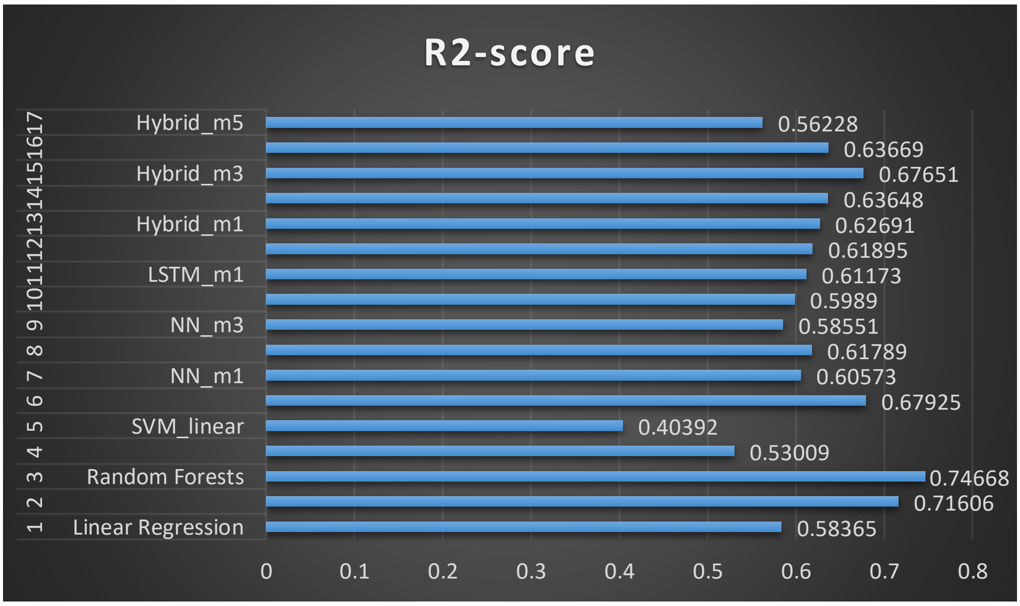


Figure 12: R2-Score

Figures 12 to 14, show the trend in the various evaluation metrices such as R2-score, MSE and MAE respectively of the various models developed.

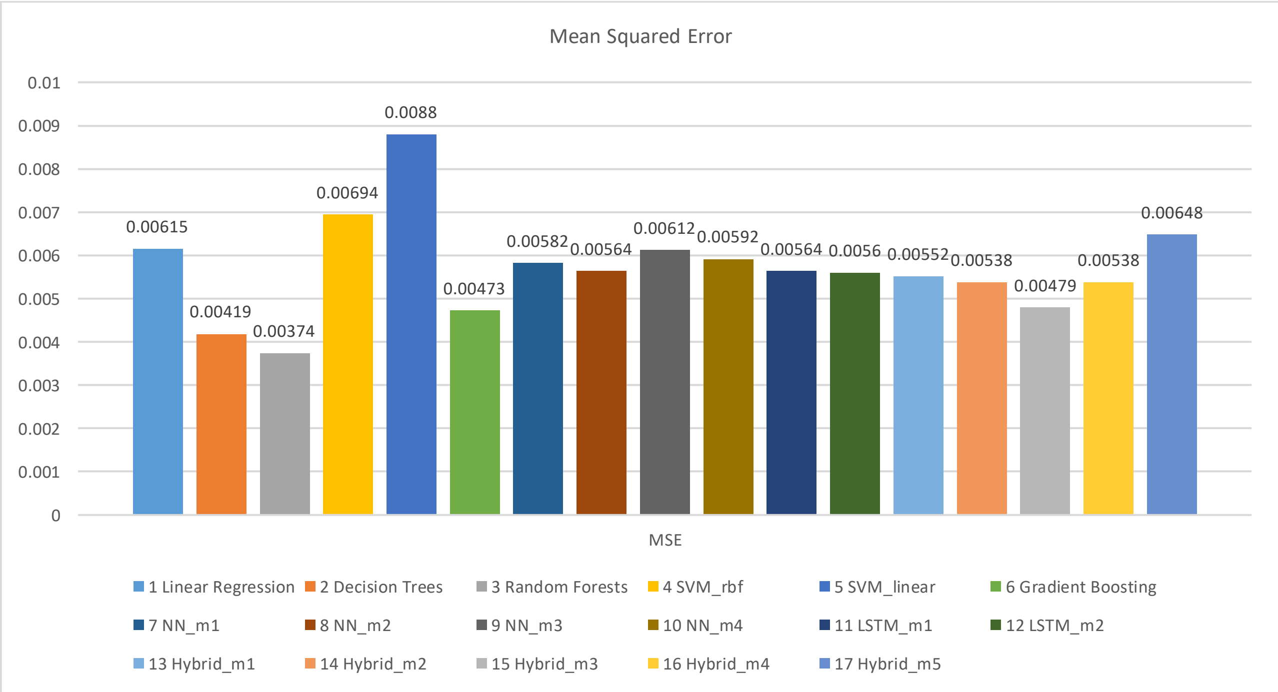


Figure 13: Mean Squared Error

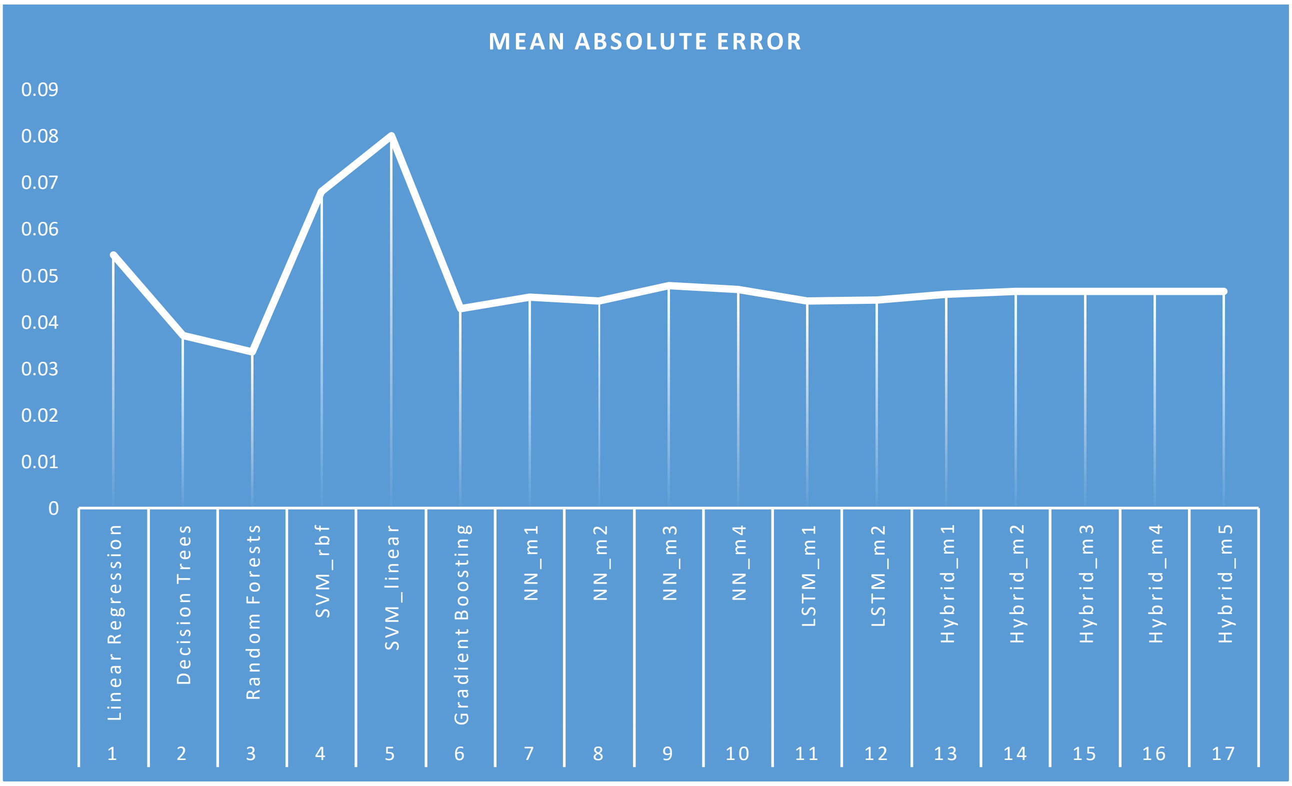


Figure 14: Mean Absolute Error

The discussions surrounding the regression model results delve into the nuances of each approach and offer valuable insights into their strengths and limitations. Linear Regression, although providing a reasonable fit, struggles with capturing intricate, non-linear relationships inherent in the data. Decision Trees and Random Forests showcase improvements but concerns about overfitting and the interpretability of complex models arise. Support Vector Machines exhibit kernel sensitivity, emphasizing the need for careful selection. Gradient Boosting performs well, highlighting the effectiveness of ensemble methods.

Neural Networks, with varying architectures, demonstrate sensitivity to hyperparameters and architecture choices. Long Short-Term Memory models stand out for their ability to capture temporal dependencies in time-series data. Hybrid models, combining traditional and neural network approaches, show promise but underscore the challenge of selecting optimal configurations.

In the discussions, it becomes evident that model performance is not solely dependent on the algorithm but is intricately tied to data quality, feature selection, and hyperparameter tuning. The variability in results across models emphasizes the need for a nuanced understanding of the problem domain and the data. While the models offer valuable predictive capabilities, achieving a balance between accuracy and interpretability remains a crucial consideration. The discussions set the stage for refining these models and advancing the understanding of their applications in real-world scenarios.

5.3 Summary:

The chapter concludes with a concise summary, synthesizing the key findings and implications derived from the model evaluations. It offers a comparative analysis of the models, highlighting the trade-offs between complexity and predictive accuracy. The results and discussions pave the way for informed decision-making regarding the selection of regression models based on the specific requirements and characteristics of the dataset.

6. Conclusions and Recommendations

6.1 Introduction

In the realm of Heating, Ventilation, and Air Conditioning (HVAC) systems, the efficient management of energy consumption is a critical concern for both economic and environmental reasons. Chiller units, a fundamental component of large-scale HVAC systems, play a pivotal role in maintaining optimal indoor temperatures. The power consumption of these chillers is influenced by a multitude of factors, including ambient weather conditions, building load, and system design. Understanding and accurately predicting chiller power consumption is essential for optimizing energy usage, minimizing operational costs, and reducing environmental impact.

The exploration conducted delves into the intricate dynamics of chiller power consumption prediction through the lens of regression modeling. The dataset under scrutiny encapsulates a rich array of variables, including the setpoint temperature, outside temperature, return temperature, supply temperature, power input to the chiller, and building load. Each of these variables carries unique information about the operating conditions of the HVAC system.

The setpoint temperature represents the desired temperature set by the building management system, serving as a reference for the chiller operation. The outside temperature is a key environmental factor influencing the chiller's workload, with extremes requiring more significant energy input. The return temperature reflects the temperature of the water returning from the building, influencing the chiller's efficiency. In contrast, the supply temperature represents the temperature of the water supplied to the building, indicating the effectiveness of the chiller in meeting the setpoint.

Power input to the chiller is a direct measure of energy consumption, and building load represents the overall thermal load on the HVAC system. These variables collectively create a complex and dynamic system, where intricate relationships necessitate advanced modeling techniques for accurate predictions.

The introduction of various regression models aims to unravel the intricacies within this dataset, offering a roadmap for understanding the nuanced interplay of variables influencing chiller power consumption. Through this exploration, we seek not only to optimize predictions but also to contribute valuable insights to the broader field of energy management in HVAC systems.

6.2 Challenges and Considerations

Despite the systematic approach, challenges and considerations arise during the development and experimentation process. These include:

6.2.1 Computational Complexity

The integration of neural networks with traditional machine learning models introduces computational complexities. Training deep neural networks demands significant computational resources, and optimizing for performance while managing computational cost becomes a delicate balancing act.

6.2.2 Hyperparameter Sensitivity

The performance of hybrid models is sensitive to hyperparameter choices. Finding an optimal configuration that balances expressiveness and generalization remains a non-trivial task, often requiring extensive experimentation.

6.2.3 Interpretability

Interpreting the inner workings of hybrid models, especially those incorporating neural networks, poses challenges. While traditional machine learning models offer interpretability through feature importance, the intricate nature of neural networks makes interpreting their decisions more complex.

6.3 Future Recommendations

To further advance the application of regression models in predicting chiller power consumption, several recommendations emerge. These recommendations aim to enhance the robustness, applicability, and real-world impact of the regression models developed.

6.3.1 Integration with Building Automation Systems (BAS):

The integration of predictive models with Building Automation Systems (BAS) could enable real-time adjustments based on predictions. This integration fosters a more responsive and adaptive HVAC system, contributing to energy efficiency and cost savings.

6.3.2 Validation Across Diverse HVAC Systems:

Extending the validation process to encompass a diverse range of HVAC systems and operational scenarios would enhance the models' generalizability. Testing the models in various settings ensures their reliability across different contexts.

6.3.3 Dynamic Model Updating:

Implementing a system for dynamic model updating could ensure that the predictive models adapt to evolving HVAC systems and changing environmental conditions. This adaptive approach aligns with the dynamic nature of HVAC systems in real-world scenarios.

6.3.4 Integration of Additional Variables:

Future studies could explore the inclusion of additional variables that might contribute to a more comprehensive understanding of chiller behaviour. Variables such as humidity levels, occupancy patterns, and equipment maintenance schedules could offer valuable insights into the dynamics of power consumption.

6.3.5 Explainable AI in Hybrid Models

Addressing the interpretability challenge by incorporating explainable AI techniques into hybrid models. This could involve developing attention mechanisms that provide clearer insights into feature importance.

6.3.6 Optimizing Computational Efficiency

Exploring strategies to optimize the computational efficiency of hybrid models. This could involve parallelization or leveraging specialized hardware to enhance training speed.

6.3.7 Ensemble Model Diversification

Investigating methods to enhance the diversity of ensemble models. This could involve exploring different neural network architectures within the ensemble or introducing additional diversity through alternative machine learning algorithms.

6.3.8 Transfer Learning Integration

Exploring the integration of transfer learning techniques to leverage pre-trained neural network features for regression tasks. This could potentially enhance model performance.

6.4 Conclusion of Experiments and Development

The experimentation and development process reveals a rich landscape of possibilities and challenges in the realm of hybrid regression modeling. Each model, from the intricacies of gradient boosting with neural networks to the innovative attention mechanisms, offers unique insights into the fusion of traditional and modern machine learning approaches. The tools and methodologies employed contribute to the robustness of the experimentation, laying the foundation for a comprehensive analysis of the results.

References

Jia, Z. and Zhao, T., (2019) The power consumption model of chiller with Elman neural networks for on-line prediction and control. In: *Advances in Intelligent Systems and Computing*. Springer Verlag, pp.281–289.

Kanewala, U., Weerakoon, S. and Nawarathna, R., (2021) Exploring Deep Learning and Tree-Based Ensemble Models for Chiller Energy Consumption Predictions. In: *2021 IEEE 16th International Conference on Industrial and Information Systems, ICIIS 2021 - Proceedings*. Institute of Electrical and Electronics Engineers Inc., pp.306–311.

Kim, J.H., Seong, N.C. and Choi, W., (2019) Modeling and optimizing a chiller system using a machine learning algorithm. *Energies*, 1215.

Kim, J.H., Seong, N.C. and Choi, W., (2020) Forecasting the energy consumption of an actual air handling unit and absorption chiller using ann models. *Energies*, 1317.

Kusiak, A., Li, M. and Tang, F., (2010) Modeling and optimization of HVAC energy consumption. *Applied Energy*, 8710, pp.3092–3102.

Kusiak, A., Zeng, Y. and Xu, G., (2013) Minimizing energy consumption of an air handling unit with a computational intelligence approach. *Energy and Buildings*, 60, pp.355–363.

Nassif, N., (2014) Modeling and optimization of HVAC systems using artificial neural network and genetic algorithm. *Building Simulation*, 73, pp.237–245.

Nisa, E.C. and Kuan, Y. Der, (2021) Comparative assessment to predict and forecast water-cooled chiller power consumption using machine learning and deep learning algorithms. *Sustainability (Switzerland)*, 132, pp.1–18.

Wei, X., Xu, G. and Kusiak, A., (2014) Modeling and optimization of a chiller plant. *Energy*, 73, pp.898–907.

Yin, H., Tang, Z. and Yang, C., (2023) Predicting hourly electricity consumption of chillers in subway stations: A comparison of support vector machine and different artificial neural networks. *Journal of Building Engineering*, 76.