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Parameter Optimization of Refrigeration Chiller by Machine Learning

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***Abstract* - The implementation of machine learning in a chiller system provides several benefits. It can improve energy efficiency by optimizing chiller operation based on predicted load requirements. It can enhance system reliability and reduce maintenance costs by detecting and diagnosing faults in advance. Furthermore, it can enable data-driven decision-making, enabling operators to make informed choices based on accurate predictions and insights. This implementation aims to leverage machine learning techniques to optimize the performance and energy efficiency of a chiller system. Chiller systems are widely used in various industries for cooling purposes, and their efficient operation is critical to reducing energy consumption and operational costs. By employing machine learning algorithms, this implementation aims to analyze historical data, understand patterns, and develop predictive models to optimize chiller system performance. The implementation process involves several steps. First, historical data from the chiller system, including sensor measurements, operating parameters and energy consumption, is collected and preprocessed. The data is then split into training and testing sets. Next, suitable machine learning algorithms, such as regression, classification, or time-series forecasting models, are selected based on the specific goals and requirements of the chiller system. Overall, this implementation demonstrates the potential of machine learning to optimize chiller system performance, reduce energy consumption, and improve operational efficiency. By leveraging historical data and advanced analytics, machine learning can play a crucial role in transforming traditional chiller systems into intelligent, adaptive, and energy-efficient cooling solutions.**
***Keywords:* HVAC, Chiller, Machine learning, Performance Prediction, IOT**

I. INTRODUCTION

The Heating Ventilation and Air Conditioning (HVAC) are one of the highest used systems in the world as they are commonly used in tertiary and commercial sectors. They can be seen used in buildings and known for consuming more than 40% of energy. Due to this reasons HVAC is becoming the center for study purposes so that energy consumption can be reduced, and systems can run more efficiently. Many studies show that major issues such as proper chiller loading, and coordination is important for improving efficiency of a chiller system and achieving a uniform control solution are being targeted [1]. Recently there has been a substantial increase in energy consumption in residential and commercial. The energy consumed by these buildings are astonishingly 60% of the whole electricity of the world and is said to increase in the future. Central HVAC systems used mainly in commercial sectors have opted to use water cooled chiller systems rather than the traditional air-cooled systems because of their high efficiency cooling output and decrease in 20% less energy consumption. To combat the chiller optimisation methodologies the most suitable way is of creating physical changes in the chiller systems [2]. Once the energy efficiency is improved our next step was to operating problems such as failed sensor working, improper installation, poor maintenance, failed implemented controls also lead to inefficient working of chillers. Using machine learning will help detect anomalities in the system by monitoring and identifying critical operations for keeping constant standardized operating procedures which can reduce maintenance costs too [3]. Data-oriented models are empirical models. It is possible to create equations that explain chiller performance without collecting chiller-specific system data. Artificial neural network (ANN) models of various structures can develop a chiller prediction model using three variables, namely refrigeration tonne, inlet temperature, and outlet temperature.

The development of prediction models can considerably increase the accuracy of energy baseline estimates. Chiller systems, on the other hand, are sophisticated pieces of machinery. Depending on the scenario, operating modes may change, and many operational parameters must be obtained. Correct data pre-processing can improve the overall efficacy of an analysis. Clustering is an excellent tool for data preparation. It operates by determining how data points are related to one another and uncovering hidden data structures [4]. The chiller plant system is generally controlled by a hierarchical control structure that comprises local and supervisory controllers. The local controller maintains the default value of each system component by using simple control methods such as proportional-integral-derivative (PID) control. The supervisory controller is a higher-level controller that issues instructions to local controllers such as temperature or voltage. In conclusion, numerous researches of machine learning techniques, such as ANN models, have been carried out in the building

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energy sector. The study of estimating a building's energy consumption, cooling load, etc. has produced highly accurate results. Nevertheless, because the majority of earlier research concentrated on the total building system, management tools like a BEMS must be able to forecast the energy consumption of subsystems like air conditioners, heat source equipment, and transportation equipment [6]. In this study a water chiller model was built from scratch and experimented for optimised efficiency. Performance calculations were done by taking different readings of chiller performance and time-oriented data was recorded by the use of sensors. Machine learning algorithms were performed on huge amounts of datasets for best predictive analysis results which gave the project the desired results.

II. MACHINE LEARNING IMPLEMENTATION

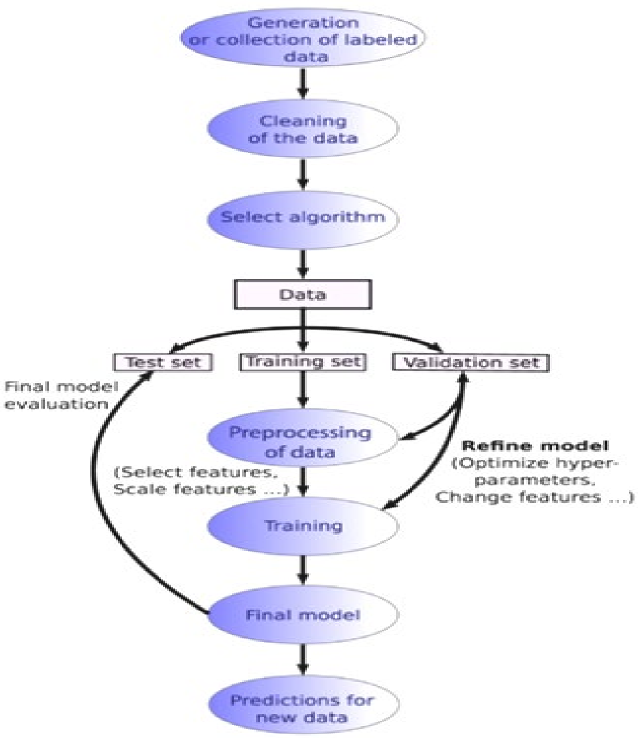

Fig. 1 Flow chart for machine learning workflow

Machine learning involves a series of steps to build and deploy a model. Here are the typical steps involved in the machine learning process.

1. *Define the Problem:* Clearly define the problem you want to solve using machine learning. Understand the business or research objectives and determine how machine learning can help achieve those goals.
2. *Gather and Pre-Process Data:* Collect relevant data that will be used to train and evaluate the machine learning model. This data should be representative of the problem domain and include both input features (attributes) and the corresponding target variable (the variable to be predicted). Pre-process the data by cleaning it, handling missing values, removing outliers, and transforming it into a suitable format for analysis.
3. *Split the Data:* Divide the dataset into two or three parts: training set, validation set, and test set. The training set is used to train the model, the validation set is used to fine-tune the model's hyper parameters and make decisions during training, and the test set is used to evaluate the final model's performance.
4. *Select a Model and Train it:* Choose an appropriate machine learning algorithm or model that is suitable for your problem and data. This could be a decision tree, logistic regression, support vector machine, neural network, or other models. Train the model using the training data, where the model learns the patterns and relationships in the data.
5. *Evaluate and Fine-Tune the Model:* Assess the model's performance using the validation set. Measure relevant evaluation metrics such as accuracy, precision, recall, or mean squared error, depending on the problem type. If the model's performance is not satisfactory, adjust the model's hyper parameters, try different algorithms, or perform feature engineering to improve the results. This process is known as model selection and hyper parameter tuning.
6. *Test the Model:* Once the model has been finalised, evaluate its performance on the test set to provide an impartial estimate of how the model will perform on unknown data. This ensures that the model generalises properly and does not overfit the training data.
7. *Deploy the Model:* Once the model has been verified and confirmed, it may be used to forecast new, previously unknown data. This includes integrating the model into a production system or application, configuring suitable input/output interfaces, and assuring the model's scalability, dependability, and security.
8. *Check and Maintain the Model:* Constantly check the performance of the deployed model to ensure its accuracy and dependability throughout time. Retrain the model on new data on a regular basis toIt's important to note that these steps are iterative, and machine learning is an iterative process. It often involves going back and forth between different steps to refine and improve the model until it meets the desired performance and objectives.

III. LITERATURE SURVEY

Jee-Heon Kim [6] The study's goal was to use an artificial neural network (ANN) method to create an energy consumption model for a chiller in an HVAC system. The effect of various input factors on the accuracy of the chiller energy consumption model was investigated. Even with a poor correlation to the output value, increasing the number of input variables enhanced prediction accuracy. The greatest accuracy was obtained when eight input variables were used, resulting in a coefficient of variation of root mean square error of 19.5% in the training period and 22.8% in the testing period. Increasing the quantity of training data also enhanced prediction accuracy, whereas lowering the amount of data had the opposite effect.

Yong Yu [2] The focus of this research study on energy savings and carbon emission reduction in buildings is critical for tackling climate change. Building energy usage and carbon emissions must be reduced in order to address climate change. The Heating, Ventilation and Air Conditioning (HVAC) system, especially the chiller plant, is an important component of a building's energy use. Previous research in mechanical engineering and building services has focused on optimising the power consumption of chiller systems, frequently using physical models based on domain knowledge. However, as big data and AI technologies progress, there is an increasing interest in applying machine learning to these optimisation difficulties. Despite the popularity of this strategy for energy conservation, incorporating machine learning into optimisation remains difficult.

Tamilarasan Sathesh [7] In the context of air conditioning chillers, this research article examines the rising relevance of energy consumption and global climate change. The research focuses on improving chiller performance through the use of absorption technologies such as absorption cooling systems and solar cooling. The authors suggest a unique technique dubbed Spider monkey Bat Algorithm (SMBat)-based Generative Adversarial Network (GAN) to properly anticipate chiller performance. This method makes use of time series data and incorporates the Spider Monkey Optimisation (SMO) and Bat algorithms. The GAN classifier, led by a fitness function, is used to predict chiller performance. The study also emphasises the importance of feature extraction, which is accomplished by utilising factors such as chilled water supply temperature, chilled water return temperature, condenser water return temperature, chiller water flow, cooling capacity, and power utilisation.

Lizhi Jia [8] This research study focuses on optimizing the operation strategy of thermal energy storage (TES) systems to align with renewable energy generation and reduce operational costs. A deep learning model accurately predicts hourly cooling load changes using historical data, while considering the nonlinear ice-charging rate. The proposed framework achieves significant cost savings of 11.2% compared to basic strategies throughout the ice-cooling season. The integration of deep learning and physics-based modelling enables TES systems to efficiently balance electricity generation and usage profiles, contributing to improved grid management. The study demonstrates the effectiveness of the framework in reducing operational costs and optimizing TES strategies.

Cheng Fan [9] The relevance of short-term building cooling load forecast for various building energy management activities is the topic of this research study. Traditional physical-principles-based approaches have limits owing to their reliance on assumptions, but data-driven methods enable flexibility and make use of the vast data accessible in modern structures. The study investigates the potential of deep learning, a strong tool in advanced data analytics, for anticipating building cooling load profiles 24 hours in advance. Deep learning algorithms can detect complicated patterns in large amounts of data and may be used for supervised or unsupervised prediction models and feature extraction, respectively. The findings show that deep learning, particularly when utilised unsupervised for feature extraction, improves the accuracy of building cooling demand prediction.

W.T. Ho [10] The k closest neighbour (kNN) regression is used in this work to optimise the operating strategies of a chiller system in order to reduce carbon emissions. Temperatures, flow rates, and component load ratios are among the 19 variables considered by the regression model in relation to the system's coefficient of performance (COP). The ideal value of k is established through cross-validation to be 3, resulting in the lowest mean square error. The most important system optimisation factors are identified, which include return chilled water temperature and flow rate, individual chiller load, and condenser water leaving temperature. The ideal variables for maximum COP are chosen from local circumstances using the existing building cooling load profile and ambient conditions.

Hanaa Salem [11] This research study explores the use of solar-driven steam materials and systems for desalination and disinfection. It leverages artificial intelligence (AI) and explainable AI (XAI) techniques to optimize water treatments with high accuracy. The study introduces a DL model with 82.64% accuracy in assessing cooling water quality and employs LIME as an explainer to enhance model interpretability. The findings highlight the importance of renewable water and its potential to increase distillation system productivity. The contributions include a reliable DL model and an interpretable explainer, bridging the gap between experts and non-experts. Future research can expand to more nations and explore alternative XAI methods. Ultimately, this work supports sustainable water distillation systems and automated water quality inspection.

Saman Taheri [12] This research study focuses on the use of deep learning algorithms, specifically deep recurrent neural networks (DRNNs), for fault detection and diagnostics (FDD) in HVAC systems. The challenges of configuring DRNNs for FDD and optimizing hyperparameters are addressed. Seven DRNN configurations are proposed and tuned to detect faults under different conditions. A comprehensive study of hyperparameters is conducted to optimize the configurations based on accuracy and training time. The best DRNN model is selected from over 200 experiments. The proposed DRNN model outperforms other data-driven techniques like random forest and gradient boosting.

N. Abdou [13] This research paper presents a metamodel-based approach to forecast and optimize heating and cooling loads in different climates in Morocco. The approach involves data collection, feature selection, and the assessment of various algorithms. Hybrid models using evolutionary-based and swarm intelligence-based algorithms coupled with learners like Artificial Neural Networks and Support Vector Machines showed the best results in terms of accuracy and reduction of input parameters. The NSGA-II algorithm was used to optimize the annual thermal load, resulting in significant reductions in total annual load and CO2 emissions. The study demonstrates the effectiveness of the approach in improving energy efficiency in different climatic zones.

IV. OUTLINE OF EXPERIMENTAL SET UP

Fig. 2 Outline of Experimental set up

A good and affordable cooling option that works well in many industrial situations are water chillers. Every industrial operator seeking to maximise output while minimising equipment downtimes benefits from having a correctly sized water-cooled chiller system. Energy conservation is one of the main benefits of employing a water chiller system for process cooling. Process cooling with a water chiller is particularly effective for a number of reasons. To begin with, water chillers function independently of environmental temperatures, which enable them to prevent system inefficiencies brought on by changes in ambient thermal conditions.

Furthermore, water chillers are particularly efficient at quickly lowering the temperatures in larger industrial applications because of their mode of operation (using water to disperse heat from a system). Recent widespread application of machine learning. Creating most efficient and energy saving systems are the future. In order to forecast the integrated, systematic operation of the chiller system, this research will analyse the input operating conditions of a chiller. The designed refrigeration chiller is made up of many parts, including a data logger, various sensors, a pressure gauge, an energy metre, and HP and LP cut-offs. The design of each individual component was developed based on the aforementioned criteria, and the associated parameter was determined. Initially, COP and chiller performance are manually determined by taking readings.

V. MACHINE LEARNING IMPLEMENTATION

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (12.0,9.0)
```

In [4]:
```
df=pd.read_csv('chiller.CSV')
```

In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 248 entries, 0 to 247
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   time               248 non-null    object
 1   inlet temperature  248 non-null    float64
 2   outlet temperature 248 non-null    float64
 3   flow rate          248 non-null    int64
 4   Unit consumption   248 non-null    float64
 5   current            248 non-null    float64
 6   voltage            248 non-null    float64
dtypes: float64(5), int64(1), object(1)
memory usage: 13.7+ KB
```

In [11]:
```
X=np.array(df.iloc[:100,1]).reshape(-1,1)
Y=np.array(df.iloc[:100,4]).reshape(-1,1)
```

In [12]:
```
from sklearn.model_selection import train_test_split
```

In [13]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=34)
```

```
In [14]: from sklearn.linear_model import LinearRegression

In [15]: lm=LinearRegression()

In [16]: lm.fit(X_train,Y_train)

Out[16]: LinearRegression()

In [17]: LinearRegression()

Out[17]: LinearRegression()

In [18]: predictions=lm.predict(X_test)

In [19]: print(predictions)

[[235.16328869]
 [240.15945293]
 [235.04338075]
 [234.54376433]
 [239.28012802]
 [239.91963704]
 [240.03954499]
 [234.42385639]
 [239.77974445]
 [239.91963704]
 [240.03954499]
 [240.15945293]
 [239.91963704]
 [239.42002062]
 [235.04338075]
 [239.04031214]
 [240.27936087]
 [239.04031214]
 [240.15945293]
 [239.77974445]]

In [21]: plt.scatter(X,Y)
         plt.plot([min(X),max(X)], [min(predictions),max(predictions)],color='red')
         plt.show()
```

Fig. 3 Machine Learning Implementation Input

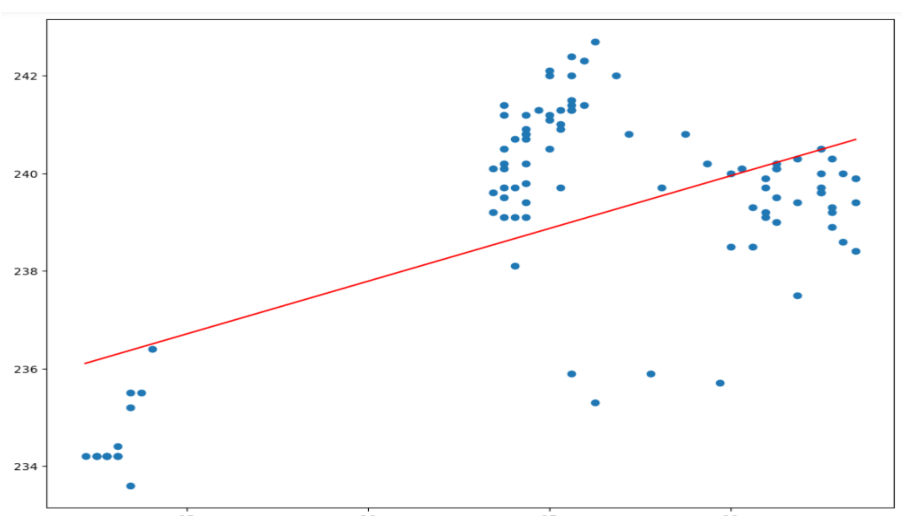

Fig. 4 Scatter Plot

In the above scatter plot (Fig. 4) the x-axis represents the outlet temperature and y-axis represents the energy consumptions of the water chiller model. We can clearly state that as the outlet temperature decreases the energy consumption of the chiller also decreases, which means that the chiller is slowly working on less capacity when temperature of water starts to deplete. The red line is the prediction line which represents the energy consumption with respect to outlet temperature.

```
In [22]: print(lm.intercept_)

[185.58135484]

In [23]: print(lm.coef_)

[[1.99846569]]

In [24]: from sklearn import metrics

In [30]: print('MAE:', metrics.mean_absolute_error(Y_test,predictions))
         print('MSE:', metrics.mean_squared_error(Y_test,predictions))
         print('RMSE:', np.sqrt(metrics.mean_squared_error(Y_test, predictions)))

MAE: 0.9302227138005605
MSE: 1.6681882605583165
RMSE: 1.2915836250736212
```

Fig. 5 Interpreted Values – MAE, MSE, RMSE

The above interpreted values such as MAE (Mean Absolute Error), MSE (Mean Squared Error) and RMSE (Root Mean Squared Error) have predicted values 0.930, 1.668 and 1.291 respectively which signifies us that the predicted values are close enough to the true values.

VI. CONCLUSION

In conclusion, water chillers play a crucial role in a wide range of applications, where chilled water or liquid is circulated to cool products and machinery. To optimize the performance of chiller systems, exploratory data analysis and machine learning algorithms have been employed. The invention of a data-driven or hybrid rule-based and data driven Energy/Building Management System further enhances the ability to learn from data and evaluate performance in chiller plants. By training prediction models and computing differential parameters, abnormalities and faults in the chiller plant can be detected, leading to more effective maintenance programs. The integration of machine learning and artificial intelligence has revolutionized various industries, including mechanical engineering, by providing solutions to new and unknown challenges, optimizing processes, and enabling intelligent and self-sufficient machines. Overall, these advancements in technology offer tremendous opportunities for improving product characteristics and internal processes. The scatter plot used for data visualisation clearly states the energy consumption of chiller can reduce if the outlet temperature reduces. The predictions made by this research also signifies that they were close enough to true values.

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