Charging Water Load Prediction with a Multilayer Perceptron for an efficient Facility Management and Maintenance of Thermal-Energy-Storage Air-Conditioning

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Abstract

This research addresses the challenges in Thermal-Energy-Storage-Air-Conditioning (TES-AC) systems by developing a machine learning model for predicting the necessary water volume for chilling. TES-AC technology, utilizing thermal energy storage tanks, offers substantial benefits such as reduced chiller operation, cost savings, and lower carbon emissions. However, determining the optimal chilled water volume poses challenges. The primary objective is to design a machine learning model leveraging Multilayer Perceptron (MLP) for predicting water load, incorporating input variables like weather forecasts, day of the week, and occupancy data.

The study validates the impact of weather data on chilled water volume, demonstrating its efficacy in prediction. The MLP-based model is fine-tuned through hyperparameter optimization, achieving a remarkable accuracy of 93.4%. The model provides specific water volume ranges, minimizing errors and aiding facility managers in informed decision-making to minimize disruptions.

Technical significance lies in the model's flexibility, allowing retraining for diverse TES-AC plants without requiring specific sensor inputs. This adaptability promotes widespread TES-AC adoption, contributing to environmentally friendly practices in building construction. The integration of the model into facility management software enhances predictive capabilities while offering common features, ensuring seamless incorporation into existing systems.

The research aligns with Sustainable Development Goals, particularly Goals 11, 12, and 13, emphasizing sustainable cities, responsible consumption, and climate action. By focusing on technical problem-solving, addressing challenges, and emphasizing the social significance through Sustainable Development Goals, this research provides a comprehensive solution to enhance TES-AC efficiency, thereby contributing to greener and more sustainable urban environments.

List of Publications

No.	Article Name
1	Application of deep learning in facility management and maintenance for heating, ventilation and air conditioning Automation in Construction 2022 by Elsevier
2	Analysis of Machine Learning Techniques for Predictive Maintenance in Cooler Condition 2022 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS) by IEEE
3	Effects of external weather on the water consumption of Thermal-Energy-Storage Air-Conditioning System Energy Nexus 2023 by Elsevier
4	Deploying a Deep Learning-based Application for an Efficient Thermal Energy Storage Air-Conditioning (TES-AC) System: Design Guidelines Journal of Electronic & Information Systems 2022 by Bilingual Publishing
5	EPoster Competition for 2023 American Association for the Advancement of Science (Semi-Finalist): Predictive Maintenance of Thermal-Energy-Storage Air-Conditioning 2023
6	Charging Water Load Prediction for a Thermal-Energy-Storage Air-Conditioner of a Commercial Building with a Multilayer Perceptron Journal of Building Engineering 2023 by Elsevier
7	Feasibility Study of an Innovative Strategy to Improve Commercial Buildings Sustainability using Deep learning, Thermal-Energy-Storage Air-Conditioning and Rainwater Harvesting Techniques by International Conference on Sustainable Development (ICSD) United Nations

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With sincere gratitude,

Mirza Rayana Sanzana

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List of Abbreviations

Abbreviation	Full Description
AC	Air Conditioning
AE	Auto-Encoders
AFD	Automatic Fault Detection
AI	Artificial Intelligence
ANFIS	Adaptive Fuzzy Neural Network Systems
ANN	Artificial Neural Network
API	Application Protocol Interface
BEMS	Building Energy Management System
BIM	Building Information Modelling
BIM-FM	Building Information Modelling- Facility Management
BMS	Building Management System
BPNN	Back-Propagation Neural Network
CAFM	Computer-aided Facility Management
CCTV	Closed-circuit Television
CMMS	Computerized Maintenance Management System
CNN	Convolutional Neural Network
DA	Discriminant Analysis
DDPG	Deep Deterministic Policy Gradient
DL	Deep Learning
DNN	Deep Neural Network
DP	Differential Pressure
DPM	Dynamic Predictive Maintenance
DT	Decision Trees
ELM	Extreme Learning Machines
FD	Fault Detection
FDC	Fault Detection and Classification
FDD	Fault Detection and Diagnosis

FDI	Fault Detection and Isolation
FGA	Fuzzy Genetic-Algorithm
FM	Facility Management
FMM	Facility Maintenance Management
GA	Genetic Algorithms
GBT	Gradient Boosted Trees
GIS	Geographic Information System
GP	Gaussian Processes
GPC	Gaussian Process Classifier
GSHP	Ground Source Heat Pump
GUI	Graphical User Interface
HVAC	Heating, Ventilation and Air Conditioning
IBMS	Intelligent Building Management System
IFM	Integrated Facility Management
IFMA	International Facility Management Association
IoT	Internet of Things
IP	Internet Protocol
IQR	Interquartile Range
IT	Information Technology
ITS	Ice Thermal Storage
KBS	Knowledge based System
kNN	k-Nearest Neighbor
LBFGS	Limited-Memory Broyden-Fletcher-Goldfarb-Shanno Algorithm
LEED	Leadership in Energy and Environmental Design
LR	Logistic Regression
LSTM	Long Short-term Memory
MACES	Multi Agent Control Energy System
MDP	Markov Decision Process
MEP	Mechanical Engineering Plumbing

MIL	Multiple Instance Learning
MILP	Mixed Integer Linear Programming
ML	Machine Learning
MLP	Multilayer Perceptron
MPC	Model based Predictive Control
MSE	Mean Squared Error
MTTF	Mean-Time-to-Failure
NDA	Non-Disclosure Agreement
NLP	Neuro-linguistic Programming
NN	Neural Network
OCSVM	One-Class Support Vector Machine
PCA	Principle Component Analysis
PSO	Particle Swarm Optimisation
QN	Q-Networks
QN + ET	Q-Networks + Eligibility Trace
QP	Quadratic Programming
RBF	Radial-basis Function
RFID	Radio-frequency Identification
RNN	Recurrent Neural Network
RPE	Relative Prediction Error
RUL	Residual Useful Lifetime
SNMP	Simple Network Management Protocol
SPC	Statistical Process Control
SQL	Structured Query Language
SRC	Sparse Random Classifier
SRC-SVD	Sparse Random Classifier-Singular Value Decomposition
SVD	Singular Value Decomposition
SVM	Support Vector Machine
TES	Thermal-Energy-Storage

TES-AC	Thermal-Energy-Storage Air-Conditioning

List of Symbols

Notation	Definition
d_{min}	minimum of data
d_{max}	maximum of data
$d(x_i, x_j)^2$	Euclidean distance squared between two points x_i and x_j
exp	exponential
k	number of neighbors
k	kernel k
$k(x_i, x_j)$	x are the inputs to find the kernel k
l	length
$2l^2$	length scale squared times 2
n	number of instances
$\sqrt{n}$	square root of number of instances
r_{min}	stated minimum range
r_{max}	stated maximum range
$\parallel x \parallel$	unit length of the feature vector
x	observation of a data value
x'	new value of x
$\text{mean}(x)$	mean value of x
$\max(x)$	maximum value of x
$\min(x)$	minimum value of x
x_{prop}	proportion of a given data value
x_{scale}	new scaled value

x_i	data value
$Q_3(x)$	upper quartile (75%) of data value
$Q_2(x)$	median (50%) of data value
$Q_1(x)$	lower quartile (25%) of data value
z	new standardized data value
μ	overall mean of data
σ	overall standard deviation

Chapter 1 Introduction

1.1 Background of Research

Facility Management (FM) is completely necessary in business to have a better decision-making process where the maintenance and repair costs of buildings are not exceeding the budget. Besides, the FM is the most expensive phase of a building life cycle of Building Information Modelling (BIM). This important action is managed by facility managers who have a significant responsibility in ensuring the systems of the built environment work simultaneously and the actions need to be economically feasible. As everything is moving towards digital and more focus on environment friendly products and approaches, the knowledge of Information and Technology (IT) Management, and sustainability have become the core competencies of facility managers (Rondeau, et al., 2017). With buildings becoming more technologically advanced, it is essential for facility managers to adapt and use digital technologies such as automation in BIM and integrating state-of-the-art technologies such as Artificial Intelligence (AI) and Internet of Things (IoT).

There are two types of FM which are hard FM and soft FM. Hard FM services involve physical materials and structures such as air conditioning and building maintenance whereas soft FM services involve non-technical tasks such as landscaping, waste management and security. Incorporating digital innovations in hard FM is absolutely crucial as hard FM services cannot be removed from the building for the direct relation to the building whereas soft FM services can be removed. Sustainable buildings are more commonly known as green buildings, and recently the acceptance of such buildings have grown popular as the demand of reducing costs and becoming environment-friendly have grown (Roper & Payant, 2014). It is normally appropriate for facility managers to accept and adopt the sustainability approaches because they always have to manage operations with constrained budgets. These green practices have not only become popular and useful in designing and construction but in the entire life cycle of the building which is the maintenance and renovation of the building after the deliverance (Roper & Payant, 2014; Rondeau, et al., 2017). Recently, companies and facility managers are driving for sustainable buildings with renewable energy sources to lower building energy and management costs and optimize energy.

Operations and maintenance (O&M) is the most important FM sector which relies on effective and prompt decision and reaction from facility managers. It is an extremely hard challenge for facility managers to cater good quality services at a minimum cost as they always have to be cost efficient and responsible. Surely maintenance is required to be monitored as accurately as possible because it plays a huge role in the sustainability of the buildings or built environment. Improper and delayed maintenance has led facility managers into challenging situations regarding repairs, high maintenance costs and arduous repairs (Sagnier, 2018). Hence, facility managers have been eager in using technological innovation to assist them in their tough tasks. The interest however is more into predictive maintenance as this sort of maintenance can warn or point out the problem before it actually happens with the implementation of Artificial Intelligence (AI) or more specifically Machine Learning (ML) as it is capable of making predictions (Carvalho, et al., 2019).

As climate change becomes evident across the globe, communities are trying to act for more sustainable living (Sharif, et al., 2020). Climate change effects such as, heat waves are being felt more along with a significant increase in heat and humidity which leads to tropical countries having even warmer weather conditions than what is generally experienced. With warmer weather conditions, the Air Conditioner (AC), a facility that is used to condition the indoor air by providing cool and desirable temperatures indoors, must work harder to provide such satisfactory outcomes (Lundgren-Kownacki, et al., 2018). A conventional AC conditions the air by removing the unwanted heat and humidity outdoors which contributes negatively to the atmosphere. More so, such conventional AC increases the overall building energy consumption mainly in tropical or subtropical countries to provide desirable temperatures and transfer heat and humidity outdoors besides releasing harmful greenhouse gasses (Ashish, 2022; Rauniyar & Sodhi, 2018). Hence, Thermal-Energy-Storage Air-Conditioning (TES-AC) systems are being focused on by some major environmentally friendly corporations as this is a more sustainable form of AC that provides similar desirable cool air conditions but with a lower energy consumption (Awang, et al., 2017). TES-ACs can chill water during off-peak hours and store it in thermal water storage tanks to use during the day, reducing electricity costs and minimising heat emissions.

1.2 Problem Statement

Global warming has become a very important issue as the effects of global warming such as rising temperatures, heat waves, hurricanes etc. are felt across the world more (Bryant, 2019). As companies started turning towards sustainable buildings and cars, innovative and eco-friendly solutions have emerged. Although buildings account for around one-fifth of global energy consumption, buildings have been in the blind spot for global warming and climate topics because people tended to be more interested about electric cars than focusing on the inefficiency of the air conditioning systems (MacMillan, 2016). Air conditioners (AC) have been emitting greenhouse gases which have always been harmful for the atmosphere and the environment. Due to the air conditioning units filtering the heat outside, an effect called the "urban heat island" effect which means an urban area that is much warmer than the surrounding rural areas, has worsened making the cities warmer (Kleerekoper, et al., 2012). This effect has caused more people to use air conditioners in their houses, shopping malls etc. as it has become a necessity in a hot city.

Some major corporations are trying a different eco-friendly solution instead of asking people to switch off AC or reduce their AC usage for their sustainable building projects to address the United Nations 17 Sustainable Development Goals (SDGs), in particular Goals 11: Sustainable Cities and Communities, 12: Responsible Consumption and Production, and 13: Climate Action. They are making use of thermal storage air conditioning systems instead of conventional AC units. For much-needed environment-friendly and sustainable technology, Thermal-Energy-Storage Air-Conditioner (TES-AC) systems are being focused on (A.Al-Abidi, et al., 2012; Sarbu & Sebarchievici, 2018; Bajaj, et al., 2021). A TES-AC system functions by simply transferring the charging load from on-peak to off-peak hours, reducing building energy consumption besides reducing greenhouse gas emissions (Sun, et al., 2013; Dincer, 2002). In addition, a TES-AC system stores thermal energy in the form of chilled water during the night to cool the building the following day without releasing unwanted heat and humidity outdoors (Mehari, et al., 2020; Guelpa & Verda, 2019). It circulates the stored energy within its system, meaning heat is dispersed only during the charging period and not throughout the day. The responsible entities for managing and maintaining this facility are facility managers who ensure the daily operations in a building go smoothly and minimize disruptions. However, the Facility Management and Maintenance (FMM) task for a TES-AC system is essentially complicated due to the fact that an incorrect charging load can more than double the building energy consumption when facility managers are required to charge during on-peak hours. Hence, predicting charging load to allow facility managers to prepare in advance during off-peak hours will be a useful contribution to the FMM and the environment with an increased shift to sustainable TES-AC systems. With a proper predictive maintenance with deep learning, facility managers will be more inclined to the shift towards sustainable technology as it will not cause occupancy discomfort or building management costs to increase (Amarasinghe, et al., 2015).

Although it is true that this innovative solution to reduce harmful emission of gases from air conditioners can benefit the society and the environment, this thermal storage AC system is not widely adopted by many companies. The reason behind this is the maintenance issues linked with the TES-AC systems along with determining the water volume needed to charge for the next day. Although facility management teams try to be diligent in this matter, a lot of times the facility managers face unexpected problems such as water pressure issues, tanks not having optimal volume of water etc. Sometimes these issues pose a system failure or significant problems during peak hours and needs a high capital to fix the issue.

However, it is necessary for commercial buildings to adopt such eco-friendly green air conditioning systems to contribute positively to the society as well as minimizing the costs. Stakeholders are not very keen on adopting TES-AC because of the complexities when it comes to managing it. Research is required to find innovative methods that can assist facility managers in operating TES-ACs in a more efficient manner so that it can be used more often.

The adoption of TES-AC systems in Malaysia is still in its early stages, but it is expected to grow rapidly in the coming years. As more commercial building owners and facility managers become aware of the benefits of TES-AC systems, the demand for these systems is likely to increase. In addition, advances in machine learning and artificial intelligence are likely to improve the accuracy and effectiveness of TES-AC predictive models, further reducing energy costs and environmental impact.

One challenge facing the widespread adoption of TES-AC systems is the cost of installation and maintenance. TES-AC systems require significant upfront investment and ongoing maintenance to ensure proper operation. However, the long-term benefits of TES-AC systems, including reduced energy costs and environmental impact, can outweigh the initial costs. The current system of charging TES-AC systems is very manual and relies heavily on guesswork which makes it not very efficient. By utilizing advanced technologies such as Machine Learning, the gap between manual guesswork and technical innovation can be minimised. This could provide enhanced operation efficiency for TES-AC plants and increase the popularity of the technology which would in turn lead to greener and more sustainable buildings. The main technical problem comes in the form of incorrect charging load where the guesswork would cause the facility managers to charge too much water and use unnecessary energy and cause extra emissions or charge too less and have to rely on using chillers during on-peak hours which causes the energy cost to spike significantly.

1.3 Aim and Objectives

The aim of the research is to forecast the water load of thermal energy storage air conditioning using a multilayer perceptron for efficient Facility Management and Maintenance. By employing Machine Learning to predict the required water charging volume for the upcoming day, substantial reductions in electricity costs and heat emissions can be achieved.

The specific objectives of this research are:

1. Assessing the performance and accuracy of various Machine Learning algorithms on a dataset with features similar to the main data, with the goal of identifying the most promising algorithms for further exploration with the main dataset.
2. Pre-processing sensor data from the TES-AC plant to identify key features.
3. Developing a Multi-Layer Perceptron regression model to predict occupancy data in the building cooled by the TES-AC, incorporating external data such as weather data and information about the days (day name, weekend, etc.).
4. Creating and evaluating a proof-of-concept Multi-Layer Perceptron model that precisely predicts the water charging load for the following day.
5. Integrating the proof-of-concept trained model into a user-friendly desktop application and incorporating basic facility management features into the software to ensure reliable TES-AC maintenance.

1.4 Research Questions

The research questions are as follows:

RQ1: Which Machine Learning algorithms are the most suitable for charging water load of TES-AC prediction problem based on preliminary analysis on a similar online dataset?

RQ2: What are the key features in the TES-AC dataset that can help in predicting the water charging load?

RQ3: What external data can be used to predict the water charging load in order to avoid relying on the specific sensor data of the TES-AC, to get a more generalized solution.

RQ4: What is the most appropriate MLP model architecture for predicting the water charging for the the TES-AC?

RQ5: What is the best way for facility managers to use the trained model to get useful predictions that will assist them in operating the TES-AC more efficiently?

1.5 Scope of the Research

The scope of the research encompasses the development of a machine learning model for predicting the water volume that needs to be chilled in Thermal-Energy-Storage-Air-Conditioning (TES-AC) systems. The research designs a Multilayer Perceptron model that takes input variables related to weather conditions, occupancy data, and the day of the week, and outputs a predicted water volume that needs to be chilled. This is to assist facility managers in making informed decisions for efficient facility management and maintenance of TES-AC systems.

The research includes a feasibility study on the concept of using renewable energy, such as TES-AC. Expert opinions are gathered from professionals working in developing and developed countries to assess the practicality and viability of implementing TES-AC systems in such contexts. The study explores the challenges, potential benefits, and barriers to adoption, taking into account factors such as infrastructure, costs, and local regulations.

The development of the machine learning model involves pre-processing the sensor data from the TES-AC plant to identify key features and develop a regression model for occupancy prediction. The main focus is to develop and evaluate the Multilayer Perceptron model that accurately predicts the water charging load for the next day. The trained model can be integrated into a user-friendly desktop application as a proof-of-concept that incorporates basic facility management features. This integration enables facility managers to utilize the predictive powers of the model while also benefiting from other common facility management software functionalities.

Essentially, the research contributes to the field of facility management by providing a practical solution for efficient management and maintenance of TES-AC systems through the application of machine learning techniques. Additionally, the feasibility study offers valuable insights into the adoption of renewable energy solutions, specifically TES-AC, in developing countries facing power challenges, thereby facilitating sustainable development, and promoting energy resilience.

1.6 Significance of Research

The research provides a novel approach for utilizing current state-of-the-art machine learning algorithms to address a specific problem faced by facility managers operating TES-ACs. The research was conducted in collaboration with a real estate company in Malaysia that owns and operates several commercial buildings across the country. The TES-AC system utilized in the specific building under study is unique in its implementation and the way it operates. The TES-AC plant in question consists of twenty thermal storage tanks that can store chilled water and maintain its temperature, as opposed to the traditional systems consisting of chillers that operate continuously, resulting in high electricity bills and carbon emissions. In this case, the TES-AC plant was installed to enable the facility managers to turn on the chillers during off-peak hours and chill enough water to be used during the building's operational hours. However, their biggest challenge was to determine the appropriate water volume that needs to be chilled to meet the building's cooling requirements for the day.

The novelty of this research lies in the development of a machine learning model that can predict the water volume required to be chilled for the TES-AC plant to satisfy the cooling needs of the building for the next day. Unlike other studies that aim to create or invent a new machine learning algorithm, this research focuses on applying existing machine learning algorithms in a novel way to solve a specific problem faced by facility managers operating TES-ACs. The proposed machine learning model utilizes input variables, such as weather data and information about the day, to make accurate predictions about the water volume required to satisfy the building's cooling needs. The research aimed to address the challenge faced by facility managers in determining the appropriate water volume that needs to be chilled to minimize electricity bills and carbon emissions, while also taking into account the variable electricity charges during peak and off-peak hours.

One of the key aspects that makes this research unique is its focus on creating a solution that can be easily adopted and repurposed for other TES-AC plants, without requiring a very specific sensor input that might not be available in a different TES-AC plant. The model was designed to avoid reliance on sensor data specific to the TES-AC plant, which makes the proposed solution widely applicable and adaptable to other TES-AC plants across various locations.

The final machine learning model was developed using a Multilayer Perceptron neural network, which provided the best prediction result. Instead of predicting an exact water volume, the model predicts a specific water range as a classification label, providing the facility managers with a small flexible range to choose from. This approach ensures that the facility managers can use their expertise to determine the best water volume within that range, thereby minimizing errors. The final model achieved an accuracy of 93.4%, which is a significant result that shows that there is potential in this work.

The use of TES-AC systems is particularly relevant in countries with high electricity costs and a need to reduce carbon emissions. Malaysia, like many other countries, is facing a growing demand for energy, particularly during peak hours. This has led to high electricity costs during peak hours, which can significantly impact the operating costs of commercial buildings. By using TES-AC systems, facility managers can take advantage of lower electricity rates during off-peak hours and reduce their reliance on energy during peak hours. In addition, TES-AC systems can help Malaysia meet its carbon reduction goals by reducing the need for constant chiller operation, which can result in significant carbon emissions.

Overall, this research offers a unique approach for optimizing the performance of TES-AC systems and reducing their environmental impact, thereby contributing to the advancement of sustainable building technology. The proposed machine learning model has the potential to be applied to other TES-AC systems and can be easily adopted by facility managers in various locations to improve the performance of their cooling systems.

1.7 Limitations

The research consists of certain limitations that might have affected the final result but did not hinder it completely. In the beginning of the research, there was a delay in obtaining the dataset from the external company due to the Non-disclosure Agreement procedures. However, this allowed for more time to explore various ML algorithms on a similar dataset to narrow down the options to try on the main dataset. Minor limitations pertaining to the actual dataset including missing data, incorrect format, etc. existed but were rectified. Other minor limitations could include high cost in operating a Machine Learning solution if the solution is uploaded on a cloud service. However, that is a common part of any Machine Learning solution and any company willing to integrate Machine Learning should be familiar with this.

Then, the TES-AC plant was sold off after two years later and this caused an insufficiency of data and the inability to carry out a small field test. Regardless, the model was tested on unseen data to evaluate its performance and achieve acceptable results. It can only be deduced that more data might have improved the accuracy even further.

A point worth noting, even though it is not exactly a complete limitation, is that the trained model cannot be used on a different TES-AC plant than the one it was trained on. That is normal however, considering the fact that every TES-AC plant will operate in a different way based on the location and climate, usage. Similar features and model design could be used however, just with a different dataset and that might still produce a decent result.

1.8 Expected Deliverable

The expected deliverable is a trained MLP model that can predict the next day's water charging load in a TES-AC plant using only external data like weather, days data, and building occupancy data. The model is to be integrated into a user-friendly desktop software for easy access and use. The MLP model may be retrained on different TES-ACs using the same external data features, but the values would differ based on the location of that TES-AC.

Chapter 2 Literature Review

2.1 Introduction

Climate change requires attention and innovative technologies that have less carbon emissions and are energy efficient, need to be adopted into buildings. Facility Management is the longest and most expensive phase of building lifecycle, hence that phase needs more focus. Machine Learning approach can greatly benefit facility management with its powerful prediction and learning abilities assisting the facility managers in their tasks. Despite the promising results of deep learning research, construction industry applications are still limited. Facility Management (FM) in construction has yet to take full advantage of the efficiency of deep learning techniques in daily operations and maintenance. Heating, Ventilation, and Air Conditioning (HVAC) is a major part of Facility Management and Maintenance (FMM) operations, and an occasional HVAC malfunction can lead to a huge monetary loss. The application of deep learning techniques in FMM can optimize building performance, especially in predictive maintenance, by lowering energy consumption, scheduling maintenance, as well as monitoring equipment. Thermal-Energy-Storage (TES) can be useful for Air-Conditioning (AC) in buildings with low heat and carbon emissions and also optimizing energy of the building reducing costs. The utilization of deep learning methods for predictive maintenance on Thermal-Energy-Storage Air-Conditioning (TES-AC) in HVAC is necessary for environmental sustainability, as well as to improve the cost-efficiency of buildings.

The chapter is organized as follows: Section 2.1 introduces the topic of this paper briefly; Section 2.2 discusses briefly how Machine Learning process works, the different learning types and how to choose the most suitable algorithm for HVAC dataset. Section 2.3 demonstrates the deep learning approaches and its useful applications in facility management along with the challenges and possible approaches. Section 2.4 gives an overview of Thermal-Energy-Storage Air-Conditioning (TES-AC) and discusses the external factors that may affect its charging water load to maximise energy efficiency. Section 2.5 gives an extensive discussion on Multilayer Perceptron and how it can be utilised in Facility Management. Section 2.6 discusses the user-friendly features for an application deploying Machine Learning model. Section 2.7 discusses feasibility study of a sponge city concept. Additionally, Section 2.8 gives a summary of the discussion of this chapter.

2.2 Machine Learning process

Machine Learning (ML), a sub-field within artificial intelligence (AI), studies algorithms and systems and allows them to automatically learn doing specific tasks using models and logics to make better decisions in the future instead of explicitly having programmed instructions. ML basically focuses on the development of computer programs which are capable of accessing data and using it for learning automatically, which is the main goal. It also performs and adjusts activities like predictions as required without any human intervention or assistance. With the help of machine learning, analysis of massive quantities of data has become possible, though significant time and resources may be necessary to train a model properly when identifying profitable opportunities or hazards (System, 2019).

For creating a machine learning (ML) model, the latter is trained with a training dataset. When there is new data input added to the ML algorithm, then a prediction is generated based on the model. Prediction accuracy is evaluated and if the prediction accuracy is not satisfactory, then the ML algorithm is trained repeatedly using enlarged data (Atul, 2019). When the prediction is satisfactory, then the ML algorithm is deployed. Figure 2.1 shows the basics of how machine learning works.

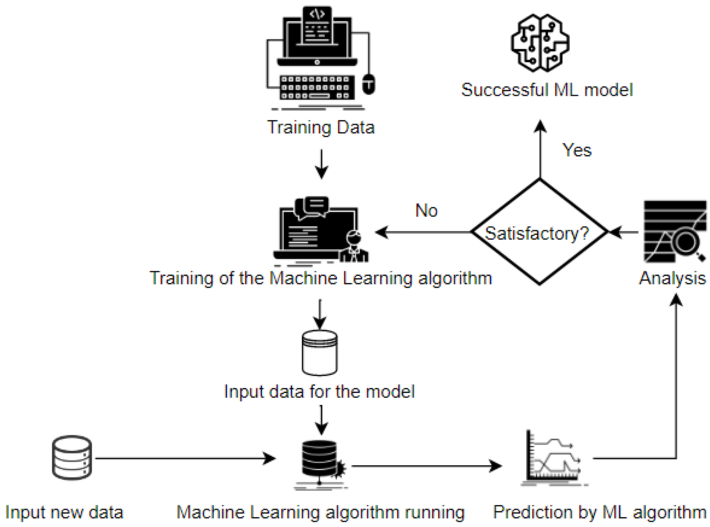

Figure 2.1 The process of machine learning (Atul, 2019)

The first step in a machine learning process is data collection which is crucial where a raw dataset is extracted. If the dataset extracted is irrelevant, then the model that would be trained would also have a poor quality. The second step would be where the relevant data would be processed such as handling missing information or outliers to ensure that it is in an applicable format for training the model. Feature engineering is done after the data has been processed as some features might need to get transformed or dropped to optimize the training process of the model on the data (Adaptilab). Sometimes new features are also created out of the existing features (Sreekanth, 2018). After the feature engineering is completed, the data is split into training data and test data as shown in Figure 2.2. The training data is used for data information and training the ML model whereas the test data is used for validating the model.

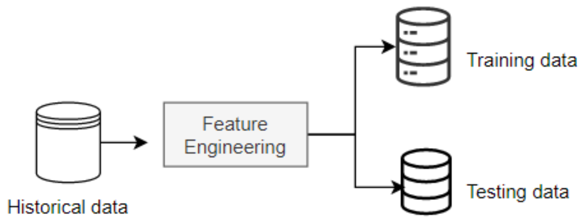

Figure 2.2 Feature Engineering (Sreekanth, 2018)

Then, a model architecture is chosen based on the dataset. Most of the tasks can be efficiently performed with an existing model architecture instead of coming up with a novel model architecture. A data pipeline is generated when the model architecture has already been selected which indicates a continuous stream of batched data for training the model intensively (Adaptilab). It is suggested to have the data pipeline as efficient as possible as training can take a long time. When the model has been trained for enough time, the performance of the model will need to be validated on a remaining portion of the whole dataset which is often referred to as the testing dataset. The testing dataset has not been previously used in training but has the same basic distribution of the training set. After the model has been validated, the persistence of the model needs to be evaluated where a process would be set up in a way so the new users would be able to use the pre-trained model for making predictions.

2.2.1 Learning Types

There are many types of uses for Machine Learning such as text generation and image recognition. Generally, machine learning tasks can be categorized into either supervised learning type or unsupervised learning type. Figure 2.3 shows two main types of learning with examples for each continuous and categorical section.

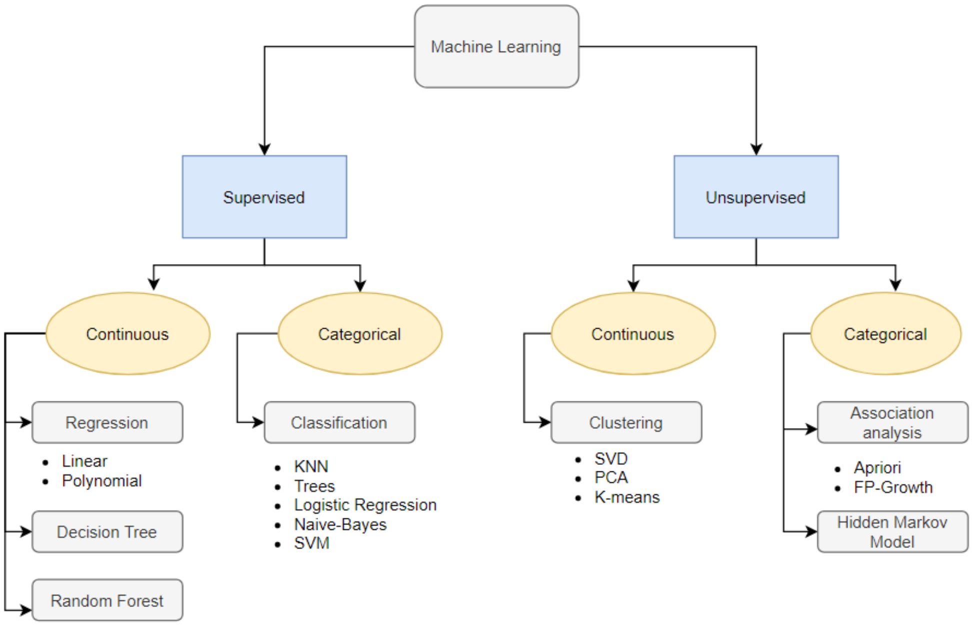

Figure 2.3 Machine Learning types

Supervised learning uses labeled data for training a model. The labels for the training dataset illustrate the category that each data observation fits in. Supervised machine learning algorithms are capable of implementing what has been learned in the past to make predictions about the future. Normally the learning algorithm starts with the analysis of a known training dataset and then provides an inferred function for predicting output values. The model would be able to predict labels for new data observations after sufficient training. The learning algorithm would also be able to compare actual outputs with the correct/intended outputs as well as detect errors to modify and improve the model (System, 2019). An example can be if a machine learning model is getting trained to predict if a picture contains a bicycle or not, then with supervised learning, the model can be trained on a dataset of pictures where labels for each picture would be either "Yes" or "No" accordingly. Then the model would be able to determine whether the picture has a bicycle.

Unsupervised learning uses unlabeled data for the model to learn relationships between data observations and also identify hidden patterns. The system explores the data and deduces inferences from unlabeled data to depict hidden structures. Unsupervised learning algorithms are typically used when the target dataset is not labeled or classified. An example can be if a ML model is trying to predict if a picture contains a bottle of coke but with an unlabeled dataset, then with unsupervised learning, the model would be able to pick up on the basic differences such as pixel color between pictures with a bottle of coke and pictures without it which would allow the model to cluster the pictures into two groups.

Semi-supervised learning is a mix of supervised and unsupervised learning as they implement labeled and unlabeled data for training the model. Normally they use a small volume of labeled data and a considerable number of unlabeled data. In this way the system can improve its learning accuracy significantly. Generally, this type of learning is preferred when the collected labeled data needs relevant resources to train the model.

Reinforcement learning, another major machine learning paradigm, interacts with its environment by identifying errors or rewards based on the best outcome (Atul, 2019; System, 2019). Following the concept of trial-and-error search with rewards is the most notable characteristic of reinforcement learning. The software agents or machines can automatically identify the ideal behavior to maximize the performance as the agent will be rewarded with points for useful behaviours or penalized for unhelpful behaviours. Simple reward feedback such as positive reward points gained lets the model train itself and after the training is done, new data can be presented to it. However, reinforcement learning is not suitable for this research because a large, labeled dataset can be retrieved from the industry for training which is consistent with Supervised Learning.

It is important to know the type of machine learning method that will be used as it is the first step in creating a machine learning model besides choosing a fitting model architecture. Supervised learning is the best option if there are sufficiently large training datasets. When it is hard to sometimes get fully labeled data in every case, then it is suggested to go for unsupervised or semi-supervised learning. The data that would be retrieved from the company is a large, labeled dataset as the data needs skilled resources to learn from for the model, hence the chosen learning type for this research will be a supervised learning method. Most importantly, the data is required to be processed into a training pipeline and then the model results need to be analyzed. In summary, the different types of machine learning are discussed and where they are most appropriate to use and what applications are most suitable for them. Understanding which type of machine learning a given problem falls under is very important in understanding which approach should be used and which algorithms to try.

2.2.2 Data Preprocessing

Working with data involves data analysis and data preprocessing and for machine learning engineers, an important task is first analyzing the data for feasible patterns and then making an effective input pipeline to train a model. This task implements libraries such as scikit-learn for data preprocessing and data mining, NumPy and pandas which manages the data handling and also implements ML frameworks such as TensorFlow to create the input pipeline and the model.

2.2.3 Feature Scaling

Feature scaling is an important matter in terms of machine learning and is a step of Data Preprocessing that is applied to data features (Uppal). While using certain algorithms, feature scaling can change the results greatly while in some there will be minimal or no effect at all. It is used for normalizing the data within a range or for facilitating calculations in an algorithm.

While using datasets in most of the occasions, the features would vary greatly in range, unit, and magnitudes but it becomes an issue because many ML algorithms use Euclidian distance between two distance points (Asaithambi, 2017). When datasets are not scaled, these algorithms just take in the magnitude of features ignoring the units which cause the results to differ by much between different units. To suppress the difference, it is necessary to do feature scaling so all the features can be brought to the same level of scaling.

The four common methods for feature scaling are:

- Standardization: This was applied in this research. Standardization rearranges the features with mean 0 and standard deviation 1.
- Mean Normalisation: Although this was not applied for this research as of now for the current dataset, Normalization generally means rescaling the values into a range of -1 and 1 with a mean 0 (Geller, 2019). The equation for mean normalization is as shown in equation 2.1 where x' is the new value and x is the observation of a data value.

Equation 2.1 (Asaithambi, 2017)

$$x' = \frac{x - \text{mean}(x)}{\max(x) - \min(x)}$$

- Min-Max scaling: This basically generates the value to be between 0 and 1. Min-max scaling is useful when dealing with features with hard limits, i.e. features that have specific, non-negotiable boundaries or constraints that need to be maintained in the scaled data.

- Unit Vector: This method also brings the value to be between the range of [0,1] like min-max scaling but scaling is performed considering the entire feature vector to be of a unit length. The equation for unit vector is in Equation 2.2 where $\| x \|$ denotes the unit length of the feature vector.

Equation 2.2 (Asaithambi, 2017)

$$x' = \frac{x}{\| x \|}$$

It is necessary to perform feature scaling when any ML algorithm calculates distance or considers normality. The algorithms chosen for this research and if feature scaling needs to be performed for them are mentioned as follows:

- *k-nearest neighbors (kNN)*: This algorithm requires all the features to be scaled equally as kNN with the Euclidean distance measure is susceptible to magnitudes.

- *Principal Component Analysis (PCA)*: This seeks to get features with maximum variance or deviation. The deviation is high for features with high magnitudes. This can make the PCA biased towards features with high magnitude, hence it is crucial to scale the features if PCA would be applied.

- *Tree-based models*: Modelling trees does not require scaling as it is not a distance-based model and can deal with varying ranges of features.

- *Logistic Regression*: This requires scaling as it performs better when the features are on a common data format.

- *Neural Network*: Scaling input and output variables is necessary in neural networks because values with a large spread can result in an unstable learning process as it might alter the magnitude of the values significantly due to large error gradients.

2.2.3.1 Standardization

Standardization is a data processing workflow which allows structural alteration of discordant datasets into a common data format. A common data format is a data model which brings the different datasets into a single consistent grouping. This is required because in hybrid datasets, the input datasets need to be transformed into a consistent model to allow aggregation or comparison to take place and allow data analysis and usage in a consistent form (IO). Standardization commonly means rescaling data to have a standard deviation of 1 (unit variance) and a mean of 0 (Geller, 2019).

Equation 2.3 (Raschka, 2014)

$$z = \frac{x - \mu}{\sigma}$$

The above equation 2.3 is a data standardization equation, where x denotes an observation or a data value, μ denotes an overall mean of the data, σ denotes overall standard deviation and z represents the new standardized data value. The new value z is gotten by subtracting μ, the overall mean from x and dividing σ, the overall standard deviation. When data can take on any range of values, it becomes hard to understand so data standardization converts the data into the standard format which refers to data that has a mean of 0 and standard deviation of 1. Standardization was utilized for Principal Component Analysis (PCA) which was applied in this research on the online dataset as PCA accepts zero-centric data (Asaithambi, 2017).

2.2.3.2 Data Range

Compressing data into a fixed range [0,1] is a form of scaling which lets the data to be viewed as proportions or percentages based on the minimum and maximum values of the data.

The formula for range scaling is done in a two-step process. Equation 2.4 shows the first step where the proportion of a given data value is first calculated which is x_{prop} with respect to the minimum and maximum of the data which are d_{min} and d_{max}. This works if all the values of the data are not the same i.e. $d_{max} \neq d_{min}$.

Equation 2.4 (Adaptilab)

$$x_{prop} = \frac{x - d_{min}}{d_{max} - d_{min}}$$

Equation 2.5 is the second step where the proportion of the value x_{prop} is used to scale the data to the stated range i.e., r_{min}, r_{max} to get the new scaled value x_{scale}.

Equation 2.5 (Adaptilab)

$$x_{scale} = x_{prop} \cdot (r_{max} - r_{min}) + r_{min}$$

2.2.3.3 Robust Scaling

A significant part of data that needs to be managed is outliers which are data points that are much further away from other data points. Standardization uses the mean and standard deviation of the features while range scaling uses the maximum and minimum feature values. This shows that both data standardization and ranged scaling can be affected by outlier values.

Robust scaling avoids getting affected by outlier values as it implements the median and interquartile range (IQR) of the data. If data is robustly scaled, then it is not affected by outliers as the median (50%) and IQR (25%-75%) are percentile measurements of the data. Equation 3.6 shows the equation for robust scaling where x' is the new scaled value and x_i is the data value. The median $Q_2(x)$ is subtracted from each data value x_i , and then it is scaled to IQR which is the subtraction of the lower quartile $Q_1(x)$ from the upper quartile $Q_3(x)$.

Equation 2.1 (Keen, 2017)

$$x' = \frac{x_i - Q_2(x)}{Q_3(x) - Q_1(x)}$$

2.2.4 Principal Component Analysis (PCA)

Nearly all of the datasets contain a huge number of features among which some can be redundant or unnecessary. On these datasets, a type of data transformation, PCA can be performed as they have correlated numeric features to reduce the number of columns in the data array, also known as dimensionality reduction. It is called Principal Component Analysis as it retrieves the uncorrelated latent variables that include almost all of the information from the original dataset which are the principal components of the dataset.

2.2.5 Data Imputation

Data imputation basically means replacing missing or inconsistent data with an estimated value based on available information. A lot of times in the real world, it is needed to deal with datasets with missing values or attributes. If there are many missing values, the dataset cannot be used but if there are few missing values, then with data imputation the missing values can be replaced with other values.

2.2.6 Choosing the Most Suitable ML Algorithm for HVAC dataset

With the emergence of technologies like Machine Learning (ML) and the recent advancements the field has witnessed, an opportunity arises to implement predictive maintenance in a real-life example. The main advantage of using machine learning to implement predictive maintenance is the fact that machine learning is adaptive, it learns and improves itself the longer it runs provided it was trained properly. Training a machine learning model is a very crucial task and not an easy one to achieve. Regardless, the results are very beneficial and when applied to implement predictive maintenance it has the potential to save a huge amount of money and reduce the risk of machine breakdowns or disruption in services significantly (Carvalho, et al., 2019).

By providing a powerful and accurate machine learning solution, data can be fed into the model and over usage time the model will be able to give an accurate prediction of maintenance requirements. Deep learning (DL), a type of machine learning based on artificial neural networks (ANNs) is considered to be very powerful for prediction and can naturally represent the probabilities that a system may fail during various times contributing to a better decision regarding maintenance (Nguyen & Medjaher, 2019; Wang & Wang, 2018). Although not many deep learning techniques have been applied for HVAC predictive maintenance, it is important to focus on utilizing this ML technique for better decision-making and optimizing building efficiency (Sanzana, et al., 2022; Lee, et al., 2017; Rahman & Smith, 2018; Beghi, et al., 2014; Deutsch, 2018).

Supervised learning is arguably the best learning paradigm in this context as the HVAC domain can provide large, labelled datasets. With new data added to the ML training process, the updated model generates potentially improved predictions. Based on standard performance evaluation methods, if the prediction accuracy is not satisfactory, then the ML algorithm can be trained repeatedly using enlarged data (Atul, 2019). When the prediction is satisfactory, then the ML algorithm is deployed. Therefore, this research focuses on an in-depth analysis of the common machine learning algorithms that can potentially be the foundation of an effective machine learning model for predictive maintenance of HVAC.

2.3 Deep Learning and Facility Management

Deep learning, a branch of machine learning has evolved significantly in the last ten years initiating drastic changes in technological approaches in various industries from medical research to electronics. In processing large amounts of data, deep learning can achieve accuracies in such an advanced way that it can exceed human-level performance and productivity, as well as save time and resources. Deep learning completely shifted the automotive industry with its applications from automated driving to automatically detecting traffic lights, stop signs, obstacles, and such. In automation in the construction industry, deep learning is also being used to detect people around heavy machinery to improve safety. The high-performance levels of deep learning in the field of computer vision have made several areas of construction adopt deep learning. For example, Zhang et al. (2019) discussed the utilization of text mining and natural language processing techniques for accident report analysis at construction sites. Computer vision-based construction safety vest detection, an earlier method of construction worker detection improves safety by detecting the motion of workers and the colour pixels of safety vests (Seong, et al., 2017).

In terms of Facilities Management (FM) in the construction industry, a large number of stakeholders handle the operation. During this process, they appear and leave at various times during the building operation life cycle which causes information to be lost or distorted if not managed properly. Operation and maintenance in the FM sector rely on effective and prompt decision-making from facility managers. It is an extremely hard challenge for facility managers to cater for quality services at a minimum cost as they are required to be cost-efficient and responsible (Connelly, 2010).

Nevertheless, maintenance is required to be monitored as accurately as possible because it plays an important role in the sustainability of buildings or the built environment. Improper and delayed maintenance has led facility managers into challenging situations regarding repairs, high maintenance costs and arduous repairs (Sagnier, 2018). Hence, it is essential for sustainability in Industry 4.0 context in the FM industry to employ advanced intelligent digital technologies as they can help facilitate the flow of information, along with drawing conclusions from predictions based on sensor data (Araszkiewicz, 2017; Xu, et al., 2020). There are quite a few reviews on Machine Learning for life cycle management implementing combinations of different algorithms and discussing solutions for various scenarios (Gao, et al., 2019; Zhang, et al., 2020). The focus however has been more on predictive maintenance as this sort of maintenance can warn of a problem before it actually happens thanks to machine learning (ML), or more specifically deep learning as it is capable of making predictions (Carvalho, et al., 2019). Facility managers want advanced predictive maintenance assistance mainly in Heating, Ventilation, and Air Conditioning (HVAC). Focusing on HVAC is important as it encompasses a significant part of building life-cycle management.

Deep Learning has gained interest in Construction and Maintenance according to the Google Keywords trends. It is more popular within Machine Learning compared to Reinforcement Learning and Transfer Learning in Facility Management and Construction. The comparison clearly validates the interest in researching and reviewing Deep Learning applications in FM in order to digitize and make it more efficient. Deep Learning has superiority in terms of prediction accuracy and better performance when trained with a large amount of data compared to other Machine Learning algorithms.

Deep learning approaches, like the You-Only-Look-Once (YOLO) network, aim to solve problems "end to end." This means that the deep learning model attempts to learn the complete task or make predictions directly from raw data without breaking it down into multiple intermediate steps. In the case of YOLO, which is commonly used for object detection in images, the model can take an image as input and directly output information about the objects present in the image, including their locations and classifications, all in one step. In contrast, many traditional machine learning techniques, such as Support Vector Machines (SVM), often require breaking down the problem into different parts or stages. These methods typically involve feature extraction, where relevant features are extracted from the raw data, and then a separate learning algorithm is applied to make predictions based on these features. This multi-step process involves breaking the problem into intermediate stages before arriving at a final solution. The key point here is that deep learning models, because of their complex neural networks, can often learn to perform tasks directly from raw data, which can be advantageous in some cases, especially when dealing with large datasets and complex patterns.

Traditional machine learning techniques, on the other hand, may require more feature engineering and multiple stages of processing. The choice between the two depends on the nature of the problem and the available data. When there is a lack of domain understanding for feature analysis which maybe the case in FM for researchers, Deep Learning techniques prove to be a better alternative since feature engineering is less of a concern. In terms of large data size, which is the case for Facility Management, deep learning outperforms other Machine Learning techniques. When it comes to solving complex problems or prediction, deep learning outshines other methods which is why it can greatly benefit FM by optimizing energy efficiency and maintenance.

However, not much research has been conducted using deep learning applications for HVAC using specific algorithms in the Facility Maintenance and Management (FMM) in the construction industry. Furthermore, not many studies have been focused on deep learning models to improve automation in construction for better maintenance of assets. Therefore, this chapter provides a thorough literature review of deep learning applications in the FMM sector focusing on HVAC which can act as a useful comprehensive guide for subsequent research studies. The aim of this research is to help researchers understand the current progress, and challenges of the various algorithms in deep learning to overcome challenges in FM for HVAC.

2.3.1 Overview of Neural Networks

2.3.1.1 Brief historical remarks

A neural network generally consists of three parts, i.e., input layer, hidden layer(s), and output layer. A deep neural network typically has *many* hidden layers, thus making the network *deep*. This in turn allows it to form rich hierarchical representations, which facilitates the capture of complex causal factors underlying the data. In other words, the rationale for depth is that it allows for the learning of abstract multi-level features of an input (Wang, 2016). In traditional feature engineering, human designers need to manually and painstakingly construct relevant features which are then fed into machine learning algorithms

(Bengio, 2009). The deep neural network approach has typically replaced the more time-consuming and traditional approach of feature engineering (Pingel, 2017).

Apart from the structural or architectural aspects of neural networks, the other key ingredient to the success of this field lies in learning algorithms. Rumelhart et al. (1986) demonstrated the effective application of the backpropagation algorithm for training neural networks, in the context of a richer and deeper history of optimization. This was a key step in the development of the area. Deep learning techniques implement the back-propagation algorithm to find complex structures in large data sets and determine how the internal parameters of a model should change to compute the representation in each layer from the representation in the previous layer and perform predictions at a high-level accuracy (LeCun, et al., 2015). As such, deep learning methods are also known as "representation learning". Other algorithms commonly known for training Artificial Neural Networks (ANNs) include, simulated annealing, and genetic algorithms. Chen et al. (2003) adapted ANNs for fault detection in engineering structures resulting from vibration or fatigue. ANNs have also been used for structural damage detection implementing backpropagation algorithms, empowered by a heuristics-based tunable steepest descent method for training, and Frequency response functions (FRF) used for structural damage detection (Fang, et al., 2005).

Since their early days, ANNs have primarily been used for classification problems or function estimation due to which they are widely used for solving complex industrial problems (Bilal, et al., 2016). Supervised learning is a type of learning where the machine is trained using labelled data (i.e., for every input the dataset has a corresponding target label) whereas in unsupervised learning, the dataset consists only of input instances without target labels (Bansal, 2021). ANNs are applicable to both supervised and unsupervised learning. Moselhi et al. (1991) mentioned how ANNs can be implemented with conventional expert-based FM systems and guarantees ideal performance over the systems. ANNs are particularly suited for Big Data which involves a very large number of data instances typically with high dimensionality, which makes it important in all the construction industry applications.

Following the early demonstrations of backpropagation, several other landmarks in the history of neural networks ensued, including the development of LeNet (LeCun, et al., 2015; LeCun, et al., 1989; Hochreiter & Schmidhuber, 1997), whose general architectures will be briefly discussed in the following sections. Other than finding it hard to get adequate amount of labelled data for training, the neural network algorithms in the initial stage faced difficulty training the network properly. The training difficulty was also due to the vanishing gradient problem when the depth of the network expanded and also the hardware that could not handle the complexity of training. Hinton and Salakhutdinov (2006) first proposed deep learning as a solution to the vanishing gradient problems in deeper neural networks. Although the early days of neural networks exhibited many of the key ingredients required for the success of the field, they still exhibited some key limitations. Some of these limitations included limited processing power, limited availability of labelled data for training, and the vanishing gradient problem. Over time, these limitations were gradually eroded due to the advancement of deep learning. Deep learning field experienced a renaissance around 2006, marked by papers such as the one authored by Hinton and Salakhutdinov (2006).

2.3.1.2 Multilayer Perceptron (MLP)

The Multilayer Perceptron (MLP) is one of the most commonly used ANNs and, as with most architectures, can be used for both classification and regression (Bilal, et al., 2016; Cheng, et al., 2020). Data samples are first normalized and then inserted into the input layer which then pass through the hidden layers resulting in the output according to the network's structure. Generally, for an MLP with a single hidden layer, the ANN topology is described as x:y:z. In x:y:z topology, x denotes the number of nodes in input layer, y denotes the number of nodes in hidden layer, and z denotes number of nodes in the output layer. In terms of the connectivity, nodes are typically referred to as fully connected, since all nodes from a layer are connected to all nodes in the subsequent (adjacent) layer. By using MLPs and Mixed Integer Linear Programming (MILP), Rajith et al. (2018) developed a real-time optimized HVAC control system that was setup on top of an existing IoT framework. The optimized control system showcased just how powerful the combination of both could be in prediction, resulting in a turnaround in terms of predictive maintenance (Rajith, et al., 2018).

2.3.1.3 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) exploit several design principles found in biological visual systems, namely the fact that representations are hierarchically composed from localized and repetitive receptive fields. In CNN terminology this translates into localized kernels that share weights across an image, both of which ultimately provide the network with prior knowledge that exploits the statistical regularities known to exist in images. In most CNNs this architectural feature is usually also combined with a more traditional fully connected structure, typically at the output side of the network. Apart from exploiting prior knowledge, which improves accuracy, CNNs also require fewer parameters compared to fully connected networks. This tends to make the learning process easier and faster and reduces some memory requirements. Today CNNs are often the method of choice in different computer vision applications, for example in object detection and image recognition. A classic early example of a successful CNN would be AlexNet, which demonstrated the power of combining deep learning, specifically a deep CNN, with very large datasets (Krizhevsky, et al., 2017).

2.3.1.4 Recurrent Neural Network (RNN)

Another classic neural network structure is the Recurrent Neural Network (RNN) which is used in time series data processing, for example in speech recognition. Two main types of RNN, and the most popular Deep RNN architectures, are Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM), which differentiate themselves from more classic recurrent architectures using gates that control the temporal flow of information (Cho, et al., 2014). LSTMs and GRUs in general are able to capture long-term dependencies in a sequence which is why they are widely used in multiple applications including natural language applications (Bouabdallaoui, et al., 2020), time-series prediction (Gasparin, et al., 2021), and anomaly detection (Su, et al., 2019) (Chalapathy & Chawla, 2019).

LSTMs have also been integrated with autoencoders (Bouabdallaoui, et al., 2021); a special form of neural network designed for unsupervised learning tasks (Fan, et al., 2018). An autoencoder consists of an encoder that transforms the input data into a hidden representation, while the decoder attempts to reconstruct the input data from the same hidden representation (Fan, et al., 2018; Li, et al., 2017) with a minimum amount of distortion and noise (Baldi, 2012). Due to this characteristic, autoencoders have been used for dimensionality reduction applications (Wang, et al., 2016), signal reconstruction applications, and anomaly detection applications (Fan, et al., 2018; Araya, et al., 2017).

2.3.2 Overview of Predictive Maintenance

Digitization and mainly the advent of big data brought about the possibility of developing efficient smart monitoring and predictive maintenance applications. Modern data-driven applications with distributed computing architectures caused major improvements in maintenance service efficiency. Predictive maintenance, an important part of the revolution of Industry 4.0 is based on the Computerized Maintenance Management System (CMMS) concept that takes advantage of state-of-the-art technological innovations (Labib, et al., 2008). CMMS coordinates all activities related to the availability, productivity, and maintainability of cyber-physical systems (CPSs). Procedures in a computerized maintenance process take place with minimal human involvement which minimizes human error. In such procedures, a high degree of automation with complex CMMS is required. However, predictive maintenance faces the challenge of bringing together technologies from different application domains including big data, Internet of things (IoT), augmented reality (AR), virtual reality (VR), machine learning and deep learning (Deac, et al., 2017).

These complex CMMS solutions work completely autonomously, and with the learning capability can collect, store, and analyze data continuously. Although, to predict future failures, or downtimes, it is required to analyze historical data, as well as constantly monitor data in real-time. With the application of mathematical and statistical methods, smart maintenance can detect where, when, and why a component may fail, hence in predictive maintenance, the component gets repaired or replaced before the failure occurs saving costs and increasing the reliability of equipment (Patwardhan, et al., 2016).

Predictive Maintenance optimizes asset management and improves overall facilities management and maintenance. Time to failure (TTF) prediction and remaining useful life (RUL) prediction are well-known features of predictive maintenance. The TTF prediction denotes the amount of time a component is expected to last in operation. Whereas RUL is the estimated lifespan of a component after which it is no longer capable of serving its intended purpose. Estimating TTF and RUL, albeit challenging, has proven to be useful for applications especially in characterizing rotating machines, such as pumps, and fans. Facility Managers can prepare to either maintain or change such machineries beforehand.

2.3.3 Applications of Deep Learning in FMM

Deep learning has greatly advanced the construction industry's FM by assisting facility managers in decision making and effective maintenance. Industrial maintenance processes are important as the productivity of the companies depend significantly on that. There are five types of maintenance that are frequently implemented in industry which are corrective, preventive, predetermined, condition-based and predictive (Sagnier, 2018). Different companies adopt different types of maintenance depending on their specific needs. Figure 2.4 shows where FMM is located in the BIM domain of construction industry. Facility managers generally conduct preventive or reactive maintenance for building maintenance management.

However, these strategies have their limitations as preventive maintenance would not be able to predict when certain mechanical, electrical and plumbing (MEP) components would need repair in advance and reactive maintenance would not be able to prevent failures. Hence, predictive maintenance strategies, incorporated with advanced technologies such as IoT have become the preferred choice to improve the efficiency of facility management and maintenance (FMM) (Cheng, et al., 2020)

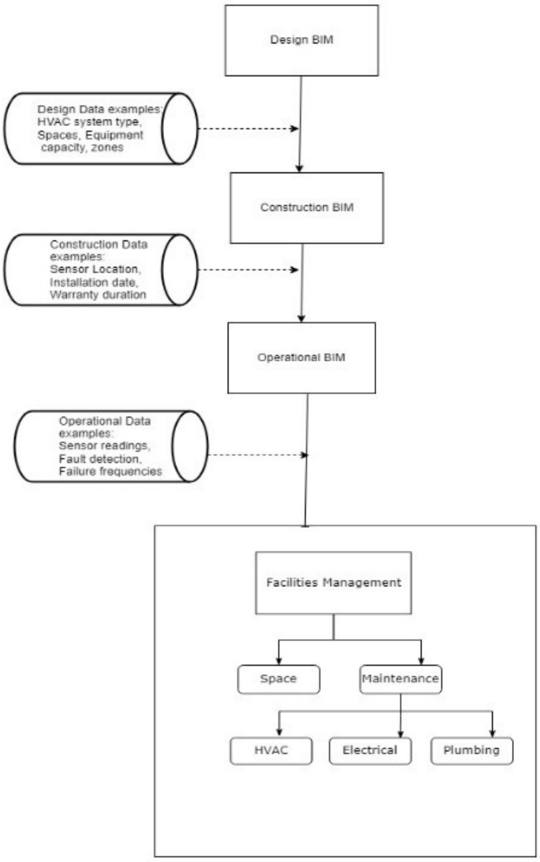

Figure 2.4 Building Information Modelling (BIM) domain.

Since deep learning is particularly well-suited for perception-oriented tasks (as applied to IoT and other data), its applications are useful in predictive maintenance (Lamnabhi-Lagarrigue, et al., 2017). According to the literature, deep learning methods were found mostly in predictive maintenance rather than other types of proactive maintenance. Applications for building operation and maintenance were found specifically in fault detection and diagnostics, occupancy evaluation, and energy efficiency improvement (Hong, et al., 2020). Common accessible tools for developing deep learning models are Python with the help of TensorFlow (Abadi, et al., 2015), Keras (Chollet, 2015), and PyTorch (Paszke, et al., 2019); MATLAB with the help of Deep Learning Toolbox (Mathworks), and R (Team, 2017).

2.3.3.1 Image classification

Predictive maintenance aims to predict equipment failures to enable advance corrective maintenance scheduling to prevent unanticipated downtime, in turn improving service quality. Marzouk and Zaher (2020) proposed a proactive maintenance application to maintain, upgrade, and operate assets of three fire protection systems in a cost-effective way with a deep-learning pre-trained model to assist facility management and maintenance. The deep learning model proposed was able to classify MEP components in the fire protection systems by image classification with a deep CNN using a support vector machine (SVM) technique with supervised learning (Marzouk & Zaher, 2020). The following research suggests an automated decision support system by integrating CNNs for image recognition to identify cracks or degradation phenomena directly in three-dimensional (3D) models (Czerniawski & Leite, 2018). By using 3D geometry, an automated decision support system could lead to suitable interventions by facility managers by evaluating multiple criteria in various scenarios.

In smart museums, computer vision algorithms are used to recognize images and to attribute an exhibit to an artist or epoch. Computer vision algorithms also analyze sentiments to identify the emotional states of images. With deep learning and computer vision techniques, it is possible to classify images into millions of predefined categories (Tregubova, 2019). It is also possible to detect image details, read printed and handwritten text, and create valuable metadata for smart museum image catalogues for better asset management (Tregubova, 2019). This research uses deep learning models for smart surveillance systems and offers mechanisms for compressing DNNs thereby improving the processing latency for a group of networked cameras (Jayarajah, 2019). A vision and learning-based indoor localization framework that uses a shared CNN for feature extraction from images was proposed (Wei & Akinci, 2019). This framework performed localization and object recognition simultaneously for facility management and did not require the deployment of radio-frequency identification (RFID) tags (Wei & Akinci, 2019). With the implementation of deep learning, RGB-D images can be automatically segmented into building components (Czerniawski & Leite, 2020).

2.3.3.2 Failure detection

Nguyen & Medjaher (2019) presented a dynamic predictive maintenance framework on a LSTM network in their research that depends on sensor measurements and prognostics according to the requirements of management planners. An LSTM can be used to compute the probabilities that a system may fail at specific times, and it thus contributes to better decisions regarding maintenance (Nguyen & Medjaher, 2019; Wang & Wang, 2018). As there is an increasing demand for the reliability, availability, safety and maintainability of systems, there is also a great interest in the development of predictive maintenance (PdM). PdM helps facility managers schedule activities in a way that reduces machine or system downtime. Intelligent sensors can help in this real-time system monitoring process, providing managers with relevant information (Sanchez-Silva, et al., 2016; Wang & Wang, 2018; Gouriveau, et al., 2016).

Limiting carbon dioxide emissions can be achieved through a general reduction of energy consumption, and by moving towards renewable energy sources. Establishing optimal energy consumption of buildings is necessary as they contribute significantly to the world's energy demand. Markoska (2019) developed a framework for optimal forecasting of expected building performance by estimating expected energy consumption and indoor climate. The framework implemented an LSTM network using the Keras library for deep learning (Chollet, 2015), which further uses the library TensorFlow, an open-source ML library (Abadi, et al., 2016). The system identified numerous faults during operation and helped facility managers find issues regarding faulty wiring in meters and defective sensors. Bouabdallaoui et al. (2021) proposed a predictive maintenance approach; an LSTM based deep learning model with an autoencoder architecture to predict failures for HVAC and validated it in a sports facility. Autoencoders were part of the proposed framework since they adopt an unsupervised learning approach, which doesn't require labelled data and can thus be easily adapted to several applications. LSTM layers allow sequential data processing such as time-series which is the case for temperature or energy consumption data.

2.3.3.3 Occupancy detection/prediction & energy management

Incorrect estimation of occupancy leads to poor management of building resources like HVAC and lighting systems. Occupancy prediction models are developed with the data collected by occupancy sensors during the occupancy monitoring period. In general, ANN models do not make assumptions about data distributions before learning, which is consistent with their applicability for occupancy prediction. These models play an important role in occupancy prediction as occupancy levels can be highly dynamic and contextual. Advanced occupancy prediction methods use assumption-independent ANN techniques to obtain the hidden patterns in the collected sensor data making their predictive power more reliable (Srivastava, 2015; Lejlic, 2017).

Mutis et al. (2020) utilize a multi-stream deep neural network to identify human activities and uses the You Only Look Once (YOLO) V3 deep CNN for multiple object detection to estimate occupancy counts in a room. The research results had a promising outcome as the application of the platform for accurate occupancy detection resulted in energy savings of approximately 10%-15%, thereby improving FM (Agarwal, et al., 2010). Martani et al. (2012) described analyzing occupancy and measuring activity of occupants for energy consumption patterns (electricity, steam, and chilled water) by employing Wi-Fi connections as a proxy for occupancy level. The results of the research also showed that the operation of the HVAC systems depended on factors such as external temperature other than human occupancy, although a minimal part of electricity consumption was correlated to occupancy (Martani, et al., 2012). An effective CNN architecture for visual parking occupancy detection was introduced in (Amato, et al., 2017), where the solution was compressed to run on smart cameras. Sonetti et al. (2018) suggests implementing deep learning to analyze human behaviors for smart and sustainable environments to lessen energy consumption.

Predicting occupancy in real buildings rather than buildings under construction is very important because actual building occupancy has a significant effect on energy consumption. Kim et al. (2019) proposed a machine learning framework with IoT data for HVAC where three machine learning based occupancy estimation algorithms, i.e., decision trees, support vector machines, and ANNs, were evaluated according to their performance in estimating occupancy status. The study showed that ANNs had an overall better accuracy in occupancy estimation compared to the other approaches.

Research is being carried out to employ new DL techniques to develop the next generation of occupancy models, that will be able to predict the behaviour of occupants with a high level of accuracy (Salimi & Hammad, 2019). Hammad (2019) proposed a method by integrating BIM with an ANN model for limiting the deviation between predicted and actual energy consumption rates. Accurate BIM representations are produced by training a deep neural network for predicting occupant behaviour that indicates the actual performance of the building under examination, which is further validated via energy simulations (Hammad, 2019). Lee et al. (2019) reported that by using thermal cameras on-site and deep learning, an adaptive comfort model could be developed. The adaptive comfort model would be capable of achieving intelligent control of an air-conditioning system considering the dynamic interaction between occupants and their environment (Lee, et al., 2019). Deep learning techniques have enabled the detection of standing/sitting postures of individuals even from a distance (Mathai, 2020). Commercial buildings, and retail shops require the constant monitoring and control of HVAC and refrigeration systems. From the IoT data collected from various sources, it has been possible to show that unnecessary energy consumption occurs due to manual activity. Recently, supermarkets have become smart and handle the HVAC and refrigeration systems automatically for improving customer satisfaction as well as optimizing energy consumption. Optimizing resources in turn optimizes the energy consumption of a building. Hence, this research proposed a firefly based optimized LSTM (FOLSTM) model with real-time HVAC and refrigeration sensor data for a supermarket (Karthikeyan & Raghu, 2020). The focus was to enable resource optimization by forecasting relevant variables such as temperature (Karthikeyan & Raghu, 2020).

For efficient energy consumption, a renewable solar and wind energy-enabled hybrid HVAC-DHW (heating, ventilation, and air conditioning-Domestic Hot Water) system utilizes an optimized nonlinear autoregressive network with exogenous inputs artificial neural network (NARX-ANN) and fuzzy controller based on user needs, dynamic behaviour of the atmospheric environment, and the spatial distribution of the energy supply (Zhuang, et al., 2020). Initially, the heating and cooling effect of the environment and building is sensed via sensors and these sensed inputs are fed into a deep learning-based NARX-ANN model that predicts internal building temperatures, which are then fed into a fuzzy controller for optimizing energy distributions based on user demands (Zhuang, et al., 2020). Deng and Chen (2020) developed an ANN model for a smart HVAC control system for multi-occupant offices to improve overall thermal comfort and energy consumption. This was done using the data collected from a thermostat that enabled a building automation system (BAS) to control the room air temperature based on physiological wristband parameters (Deng & Chen, 2020). The wristband parameters represented the thermal sensation of occupants. Revati et al. (2021) suggested a hybrid model implementing RNN and BiLSTM for load profile prediction in smart buildings. The results showed that the proposed hybrid model outperformed other deep learning models (Revati, et al., 2021).

Human occupancy prediction is more meaningful if occupant crowdedness can be predicted a day prior to improve facility management. However, most research so far involves estimating the current number of people in a specific location, though the data can be used to further predict the occupant crowdedness in the future to improve decision-making processes (Kumar, et al., 2013; Zou, et al., 2020). Deep learning-based time-series crowd prediction is formulated to help facility managers schedule maintenance during periods of lowest pedestrian movement, i.e., an off-peak hour, thus minimizing disturbance (Poon, et al., 2022). Poon et al. (2022) overcome the two primary limitations where prediction accuracy decreases as prediction time increases (Hewage, et al., 2021), and only the consecutive time steps in the most recent input data get exploited (Ma, et al., 2019), by adopting a Long-Time Gap Two-Dimensional method (LT2D) to increase the crowd prediction length with high accuracy. The LT2D approach consists of long-time gap prediction, which extends the prediction length to 1 day with high accuracy, and 2D inputs, which exploit temporal patterns from previous days. By integrating the proposed LT2D-method into different baseline models like LSTM, BiLSTM, and GRU, the accuracy is generally improved by around 22% (Poon, et al., 2022).

2.3.3.4 Anomaly detection and analysis

An anomaly is essentially an odd occurrence, which typically requires the facility management to take corrective measures. Anomaly detection can become problematic for HVAC systems because sometimes odd patterns in the data can happen due to the normal operation of the system. Data variability usually occurs because of common changes in various operating conditions. The following paper suggested an anomaly detection system based on a kernelized One-Class Support Vector Machine (OCSVM) classifier reinforced by Principal Component Analysis (PCA) to understand the difference between variabilities due to anomalies or standard system operation (Beghi, et al., 2014).

Katona and Panfilov (2018) recommended a predictive maintenance framework for a smart HVAC application system with IoT that would handle big data streams from various data sources. It would also utilize deep learning for anomaly detection or outlier detection on the data based on a Gaussian model to alert the connected system in case of unexpected behaviors (Katona & Panfilov, 2018). The classification problem depended on recorded (historical) data which analyzed the incoming temperature and humidity measurements and flagged them by assigning them to an "anomalous" class in case of suspicious behavior (Katona & Panfilov, 2018). Guss and Linus (2020) discussed the improvement of energy efficiency by detecting anomalies through developing a model using the K-means method. The model was used for clustering substations with similar consumption patterns to create electricity profiles and using Gaussian process regression for electricity consumption prediction with a 24-hour time frame (Guss & Linus, 2020). Although both models performed anomaly detection in electricity consumption data, the K-means based model was faster and more reliable (Guss & Linus, 2020).

Jung et al. (2021) focused on anomaly analysis using a long-short term memory (LSTM) model. High prediction accuracy was reported based on time-series data collected from Internet-of-Things (IoT) devices at indoor office space conditions, for facility management.

2.2.3.5 Fault Detection

ANNs and deep learning models have been used in both supervised and unsupervised fault detection and diagnostics (FDD) (Gourabpasi & Nik-Bakht, 2021). Kumar and Abraham (2019) used a two-step defect detection framework by automatically interpreting images with a 5-layered CNN for classification followed by a YOLO model for detecting pipe fractures from closed-circuit television (CCTV) videos. Most of the studies reviewed that implement automated fault detection and diagnostics (AFDD) are supervised methods and treat the FDD as essentially a classification problem (Gourabpasi & Nik-Bakht, 2021). Unsupervised methods are mainly adopted in a pre-processing phase or are used for fault detection through clustering.

Pump faults can be diagnosed if data and analytics are closely monitored; conversely, false negatives are a common occurrence when limited monitoring is employed. By closely monitoring MEP components, an effective asset management can be carried out. There sometimes may be the occurrence of false alarm but it can be quickly checked which is better than an underlying defect. Some researchers have explored using Digital Twin (DT), which is a relatively new framework for real-time intelligent asset maintenance, energy servicing, and condition monitoring (Errandonea, et al., 2020; Wang, et al., 2021). Hallaji et al. (2021) suggested a BIM-enabled DT (Digital Twin) framework to enhance the performance of deep learning methods for handling multivariate and low-quality, high-volume data after a thorough analysis.

2.3.3.6 Maintenance scheduling/monitoring

Cheng et al. (2020) proposed a data-driven predictive maintenance planning framework based on BIM and IoT technologies for FMM of MEP components consisting of an information and an application layer. Data was collected and integrated among a BIM/IoT framework with an of FM system in the information layer. The application layer contained modules needed for attaining predictive maintenance utilizing ANN and SVM models. Braun (2020) addressed the automation of construction progress monitoring using computer vision to detect construction elements in progress, and a CNN based framework to identify deviations between the as-planned and the as-performed schedule automatically. González-Domínguez et al. (2020) proposed a preventive maintenance scheduling tool for healthcare centers using Markov chains. The tool proved to be useful in choosing the most suitable maintenance policies for each healthcare building without exceeding a specific degradation boundary, in turn allowing an ideal maintenance frequency to be achieved. Markov chains have also been shown to be effective in optimizing routine maintenance tasks, guaranteeing a suitable level of maintenance according to the frequency of failures and reducing costs and the associated carbon footprint (González-Domínguez, et al., 2020).

Unsolicited building occupant complaint logs can result in unstructured data sets, so the following study focused on a data driven MLP model to predict the number of thermal complaints as a predictive maintenance strategy (Assaf & Srour, 2021). Thermal complaints are one of the most common complaints (Goins & Moezzi, 2013), and the developed MLP model showed that it can assist facility managers in planning for the staffing resources needed to handle these complaints thus enhancing the satisfaction of occupants as well as the building performance (Assaf & Srour, 2021). Assaf and Srour (2021) reported that the MLP model showed a 21% lower Root-Mean-Square-Error (RMSE) when compared to a traditional Autoregressive Integrated Moving Average (ARIMA) model related to cooler complaints.

The urban building energy model (UBEM) is the foundation to support the design of energy efficient communities, but it is limited in its abilities to capture the inter-building interdependency due to its dynamic and non-linear characteristic. The data-driven UBEM synthesizing the solar-based building interdependency and spatial-temporal graph convolutional network (ST-GCN) was developed for predicting hourly energy consumption and showed significant improvements in building energy simulation based on a case study (Hu, et al., 2022). Tsai et al. (2021) proposed a system to assist in the management of site equipment for construction management called SEMA that collects data from raw videos, extracts equipment-related information, and delivers that information based on a deep learning model that was first trained to automatically identify and track construction equipment passing by the site monitor (Tsai, et al., 2021). SEMA also integrated a user-friendly chatbot interface to obtain data from the database containing the extracted information from videos such as date, time for equipment entering, exiting construction site, as well as the quantity, and it was proven to effectively save valuable time in getting related information for facility managers (Tsai, et al., 2021).

2.3.3.7 Data Classification

Large buildings have been using IoT platforms for managing indoor climate ever since the growth of wireless smart HVAC systems. However, the controllers and sensors are from different manufactures and communication between these devices requires a human translator to make them compatible for integration purposes. Cashion et al. (2017) suggested a smart translator for the inter-communication of IoT devices using Deep Neural Networks (DNNs) for assigning registers exhibiting identifiable data patterns to standardized labels automatically. Jeong (2018) mentioned how deep learning can be useful in dividing BIM data into structured and unstructured types in the developed Evaluation, Analytics, and Prediction (EAP) Framework. The accuracy of supervised deep learning methods in 3D scene selection has improved drastically since 2017. The drastic change has been possible due to the availability of large, labelled datasets of indoor spaces, but the semantic object categories generally do not cover HVAC and plumbing systems. An annotated dataset of 3D reconstructions of building facilities such as HVAC called 3DFacilities, was presented where supervised deep learning for Scan-to-BIM, i.e., a process of converting 3D reconstructions into BIM, was implemented (Czerniawski & Leite, 2018).

2.3.3.8 Natural Language Processing

Automated energy compliance checking focuses on automatically checking the compliance of a BIM with appropriate energy requirements. Existing automated compliance checking (ACC) mostly focuses on code-checking and still requires manual extraction from text into computer-processable representations and then matching these to BIM standards. Zhou

(2018) proposed an automated ACC to check compliance of BIM-represented building designs with energy codes and contract specifications by developing a semantic, natural language processing (NLP)-enabled, rule-based information extraction method. A variant of a three-layer feedforward neural network, the hierarchical softmax skip-gram, was used to learn the distributed representation. The network exhibited promising performance due to its computational efficiency and accuracy on large datasets (Zhou, 2018). Deep learning further enriches the applications of NLP. A residual convolutional neural network (Res-CNN) model was selected for its training speed and high accuracy, to perform the task of distantly supervised noisy relation extraction (Huang & Wang, 2017). Generally, knowledge regarding Mechanical, Electrical, and Plumbing (MEP) is represented in unstructured text form and heterogeneously dispersed in design documents and the Internet. To address this issue, MEP text documents were collected from multiple websites and then text segmentation was carried out by implementing NLP models to extract entities and find out the relationship from the documented information to speed up the process (Leng, et al., 2019).

Different personnel in the property management business, including owners, property managers, investors, vendors, as well as other users like tenants and renters, use property management software (PMS) technology. These personnel use PMS to collect, share and distribute data related to property management. PMS refers to online platforms that facilitate the management, maintenance, and operation process of properties and increase efficiency simply by updating and visualizing all data via a centralized computer system. The following research reported how deep neural networks advance the automation of property management, focusing on integrating a smart chatbot into a PMS for real-time automated customer support, engaging website/platform visitors, and understanding their intent (Sapkota, 2019). Bouabdallaoui et al. (2020) proposed an NLP based solution to classify maintenance requests in healthcare facilities thus assisting FM to handle day-to-day maintenance activities.

2.3.3.9 Object/Movement Detection

Region-based convolutional neural networks (R-CNN) have made major advances in object detection. Such advances involve scanning an input image for desirable objects using selective search, which in turn generates region proposals from which features are extracted and then classified.

Arslan et al. (2019) used a Hidden Markov Model (HMM) to improve worker safety in dynamic environments by categorizing the trajectory movements and extracting movement patterns because human mobility is described as a series of Markovian stochastic processes. In HMMs, minimal training data is required. The probability distribution of a future state in a series (i.e., safe, or unsafe behaviour, or a subsequent location) of a of a Markov stochastic process is only dependent on its current state or a present location. Hence, it eliminates the need of incorporating the whole history of preceding states. Baek et al. (2019) proposed a two-module system where an Augmented Reality (AR) device captured a holographic image of a sanitary pipe and then indoor location, and orientation were estimated with a CNN.

2.3.4 Challenges and Possible Approach for Deep Learning in FM

2.3.4.1 Challenges

Despite the promising outcome in automating and assisting FMM, it is still a big challenge to make the majority of the industry employ deep learning techniques (Rondeau, et al., 2017). An important limitation and contributing factor consist of the lack of good quality labelled data, specifically related to FM of HVAC (Hong, et al., 2020). This hampers the creation of large training sets, which in turn dampens the performance of deep learning algorithms. Useful industry applications of deep learning for energy optimization and building life-cycle management are still limited (Hong, et al., 2020). Transfer learning utilizes and reuses the relevant parts of a pre-trained model and applies it to a similar problem speeding up and overcoming the issue of data availability (Pinto, et al., 2022). The main applications of transfer learning albeit mostly limited to smart buildings involve load prediction, occupancy detection, activity recognition, building dynamics prediction, and energy systems control (Pinto, et al., 2022). In the future, transfer learning techniques may reduce the demand for large volumes of data as currently only a few studies have been deployed in real world (Pinto, et al., 2022). However big data is still required to build the first models from which transfer learning can then be applied. Lack of data happens mostly because of the manual nature of data handling and collection.

Reinforcement learning may pose to be a better alternative as well compared to conventional HVAC FM. Nonetheless, actual applications in real buildings are scarce; Wang and Hong (2020) report only three reinforcement learning applications for HVAC. Although deep learning methods are popular for sentiment analysis, they can be generally semantically weak, requiring large amounts of text input (Cambria, 2016). Hybrid approaches, combine both knowledge-based and statistical methods like deep learning to achieve objectives such as emotion recognition for commercial building occupant satisfaction and polarity detection from text or multimodal data (Cambria, et al., 2020; D'Orazio, et al., 2021). Another problem of implementing deep learning methods for fault detection and diagnosis is the lack of data containing information about the system's operational conditions. It poses as a hindrance when it comes to developing effective Fault Detection (FD) methods for HVAC installations. More research needs to be done on improving automated fault detection and diagnosis methods for HVAC.

2.3.4.2 Possible Approach

Regulating an appropriate indoor temperature has clearly been a primary objective for facility managers. Crowd prediction, occupancy detection, and prediction with deep learning has successfully proven to make a building more energy efficient. For a more sustainable environment, decreasing carbon dioxide emission is necessary, which means optimizing the energy consumption of a building due to the fact that people stay mostly indoors. Many research studies have focused on optimizing energy consumption, but not much research has been done on the application of deep learning techniques to green and sustainable methods. Such sustainable methods involve thermal-storage air-conditioning (TS-AC) systems rather than conventional ACs, which could improve the energy efficiency of a building and lower carbon dioxide emission for a better environment. It would be a promising future direction to use deep learning methods to predict how much water the chiller of a TS-AC system requires for water circulation the next day.

Utilizing deep learning techniques to estimate energy requirements for commercial buildings by predicting peak and off-peak hours depending on the number of building occupants during a certain time period could greatly reduce energy loads. This would also be useful for scheduling HVAC maintenance by predicting peak hours a day before, increasing occupant satisfaction. More research studies need to utilize deep learning for increasing prediction timespans.

The field of deep learning has grown substantially in the last five years. With the growth of deep learning, automatic detection of faults and failures with deep learning is becoming common due to its adaptability in a dynamic environment. However, it requires added focus on automatic fault detection in HVAC equipment and automatic maintenance scheduling for optimizing building performance. Many previous techniques for fault detection include IoT implementations, but many commercial buildings show unwillingness to change their current HVAC equipment and update it with IoT. Because of this, it is necessary to further explore how deep learning can help when such IoT features are absent from existing equipment.

Since deep learning requires data for training, it is crucial to establish one or more public datasets relevant to facility management and predictive maintenance. The quantity and quality of this data significantly affects the performance of deep learning solutions. Public datasets are limited in terms of buildings and energy systems. This makes it more challenging for researchers to focus on building energy management and maintenance. Building energy related public datasets for maintaining or managing HVAC equipment will allow researchers to focus more on deep learning techniques for improving facility management and maintenance.

2.4 Thermal-Energy-Storage Air-Conditioning

2.4.1 Overview of Thermal-Energy-Storage Air-Conditioning

Thermal energy in the form of chilled water for warmer countries or hot water for colder countries is produced during periods of off-peak electrical demand and then collected in a thermal energy storage tank. Afterward, the stored thermal energy is withdrawn and distributed to the building during on-peak periods. Warm and chilled water enters and exits the tank through diffusers located at the top and bottom to eliminate turbulence and allow the water in the tank to stratify, with the colder water at the bottom and the warmer water at the top to form a sharply defined thermocline i.e., a transition layer of water, between the warm and cold-water regions. All through the discharge mode, the chillers and related condensing equipment are de-energized, and chilled water from the TES tank is circulated to the building facility for cooling the air (Si, 2015). After the discharge operation is completed, the tank will contain mostly warm water and is prepared for the “charging” mode phase where warm water is withdrawn through the top diffuser, dispatched to the chiller plant, and then cold is returned to the tank through the bottom diffuser after being cooled by a chiller system (Frankenfield, n.d.). When that process is finished, one thermal energy storage cycle is completed, and the tank again is ready to be discharged. It is clear from the operating system of TES-AC that water is an essential component and being used for charging the system.

Besides, the way TES-AC systems achieve lower energy consumption is simply by transferring the charging load from the on-peak hours to off-peak hours, and load shifting control is one of the most effective peak demand management methods (Sun, et al., 2013). It is to be noted that in warmer countries, the tanks of the chiller plant system of a building facility are generally located in the basement underground as a sensible heat storage strategy to minimize energy loss in the form of evaporation (Sarbu & Sebarchievici, 2018). As much as a TES-AC system lowers building management costs, it is tedious for facility managers to ensure smooth ongoing of daily operations with this system including keeping the management costs low since, if the charging load is not handled appropriately, it can more than double the energy consumption. Such maintenance of a TES-AC system is complicated and to ease the process of managing and maintaining this facility, one can rely on computational intelligence to benefit facility managers from the perspective of predictive maintenance (Sanzana, et al., 2022). However, before implementing advanced computational intelligence, such as deep learning techniques for the predictive maintenance of a TES-AC system, it is important to establish the impact of weather on TES-AC water consumption, in order to consider it as a feature. Although various other influential parameters have been investigated such as inlet temperature of heat transfer fluid during charging and discharging periods, air flow rate, and surrounding temperature, not much research has focused on analyzing weather data and determining which weather factors might affect the TES-AC system's water consumption (Salaudeen, 2018).

2.4.2 Relationship with external factors

Thermal-Energy-Storage (TES) plays an important role in eradicating the discrepancy between energy supply and energy demand and it is discussed how latent heat thermal energy storage (LHTES) is more useful than sensible energy storage due to the high storage capacity per unit volume/mass at nearly constant temperatures (A.Al-Abidi, et al., 2012; Lorsch, et al., 1975). Due to the efficiency in energy consumption, various forms of TES applications are being investigated and phase-change materials (PCM) based TES applications are thoroughly reviewed through which it is demonstrated that air-conditioning is one of the main applications of TES (Nie, et al., 2020). Application of TES for AC systems and its benefits have been investigated where long lifetime energy storage without typical issues such as hysteresis cycles are highlighted (Congedo, et al., 2020). Mehari et al. (2020)mentioned that absorption TES is appealing for utilizing solar energy, waste heat, off-peak electricity demand due to its high energy storage density and long-term storage capability. Dincer (2002) discussed various methods and applications of TES systems in buildings and how the applications with energy saving techniques can have environmental benefits.

A thorough review is presented regarding the evolution of TES and how utilizing this technology for cooling-based applications such as conditioning indoor air to provide cool air can benefit the environment (Lindsay & Andrepont, 2019). In previous research it was established that there is a link between different components and system performance and additionally that thermal front degradation negatively affects plant efficiency which indicates more research needs to be conducted that will facilitate the application of TES (Sciacovelli, et al., 2017). Sorption TES, a promising technology for effectively utilizing renewable energy, industrial waste heat, and off-peak electricity, is the latest thermal energy storage technology in recent decades. It is currently in the laboratory investigation stage and its advantages include high energy storage density and achievable long-term energy preservation with minimal heat loss (Zhang & Wang, 2020). It is evident that researchers are focusing on minimizing heat loss when it comes to utilizing the TES system. Stropnik et al. (Stropnik, et al., 2019) conducted an experimental analysis for nearly zero energy buildings utilizing latent PCM-based TES tanks.

Through a critical review, implementation of TES in district heating and cooling is explored as the heat reservoir of a TES system has characteristics of optimally tackling heat and electricity demand evolution, changes in energy prices, extreme weather conditions and intermittent nature of renewable sources (Guelpa & Verda, 2019). Tang and Wang (2019) proposed a model predictive control for TES where the maximum indoor temperature is reduced without extra energy being consumed whilst achieving the expected building power reduction. Kohlhepp et al. (2019) demonstrated how advantageous it was to implement TES due to its potential utilization of renewable energy by conducting an international field study of 16 mass integration of residential TES-AC. A hypothesis related to thermal energy storage with unconventional methods is discussed for small residential use and it outlines the low environmental impact of such methods (Congedo, et al., 2020). Huang and Khajepour (2022) proposed a novel approach with TES which showed an improvement in expansion and compression efficiencies. As the interest in using TES at a large scale for cooling is growing, the time is due to research further into optimizing TES-AC systems to ease the transition process from conventional AC to TES-AC (Sanzana, et al., 2022).

When there are warm weather conditions, people tend to use Air Conditioners (ACs) as a basic amenity to reduce the discomforts of nature, which consumes a lot of electrical energy (Cruse, 2020; Nguyen, et al., 2017; Allouhi, et al., 2015). Nguyen et al. (2017) proposed a short-term prediction of energy consumption due to air conditioners in residential buildings as they are a main source of building energy consumption based on weather forecast information to improve energy efficiency with a thermal simulation. In the study conducted to measure household electricity demand under hot weather in a residential area in Kuala Lumpur, Malaysia, which included total and AC electricity consumption (Ranjbar, et al., 2017). The results from the study (Ranjbar, et al., 2017) of the residential area indicated that the average AC electricity consumption extended from 19.4% to 52.3% during the measurement period and the values suggest the AC electricity contributed to a major portion of total household electricity consumption.

According to the previous studies, AC usage drastically increases electricity consumption during hot weather conditions which shows that people require AC usage more in hot weather (Anderson, et al., 2016; Ranjbar, et al., 2017; Hor, et al., 2005). Besides temperature, humidity is an important weather metric as dehumidification in buildings remains as a primary contributor to cooling load in hot-humid climate regions, thereby consuming much energy, and contributing to environmental impact through greenhouse gas emissions (Adjei, et al., 2021; Adjei, et al., 2015). Shehadi (2018) discussed humidity control in a building to meet the comfort level of building occupants. Since high levels of thermal comfort come at the expense of high energy demands, researchers are focusing on adaptive approaches to achieve thermal comfort. This research (Sánchez-García, et al., 2020) analyses the climatic zones to propose a prediction model that reduces energy demands and has better thermal comfort which shows that there is a relationship between weather variables and energy demand and consumption. Sun et al. (2013) mention how further efforts are required to develop more applicable load-shifting strategies that will optimize the energy efficiency of buildings that use TES-AC.

Recent studies regarding water demand prediction have shown that water demand is driven by weather variables, but it does not determine the extent of the effect on water consumption (Sarker, et al., 2013). Zubaidi et al. (Zubaidi, et al., 2018) tried to better understand the effects of weather variables on water demand demonstrating that there is a relationship between water demand and weather (Zubaidi, et al., 2018). With a proposed novel methodology, Zubaidi et al. (2022) predicted the monthly municipal water demand based on weather variables**.** Water demand has a relation with weather variables, and since TES-AC depends on water as a charging load, there is also a relationship between load demand and weather variables. The research in (Upshaw, et al., 2015) proposed a model for the evaluation of peak load reduction and change in overall energy consumption for a residential AC condenser with and without thermal storage. Any type of on-site water storage or even stored water can be utilized as a heat sink for the condenser during peak hours, which allows even more efficient and lower power compressor operation, and can be re-chilled at night during off-peak hours. The model used by Upshaw et al. (Upshaw, et al., 2015) used simulated cooling load data for a typical home in Austin, Texas based on the summer of 2011 and typical meteorological year (TMY) datasets where the system demonstrated that the performance varied depending on weather data, the individual compressor as well as the thermal storage volume in the tanks. Additionally, it also mentions that total compressor energy consumption increases 5–15% due to the inefficiencies of re-cooling the thermal mass during the summer (Upshaw, et al., 2015).

Shan et al. (2019) suggested a new model predictive control strategy for controlling the charging/discharging of TES and the on/off behaviour of chillers to achieve high efficiency. The suggested model partially dissociates the demand side and the supply side, so that the large chillers are either operated in high efficiency or turned off and solves the problem of frequent chiller fluctuations due to too low load in winter conditions (Shan, et al., 2019). Shan et al. (2019) validated a proposed strategy on a dynamic platform based on the existing chiller plant in a high-rise commercial building during both summer and winter conditions based on real operational data which showed an improvement in the efficiency of chillers by 3.10% and 22.94% in summer and winter conditions, respectively. From these efficiency results, it is quite evident that TES-AC systems are susceptible to weather conditions. As a TES-AC system depends on water volume as charging load, it is important to understand how weather conditions have an impact on this system. As shown in the literature review above, aspects of temperature and humidity play important roles in the system, and these roles have yet to be fully investigated.

2.5 Multilayer Perceptron for Charging Water Load Prediction

2.5.1 Overview of Multilayer Perceptron (MLP)

Deep Learning is a field that encompasses neural networks with many layers that allow the deep neural network to learn from large amounts of data with improved accuracy (LeCun, et al., 2015; Education, 2020). The additional layers of the neural network make the neural network deep, as well as optimize and refine the prediction accuracy in big data i.e., large amounts of data (Mathworks; Pingel, 2017). The Multilayer Perceptron (MLP) is a deep learning method which was first introduced in 1958 by Frank Rosenblatt (1958) where the basic structure consists of an input layer, hidden layer(s), and an output layer. Being a type of feedforward neural network, the network parameters in an MLP are typically trained with the backpropagation algorithm. The input layer processes the input signal, an arbitrary number of hidden layers are placed in between the input and output layer, and then the output layer carries out the required task such as the prediction (Abirami & Chitra, 2020). MLP is one of the most common neural networks and is used in various disciplines for both classification and regression problems due to its architecture (Taud & Mas, 2017; Murtagh, 1991).

The reason why MLP falls under a feedforward architecture is because the inputs are combined with initial weights in a weighted sum and then subjected to the activation function and each neuron output is then propagated forward to the next layer. This way, every layer is feeding the next layer with the result of their computation which is their internal representation of the data, and this process is carried out through the hidden layers to the output layer. Backpropagation is implemented to iteratively adjust the weights in the network to minimize loss or error. The activation function that is applied to the weighted sum needs to be differentiable, which is a hard requirement of the backpropagation algorithm. Such functions e.g., Rectified Linear Unit (ReLU) need to have a bounded derivative as Gradient Descent is the optimization function for MLPs normally. During each iteration, after the weighted sums have been forwarded through all layers with their activation functions, the gradient of the Mean Squared Error (MSE), for example, is calculated across all input-output pairs. Then during backpropagation, the weights of all hidden layers get updated according to the gradients computed for a particular mini batch. This process continues until one or more convergence criteria are met (e.g. maximum number of epochs reached or validation error stagnation).

Examples of activation functions for the hidden layers include the identity, logistic, tanh and ReLU functions (Buitinck, et al., 2013; Pedregosa, et al., 2011). The activation function, ReLU has been widely adopted because of its enhanced optimization, with Stochastic Gradient Descent, improved efficiency in computation, and its scale-invariance (Bento, 2021).

The four types of activation functions mentioned above are defined as follows:

1. identity: no-op activation, useful for linear bottleneck, has the formula, $f(x) = x$.
2. logistic: the logistic sigmoid function, has the formula, $f(x) = 1 / (1 + exp(-x))$.
3. tanh: the hyperbolic tan function, has the formula, $f(x) = tanh(x)$.
4. ReLU: the rectified linear unit function, has the formula, $f(x) = max(0, x)$.

Mathematically, even a one hidden layered MLP model is able to predict the mapping of any continuous function (Meyer-Baese & Schmid, 2014). For all neural networks, the input vector's dimension determines the number of neurons in the input layer, whereas the number of neurons in the outer layer depends on the classes to be learned. Through experimentation (or neural architecture search, or hyperparameter tuning, or meta-learning, or other approaches), the choice of the number of hidden layers is determined along with the number of neurons in each hidden layer. Determining the number of neurons is crucial because it can compromise the model's efficacy as too many neurons can result in overfitting, and too few neurons can lead to underfitting. While selecting the training dataset, it needs to be noted that a training set typically requires a rich and balanced representation of all classes for a proper generalization to occur. During training, input vectors are in a random order to ensure the model achieves global learning and does not lead to biased outputs due to class-selective learning. MLPs can be trained to implement any given nonlinear input-output mapping and in the resulting testing phase, MLPs prove their ability in interpolation by generalization even in data sparse regions (Meyer-Baese & Schmid, 2014).

The Perceptron is recognized as an algorithm, and essentially gets its name from imitating the human-like function of perception. Rosenblatt's perceptron machine (1958) depended on a fundamental unit of computation, the neuron, and inputs in the input layer are connected in a weighted sum. When the weighted sum surpasses a pre-determined threshold, the neuron generates an output. Learning in MLPs requires adjusting the weights of constituent perceptrons to yield low error on the training data which is normally carried out with the backpropagation algorithm as it tries to minimize the loss function (e.g. Mean Squared Error (MSE)) though other algorithms can be used for this purpose as well (Menzies, et al., 2015). Various techniques can be implemented to handle overfitting of the training data which often happens when models are too complex and exhibit low predictive performance due to modeling random error or noise in the training data. Generally, to avoid this overfitting issue, a higher error on the training data can be allowed and a large variety of regularization methods can be adopted (Bento, 2021).

2.5.2 Research studies utilizing Multilayer Perceptrons in Facility Management

Some of the common practical use cases of MLPs are pattern classification, recognition, prediction, and similarity estimation (Sanzana, et al., 2022; Sanzana, et al., 2022). In the Construction Industry, deep learning has been used in various instances for construction project management, and also in the Facility Management of the Building Lifecycle Management phase in improving occupancy satisfaction, occupancy comfort, and building efficiency. As vibrating engineering structures can result in faults due to fatigue and cracks or loose joints, and fault detection can assist the FMM, Chen et al. (2003) proposed an approach with MLP and verified it with a steel framework and a sandwich beam with a viscoelastic damping core to identify fault patterns as a classification problem. The MLP classifiers showed clear fault diagnostic messages on the faults that were being introduced into the structural systems for structural fault diagnosis and damage detection (Chen, et al., 2003).

Maintenance costs are also a significant concern for facility managers leading many researchers to focus on predicting maintenance costs. A comparative analysis conducted by Edwards et al. (2000) showed that the developed MLP model generated better results i.e., an accuracy of 95%, compared to multiple regression analysis in predicting the average hourly maintenance costs of tracked hydraulic excavators in the mining industry. MLPs were also utilized for predicting construction project duration with a time-cost predictive model and obtained better accuracy compared to linear regression with data that involved information of contracted and real time of construction and contracted and real price of construction (Petruseva, et al., 2013).

Optimizing energy efficiency has always been a focus of facility managers and it is a key aspect of international energy policies. Reliable prediction methods are necessary to be implemented for optimal energy management to deal with uncertainties in generation and demand, especially for electric energy systems. Bagnasco et al. (2015) present a load forecasting model for electrical consumption of a medical clinic with an MLP where the inputs consisted of loads, data concerning the type of day (e.g. weekday/holiday), time of the day and weather data as an innovative technique that can be easily implemented into a

Building Automation System (BAS). Moreover, MLPs were also used for dispute avoidance by predicting the dispute outcome for construction projects based on the intrinsic factors existing in the construction dispute case (Chaphalkar, et al., 2015).

As HVAC contributes to high energy consumption within corporate buildings, constant monitoring is required so energy efficiency or occupancy satisfaction is not compromised. A simple optimized HVAC system with Internet-of-Things (IoT) is suggested for automating HVAC with demand response (Rajith, et al., 2018). The thermal parameters from the sensors and occupancy feedback are collected for real-time processing in the distributed cloud environment and MLP was used for the predictive model of time-series forecasting and Mixed Integer Linear Programming (MILP) problem was used for optimizing the HVAC control (Rajith, et al., 2018). The results from the research by Rajith et al. (2018) showed 20%-40% reduction in energy consumption while maintaining thermal comfort of occupants, consistently proving MLP to be an optimal choice for prediction. As data centers have complexities of overcooling and increased energy consumption, a real-time MLP-based control framework on various thermal parameters is proposed to tackle such issues and reduce energy consumption (Saiyad, et al., 2021). The data-driven MLP based model proved to be useful in predicting thermal variables such as rack temperature inside data centers and the study suggests using deep learning for real-time energy-efficient control of data centers (Saiyad, et al., 2021).

Landslides, a serious type of geological hazard can cause significant losses of life and property which is why landslide susceptibility prediction is necessary to be implemented for certain areas where it is a common occurrence. By implementing landslide susceptibility prediction, this serious type of hazard can be prevented and reduced. A study proposed a particle-swarm-optimized multilayer perceptron (PSO-MLP) for landslide susceptibility prediction to establish the optimal parameters for the MLP, besides overcoming the drawbacks of the conventional gradient descent algorithm with high prediction and classification performance (Li, et al., 2019).

Occupancy satisfaction is a crucial goal for facility managers and one way to reduce the dissatisfaction of occupants is with an efficient facility management capable of addressing maintenance issues and planning for them in advance. Thermal discomfort is a major part of occupancy dissatisfaction in indoor environments and has been one of the most common complaints that require attention and addressing in buildings (Assaf & Srour, 2021). To address this Assaf and Srour (2021) proposed a predictive maintenance strategy with MLP to analyse and then predict the number of thermal complaints for the upcoming week to allow facility managers in allocating resources to handle such complaints thereby improving occupancy satisfaction and building performance.

Energy consumption is not only related to building management costs but also to different types of environmental problems and emphasises on implementing deep learning for building energy consumption prediction to improve decision-making in decreasing energy usage (Olu-Ajayi & Alaka, 2021). Not much research has been dedicated to exploring building energy consumption prediction at the construction phase, though predicting energy usage by utilizing deep learning with input key features of a building design before construction can decrease the construction of non-environment-friendly buildings (Olu-Ajayi & Alaka, 2021).

Financial resources in the public sector are associated with management problems when unforeseen costs occur during the handing over of a project. Pessoa et al. (2021) uses MLP for predicting the execution cost of construction projects for public educational institutions with a variance of 5% and 9% in average percentage errors between predicted and actual values. This research by Pessoa et al. (2021) proved that using a deep learning technique can be an auxiliary mechanism for planning public construction projects with a budget constraint.

For classification problems, MLP is being widely used and the research conducted by Zhao et al. (Zhao, et al., 2022) achieved an accuracy of 82% in classifying rooms into nine different types for Two-Dimensional (2D) residential building plans. Generally, the prediction accuracy in automatic room classification is low when a 2D plan has insufficient details with missing attributes such as furniture information (Zhao, et al., 2022). This shows that MLPs can still give satisfactory results in contexts with insufficient information. The literature review section demonstrates that MLPs are a viable choice for this research study, whilst covering broader ground which includes various other MLP applications in facility management. With appropriate design of the hidden layers, an efficient MLP model can be developed, and hence, this research utilizes MLPs for charging load prediction with external factors only.

2.6 Human-Computer Interaction deploying Machine Learning Application

Human-computer interaction is defined as a way a human interacts with a computer and is a crucial part in designing the GUI of applications. For human-computer interaction research, proper user engagement is a desirable effect and O'Brien et al. (2022) suggest focusing on disengagement as a necessary human-computer interaction design. There are many challenges in designing graphical user interfaces due to lack of availability in guidance and targeted experience (Lee, et al., 2020). Various graphical objects, such as cursors, rendered objects are analyzed in user-interaction (Seinfeld, et al., 2021). In advanced applications where there is complex computational intelligence deployed, it becomes even more of a necessity to gather design guidelines so non-experts can benefit from it. Chaudhari et al. (2020) focus on finding key characteristics of advanced applications for design considerations guidance.

However, in many cases, applications are developed without consulting the target audience which makes the application cumbersome and not targeted towards the actual needs but solely based on the developer's intuition. Stephanidis (2001) thoroughly discusses the appropriate methods to undergo for developing a computational environment that caters to the preferences, usability, and skills of non-experts as well so an advanced application can be used by the widest user base. Before an advanced application is developed for a specific use, experts can share valuable information such as point out which features they would want. This allows for sound development including the necessary features. When there is big sensor data involved, and when deep learning requires powerful Graphical Processing Units (GPUs), the application needs to be well-planned and useful for the target audience (Education, 2020). Martin-Rodilla et al. (2014) mentioned how suitable interaction techniques are required to understand large data dependent systems and discuss the challenges faced between human-computer interaction and data analysis applications. Using deep learning techniques, this study suggests improving the usability of graphical user interfaces as compared to the manual process of fruit and vegetable identification with Internet-of-Things (IoT) (Femling, et al., 2018).

Before an application is deployed, it is better to test the user-friendly aspect of the application. It is important to note the way the target audience manages to interact with the application's GUI. The GUI involves how the application looks, and whether the features in the application manage to execute its actual purpose. It is required to have a methodology that will not let the users be overwhelmed when they are interacting with the GUI and the methodologist can implement new computational methods which will be already integrated into the GUI for ease of use (Wallace, et al., 2012). It is also important to note if the ambience, background, fonts, and navigation are causing any visual disturbance to the users. A dark interface for an application is preferred as it causes less strain on the eyes mainly when it is used for long. Recently, there has been an increase in dark user interface trend to reduce ocular diseases of people in continuous use of digital devices (Eisfeld & Kristallovich, 2020). Yang et al. (2020) suggests a natural user interface to lessen cognitive load. This study mentions the importance of having a user-friendly environment to run deep learning models (Gómez-de-Mariscal, et al., 2021). Underlying human factors are reviewed by Leung and Cockburn (2021) to understand how targeted users may interact with the research area of highlighting techniques. The way users perceive an application is an important evaluation before an application is deployed.

2.7 Feasibility Study for a Sponge City Concept

Finally, a feasibility study will be conducted to understand the future directions of the research. Sponge City, a novel city strategy introduced by China to address frequent urban flood problems, has gained significant attention as a water resource management approach. This paper aims to review the development of the Sponge City initiative, analyze the challenges faced during construction, and propose potential solutions (Li, Ding, Ren, Li, & Wang, 2017). Recommendations based on the study's findings include urging local governments to adopt sponge city regulations and permits, which would alleviate water quality issues and urban pluvial flooding (Li, Ding, Ren, Li, & Wang, 2017). It is essential to thoroughly measure and account for the economic and environmental benefits of the program. Embracing regional flexibility and adopting a results-oriented approach are crucial for success. Additionally, a wider range of funding resources should be explored to finance the sponge city program. Coordination among government agencies at all levels is critical to ensure meaningful and sustainable progress.

A crucial aspect of Sponge City construction is the selection and application of pavement materials, which play a vital role in achieving the desired outcomes. Guan et al. (2021) begins by introducing commonly used permeable pavement materials, such as permeable asphalt concrete, permeable cement concrete, permeable brick, and novel pavement materials. These materials are designed to be porous to meet the requirements of infiltration, retention, purification, evaporation, and drainage. Although the findings suggest that permeable pavements may not always be more environmentally friendly than traditional pavements, they offer notable benefits such as water purification, reduction of traffic noise, mitigation of Urban Heat Island (UHI) effects, and recycling of waste materials (Guan, Wang, & Xiao., 2021).

Rapid globalization, urbanization, and modernization have contributed to the degradation of our surroundings, negatively impacting natural rainfall patterns (Ranjan, Reddy, Irshad, & Joshi, 2020; Zhang & Wang, 2020). The emission of gases like Sulphur Dioxide and Nitrogen Dioxide from burning fossil fuels, transported through air and wind currents, mixed with water and other substances to form acid rain, further compromising water quality. Harvesting such contaminated water poses challenges, as storing it alongside slightly better-quality water can lead to degradation of the latter. To address these issues, Ranjan et al. (2020) suggests IoT based smart water harvesting system. Guan et al. (2021) highlights the importance of addressing the challenges associated with urban water management, including climate change, rapid urbanization, and inadequate urban planning policies that have led to various water-related issues. By embracing innovative solutions, and fostering cooperation among various stakeholders, the vision of a well-functioning and resilient Sponge City can be realized, contributing to sustainable urban development and effective water resource management.

Another important addition to a sustainable city is Thermal-Energy-Storage and the construction industry requires to consider such innovative solutions during a city design. The construction industry's adoption of deep learning techniques for facility management and maintenance (FMM), particularly in Heating, Ventilation, and Air Conditioning (HVAC) systems, is still limited (Sullivan, 2016). However, the potential benefits of utilizing deep learning in FMM, such as predictive maintenance, energy consumption optimization, and equipment monitoring, are significant (Sanzana, et al., 2022; Marzouk & Zaher, 2020). The importance of applying deep learning methods for predictive maintenance in Thermal-Storage Air-Conditioning (TS-AC) systems, not only for environmental sustainability but also for cost-efficiency. Additionally, the utilization of machine learning techniques for predictive maintenance in facility management is explored, focusing on analyzing common supervised learning algorithms for cooler condition prediction (Sanzana, et al., 2022). Furthermore, Sanzana et al. (2023) investigates the relationship between external weather conditions and water consumption in Thermal-Energy-Storage Air-Conditioning (TES-AC) systems, highlighting the importance of considering weather factors in computational intelligence and predictive maintenance strategies. Finally, a machine learning model is developed for predicting water volume in TES-AC systems by incorporating input variables related to weather, day of the week, and occupancy data (Sanzana, et al., 2023). The model achieves an accuracy of 93.4% and provides facility managers with target water volume ranges, offering informed decision-making support and contributing to greener buildings and environmental benefits (Sanzana, et al., 2023).

Sections have been taken from the author's published works from (Sanzana, et al., 2022; Sanzana, et al., 2022; Sanzana, et al., 2023; Sanzana, et al., 2022; Sanzana, et al., 2023).

2.8 Summary

An occasional HVAC malfunction can lead to a huge financial loss for the FM in the construction industry. This is why it is important to utilize Machine Learning such as deep learning techniques for handling FMM effectively with predictive maintenance. By preparing in advance the charging water load required for the TES-AC, the chiller of the system will not be required to be on for the whole day. Only by keeping the chiller on during specific time throughout the day, the energy consumption of the building will greatly reduce besides lowering carbon emissions into the environment. Hence the goals of lowering carbon dioxide emission as well as optimizing the energy consumption utilizing Machine Learning of a building, are the primary research focus areas. In this era, it is essential to utilize deep learning techniques by developing models for targeted domains, since this effort can generate environmental benefits by facilitating HVAC to be green and sustainable.

However, most research so far involves estimating the current number of people in a specific location, though the data can be used to further predict the occupant crowdedness in the future to improve decision-making processes. Additionally, more focus needs to be on automatic fault detection on HVAC equipment and automatic maintenance scheduling to ensure building efficiency and occupant comfort. DL shows promising results in improving the FMM of building efficiency, and hence requires more research in developing DL applications for FMM of HVAC. The literature surveyed in this research, indicates the importance of implementing Machine Learning techniques to optimize energy consumption of TES-AC as it is an extensively employed part of a building for occupancy comfort and satisfaction. Furthermore, the relationship of external factors on TES-AC is analysed followed by a discussion of the application of MLPs to charging water load prediction of

TES-AC to understand how they can be useful in developing a model to optimize energy efficiency in a commercial building. Additionally, the developed model needs to be deployed in a user-friendly application that facility managers can use by gathering appropriate design guidelines.

In conclusion, the literature review underscores the necessity of incorporating deep learning techniques to advance facility management practices. The convergence of deep learning with IoT and TES-AC systems presents a groundbreaking opportunity to transform urban water management and bolster energy efficiency. Future research endeavors should prioritize the development of sophisticated IoT systems capable of proficiently monitoring rainwater collection and utilization. Simultaneously, emphasis should be placed on optimizing TES-AC system operations in correlation with rainwater availability. This involves leveraging advanced deep learning algorithms and models for comprehensive analysis and optimization of facility management operations.

Furthermore, there is a critical need for exploration into innovative materials, designs, and control strategies for TES-AC, aiming to amplify its performance and potential impact on citywide sustainability. The technical contribution lies in the strategic integration of deep learning, particularly Multilayer Perceptron (MLP) architectures, into TES-AC systems. MLPs can play a pivotal role in enhancing the efficiency and adaptability of TES-AC by providing intelligent decision-making capabilities based on complex data patterns.

In essence, the integration of deep learning into facility management practices, particularly through the utilization of MLPs in TES-AC systems, is paramount for realizing efficient and sustainable urban designs. Ongoing research and innovation in this domain are indispensable for advancing the frontiers of knowledge and implementing practical solutions for more sustainable and technologically sophisticated city designs.

Chapter 3 Methodology

3.1 Introduction

This chapter discusses the main research framework and the steps taken to achieve the desired outcome of the research. It is divided into sections for clarity with section 3.1 introducing the chapter. Section 3.2 discusses the general research framework and the steps taken to go from the conceptual phase to the final outcome. Section 3.3 discusses the software tools that were required to conduct this research and why they were needed. Section 3.4 describes the smaller scale research that was conducted on a similar dataset to test out the different Machine Learning algorithms and filter out the best performing ones for later use on the main big dataset.

Section 3.5 explains the importance of weather data in this research and how it impacts the water consumption of the TES-AC. It describes the steps taken to prove that the weather data can be impactful and why it is important to use. Moreover, it also explains in detail how the TES-AC works and how the water flows inside the system. Section 3.6 discusses the water load prediction of the TES-AC and how the final data used to train and test the model was prepared and extracted. It also discusses the pre-processing steps taken and explains in detail how the final dataset looks like. Section 3.7 discusses the final model developed and how it was designed. It explains the challenges faced with the data and the model and the steps taken to rectify those issues. Section 3.8 discusses the research conducted for the user-friendly application that will integrate the trained model for the facility managers to use. Section 3.9 discusses potential application of the developed model. Finally section 3.10 contains a summary of the chapter.

3.2 Methodology Framework

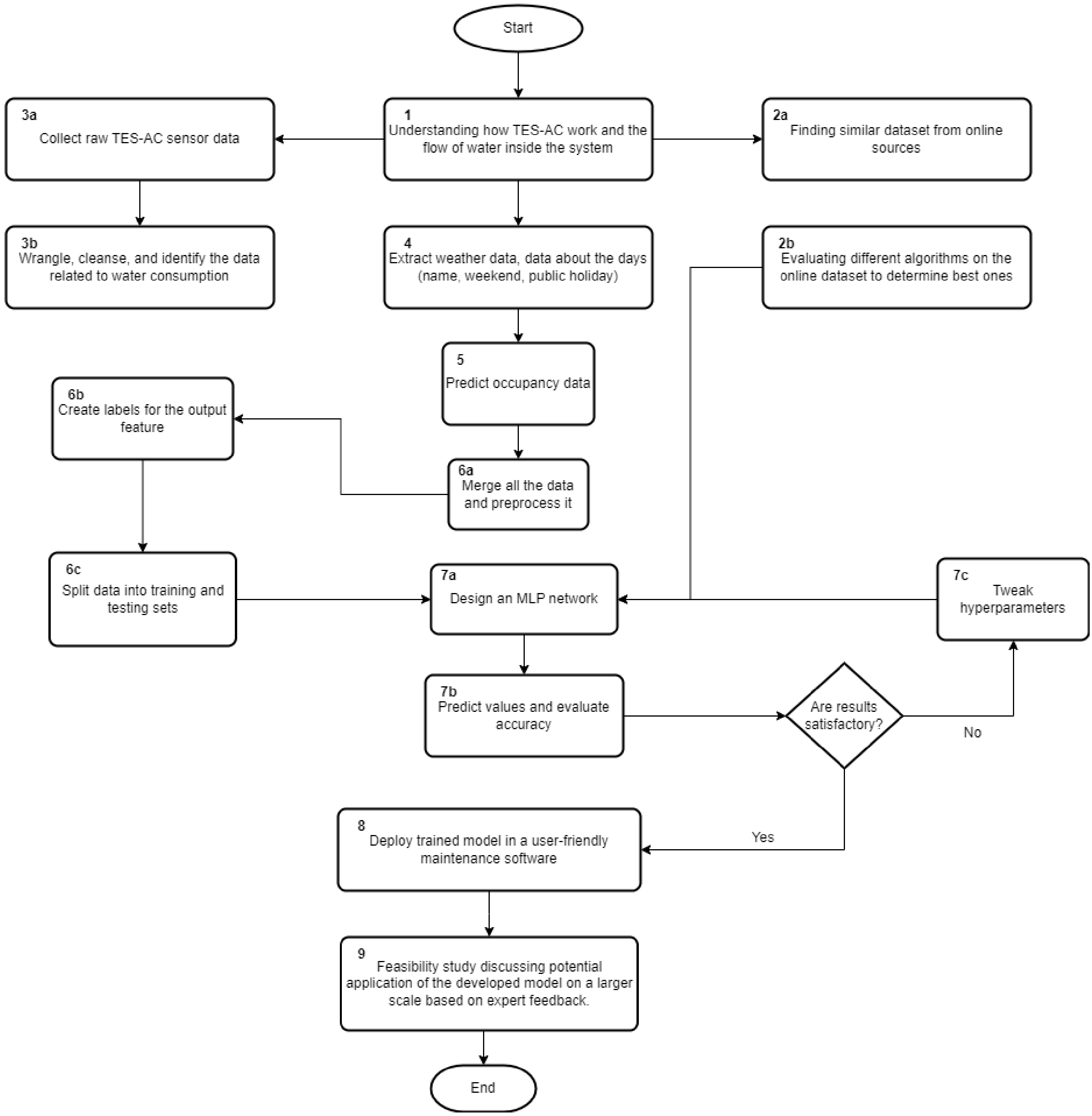

Figure 3.1 Research Methodology Framework

The flowchart of the methodology is in Figure 3.1 and the steps of the methodology for this research are explained below.

1. The first step will be to research about the chiller plants and to understand how TES-AC works.

2. This step involves identifying the most suitable algorithms for this kind of problem as discussed in Section 3.4.
    a. Find a similar dataset to the expected TES-AC from online sources.
    b. Evaluate the different algorithms used on the dataset in step 2(a) and identify best algorithms to use.

3. The next step will involve collecting the raw TES-AC data as discussed in Section 3.5.
    a. Collect the raw TES-AC sensor data.
    b. Wrangle, cleanse and perform analysis to identify the data related to calculating the daily water consumption in the TES-AC.

4. Extract weather data, data about the days like name of the day, if the day is a weekend or not, etc (discussed in Section 3.5).

5. Perform a regression prediction on the occupancy data to predict the next day's occupancy. That will be one of the input features of the final prediction (as discussed in Section 3.6).

6. This step prepares the final version of the data as mentioned in Section 3.6.
    a. Merge all the data together and pre-process it (water consumption data, weather, days, occupancy)
    b. Create labels based on the water consumption values to turn the problem into a classification problem instead of regression. Each label is based on a specific water consumption range.
    c. Split the data into training and testing.

7. This step involves designing the MLP network as discussed in Section 3.7.

a. Design the MLP network and set the hyperparameters. Use a grid search to try out different hyperparameters.

b. Predict the testing data and evaluate the accuracy.

c. If the accuracy is not satisfactory tweak the model's hyperparameters and try again.

8. Deploy the trained model in a user-friendly maintenance software for facility managers to use as mentioned in Section 3.8.

9. An additional procedure to determine the feasibility of the developed model on a larger scale will be analysed by collecting expert feedback as discussed in Section 3.9.

3.3 System Overview

System Overview will discuss the software used for this research.

Programming language, libraries, and framework

The programming language Python is used for this research because code written in Python is concise and readable and the simplicity of the Python code can be interpreted by humans which allows to build machine learning models. It is capable of doing a set of complex ML tasks that enables making quicker prototypes for testing the product for ML purposes.

It can be complicated and can take a substantial amount of time for implementing ML algorithms in a well-structured form. Python libraries and frameworks are used by programmers to reduce the development time. The following Python libraries and frameworks are used for this research.

- Scikit learn- Scikit learn is a robust Python library for ML built on top of SciPy which is used for advanced computational purpose and requires SciPy. It focuses on making it easy to use and mainly for modelling data. Some models provided by scikit learn used in this research are dimensionality reduction, clustering of unlabelled data, feature selection to create supervised models, for test datasets and generating datasets to examine model behaviour and for supervised models which are not limited to general linear models.

- NumPy-This stands for Numerical Python (NumPy) which a core library for Python programming language and is used for working with arrays and matrices in a much faster way than traditional Python lists. It is good for analysing the data and high-performance scientific computing.

- Pandas- It is also a software library like NumPy and is used for general purpose data analysis and manipulation. Pandas is fast and adaptable and makes it easy to work with both structured data including multidimensional as well as possibly heterogenous and time series data besides having many uses. Specifically, Pandas is appropriate for tabular data such as in Excel Spreadsheet or SQL table with heterogeneously typed columns and inconsistent matrix data with column and row labels.

3.4 Comparing Machine Learning Techniques for Predictive Maintenance in Cooler Condition

This part of the research aims to analyze with an in-depth comparison regarding the prediction accuracy of machine learning with supervised learning and an additional consideration of speed to determine the efficacy of machine learning algorithms for predictive maintenance by predicting cooler conditions for a hydraulic test rig. The research study focuses on evaluating the prediction accuracy of various algorithms for predictive maintenance of HVAC as a step in investigating appropriate ML algorithms for HVAC. An appropriate HVAC dataset was chosen depending on common prerequisites from an online source to be analysed and then different ML models were trained for a thorough comparison.

The open access dataset (Helwig, et al., 2015) is from an experiment with a hydraulic test rig which consisted of a primary and secondary cooling-filtration circuit connected via an oil tank, with 2205 instances, and 43680 attributes (8x60 (1 Hz) + 2x600 (10 Hz) + 7x6000 (100 Hz)). Attributes were all from sensor data, continuous and numeric and consisted of 6 pressure sensors,4 temperature sensors, 2 volume flow sensors, and 1 vibration sensor, efficiency factor, motor sensor, virtual cooling efficiency sensor and virtual cooling power sensor. The framework consistently rehashes steady load cycles of 60 seconds span and measures values of pressure, volume flows and temperature. There are 4 values keeping track of cooler condition, valve condition, internal pump leakage, and hydraulic accumulator. These are distinct numbers that can describe the condition of said component. There is another variable called stable flag which is just either a 0 or 1. These values would help to understand the condition and the quantitative fluctuation of the four hydraulic components which are cooler condition, valve condition, internal pump leakage, and hydraulic accumulator. There is also a class value vector called the stable flag that depicts the degradation process after some time which consequently displays continuous values instead of distinct categories.

In order to demonstrate both classification and regression predictions, two example problems were chosen. The first problem (i.e., a classification problem), is to predict the cooler condition value based on the sensor values. The cooler condition value is one of three values 3, 20 and 100; a value of 3 denotes close to total failure, 20 denotes reduced efficiency and 100 denotes full efficiency. The second problem (i.e., a regression problem) is to predict the values of one of the sensors over a period. For this particular problem, each sensory reading is assumed to be after a second, resulting in a total time frame of 2205 seconds.

Working with data involves data analysis and data pre-processing and for machine learning engineers, an important task is thus to first analyse the data for meaningful patterns and then to build an effective input pipeline to train a model. This task often involves libraries such as scikit-learn for data pre-processing where libraries like PCA and RobustScaler were used. The data splitting was also done using scikit-learn. Keras models were used for LSTM and MLP models whereas scikit-learn models were used for the rest (K-neighbours, gaussian, etc.).

Principal Component Analysis (PCA) was conducted on the data as it retrieves the uncorrelated latent variables that include almost all the information. The dimensionality was reduced by PCA from 44820 features to 11 features i.e., 99.97% compression. After PCA, data imputation was applied, which involves replacing missing or inconsistent data with an estimated value based on available information.

Both classification and regression algorithms were evaluated and tested to analyse prediction accuracy and the pros and cons of each. The number of runs was different between the algorithms, but for most of them it was the default number. For LSTM it was 150 epochs. As for the training and testing split it was a 70:30 ratio. As a classic representative of a feedforward neural network approach we opted for the Multilayer Perceptron (MLP) which can be easily adapted to both classification and regression (Cheng, et al., 2020). Besides, an MLP-LSTM also has shown promising outcomes in previous studies (Nguyen & Medjaher, 2019; Wang & Wang, 2018), and so, was chosen as another suitable neural network approach to compare. Other than MLP and LSTM, other common ML approaches were taken for evaluation. These evaluations would help in determining which algorithms might be used in a novel ML solution to assist the predictive maintenance.

The analysis was done on ML algorithms applied to an online dataset for both classification and regression problems. The ML algorithms that were analyzed for the classification problem were Logistic Regression, Decision Tree, k-Nearest Neighbors, Gaussian Processes, and Multilayer Perceptron (MLP) with three different solvers 'adam', 'lbfgs', 'sgd', and two different combinations of hidden layers (5,2), (100,).. For the regression problem, the ML algorithms that were analyzed were Long Short-term Memory (LSTM) including Simple LSTM, LSTM window method, LSTM with Time Steps, LSTM Memory with Memory Batches, Stacked LSTM with Memory between Batches and MLP Regressor. The ML algorithms were analyzed for classification based on their prediction accuracy, prediction time, and fitting time whereas, for regression, the ML algorithms were analyzed based on their fitting time, prediction time, Mean Squared Error (MSE), and Root-Mean-Square Error (RMSE). The MSE and RMSE help define the performance of the ML algorithms for regression problems. Based on the comparison, the most promising algorithm for this type of dataset was used to design the final model.

The results and insights obtained from this evaluation provided the basis on which the main model was designed. There are many ML algorithms to try, and some are more suited for certain tasks than others. The decision to use MLP was derived from the way it performed in this section.

3.5 Relationship with External Weather Factors on TES-AC

This research has been conducted with an industry collaboration that utilizes TES-AC for its commercial building operations and working with their data which spans several years.

Subsequently, the weather data based on the location of the chiller plant is retrieved to conduct an analysis in determining the impact of external weather data to the water consumption of the TES-AC system. Figure 3.2 shows the steps taken to determine the impact of external weather on the TES-AC water consumption.

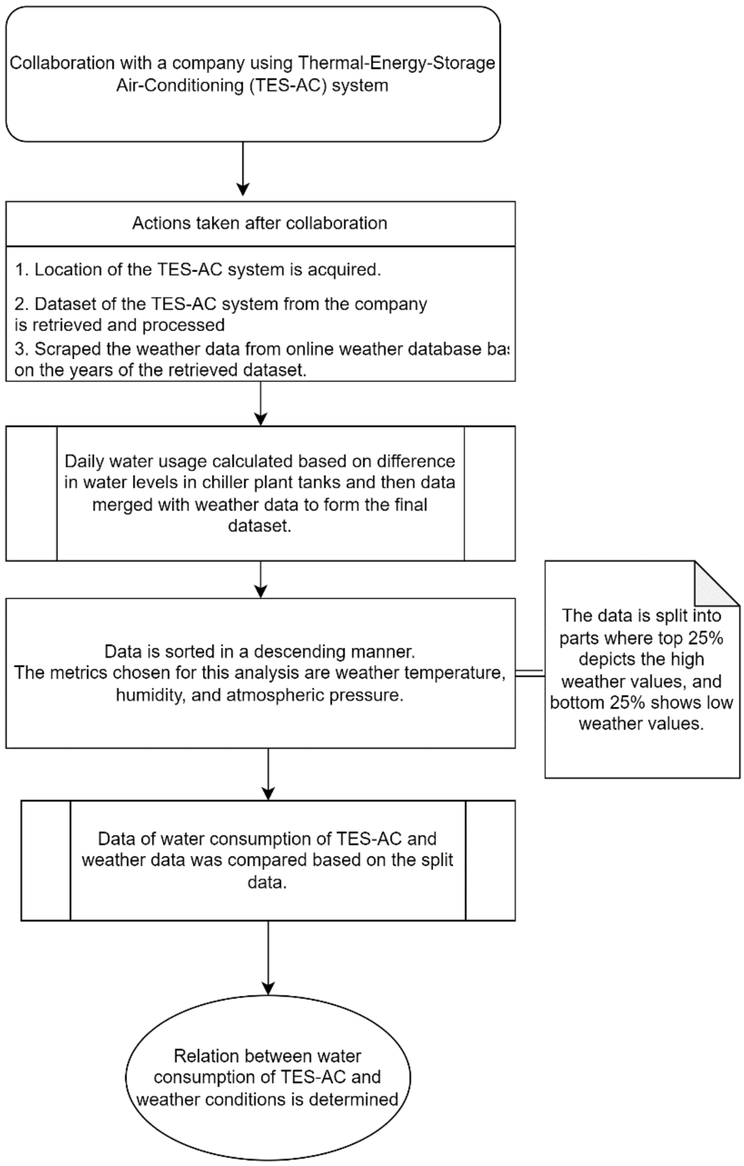

Figure 3.2 A summary of the steps taken to determine relationship of TES-AC with external factors.

3.5.1 TES-AC HVAC System Operation

The TES-AC in this HVAC system consists of three main components, i.e.: the water-cooled chillers that use a liquid refrigerant to cool water, the water thermal storage tanks that store the cooled water from the chiller, and finally the cooling tower on the rooftop that cools down the refrigerant in the chiller. The process is straightforward. Initially water is pumped throughout the chillers that cool down the water using the refrigerant and send it for storage in the water tanks. Condenser water carries over the heat from the refrigerant and heads to the cooling tower where excess heat is emitted outside. The cooled condenser water is sent back to the chiller to get more heat from the refrigerant. During building operations, the stored chilled water is sent to the Air Handling Units (AHUs) throughout the building using risers to cool down the air. The returned warm water gets sent back into the tanks. The system has enough tanks to hold cold water and warm water separately. If the stored chilled water is not sufficient for a day, then the chiller starts chilling water once again and sending it directly to the building. The warm water in the tanks can be sent again to the chiller for cooling the next day. Figure 3.3 depicts the aforementioned TES-AC design.

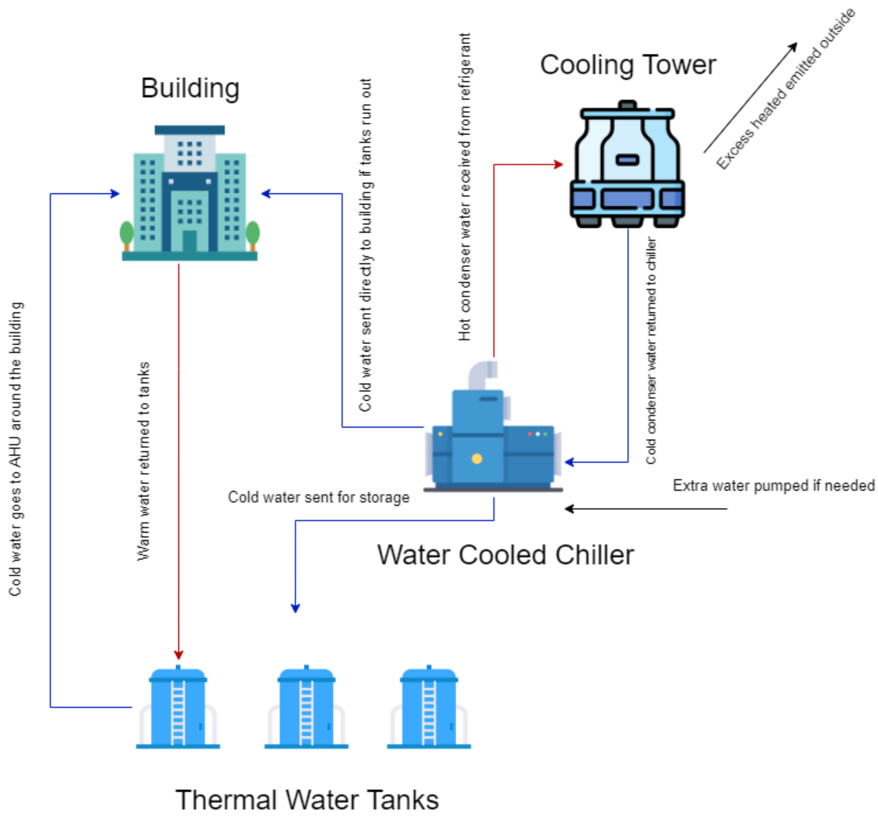

Figure 3.3 Design of the TES-AC HVAC system used for this research

3.5.2 Instrumentation

When solving a Machine Learning problem, it is important to have the right data to get the right results. A TES-AC system is very useful to reduce the negative effects on the environment compared to the traditional ACs. One of the main elements that could allow the TES-AC to function in a more efficient and energy-saving way is the volume of water that needs to be chilled (or charged) during the night. This research aims to investigate external data that might be impacting the volume of water charged, besides using only the conventional data that can be obtained from TES-AC sensors.

As already mentioned, weather is one of the main external factors that may affect the TES-AC systems. Generally, it is assumed that harsh weather conditions may impact the amount of water charged in TES-AC, especially in hot countries, where the AC needs to function more to lower the temperatures down to a comfortable level. Regardless, this relation between weather conditions and water consumption of TES-AC requires further investigation through computational analysis.

3.5.2.1 Data Overview

This research is conducted on a TES-AC in Subang Jaya, Malaysia, a tropical country with warm weather conditions. The chiller plant is responsible for a commercial building that houses 222 office units and 250 retail shops. The building operates every single day at the standard operating hours which are usually from 8 in the morning till 10 at night. The data was collected for 2473 days i.e. approximately 6 years and a half until the chiller plant was sold to another entity. Details about data will be discussed in the following subsections. Occasionally, some events are hosted in the building which cause an unusual increase in occupancy for those days. Initially the weather data was scraped using the Beautiful Soup Python library from timeanddate.com. A simple scraping script was run to automatically navigate through the weather table on the website and save the data into CSV files.

There were multiple data types in the scraped data, however, the focus was on three main types i.e. temperature, humidity, and atmospheric pressure. This is because they are most impactful on the weather and consist of numeric values which are easier to calculate and analyze, compared to weather descriptions for example.

The objective here was to determine whether the extreme values in these different weather data types have a noticeable impact on the volume of water used in the TES-AC For it to be a noticeable impact it does not need to have a very obvious difference compared to the days with less extreme values. Even a slight difference in the water consumption could indicate that weather impacts the water consumption. Furthermore, data about the days were obtained using Python libraries. Information like which day of the week it is based on the date and whether that day is a public holiday or not were extracted. The significance of this data is because the usage of the building might differ based on which day it is and if it is a holiday or not, which might affect the operation of the TES-AC plant.

In order to set an easy reproducible way of conducting this analysis, water usage or chilled volume data was converted into different classes of water level based on an even set range. This is because it is easier to carry out an analysis by checking if the water consumption falls into specific water level categories more often in the more extreme weather values.

3.5.2.2 Data Classification

The water consumption data was therefore classified into 10 different levels, consisting of three low consumption levels, three medium consumption levels, three high consumption levels, and one level for extremely high consumption. By classifying the water consumption data, it is easier to draw conclusions and make comparisons. All the water values are in tons and were grouped into categories based on a range of water consumption values. Water consumption was calculated by increasing the water values that decrease from the storage water tanks during operation hours. This ensures that we are calculating the water consumed to cool the building. During the period where the water tanks are being charged the water levels decrease to send warm water back to the chiller, but this is not calculated. Water level sensors are already placed inside the water thermal tanks in question by the manufacturer of the TES-AC system.

The weather data was based on a 15-minute interval and therefore the data had to be calculated based on daily averages to match the water consumption format, which is one value per day. It should be noted that this problem was purposefully designed to consider values on a daily basis and not based on 15-minute intervals, despite the water consumption value being available on a 15-minute interval basis as well. The reasoning is that the differences in the values for every 15 minutes would be too small and negligible to draw any useful conclusions out of it. As stated earlier, the differences in water consumption using a small-time lag were not expected to be significant in realistic circumstances, and therefore conducting this analysis on a 15-minute interval data was expected to not be productive.

Finally, the two datasets were merged based on the date. If any row in the combined dataset contained any missing values, it was removed, which removed 55 records. The final dataset contained data for 2418 days and the next step was to start sorting the data by each of the weather data types and do comparisons.

The main idea here was to check how many times high water consumption occurs when the weather values are high compared to when those values are low. However, it is important to determine how many days should be considered as the dates with high or extreme weather values. Initially the top 10% and the bottom 10% were considered for the comparisons, however, the number of high-water consumption days was insufficient for a meaningful comparison. Eventually, it was set at 25%. That takes into consideration the top quarter and the bottom quarter while assuming half of the data, which lies in the middle, as non-extreme values.

3.5.2.3 Data Evaluation

Each of the three weather data types (temperature, humidity, atmospheric pressure) was evaluated separately by sorting the data based on that weather data type in a descending order, to keep the highest value at the top. After the sorting was done, the top 25% of the data was split into a separate set, and the same procedure was done with the bottom 25%. Moreover, each of the separate sets was then looped through and the classifier in each day was compared with the eligible values and the count of high-water consumption days and low consumption days was recorded for each. Finally, the sum of those counts was calculated and set aside for comparison. The same procedure was applied to each of the three weather data types for temperature, humidity, and atmospheric pressure.

It is to be noted that the research was conducted while being fully aware that weather is not the only external factor that might be impacting the water consumption in the TES-AC. Other factors, such as which day of the week is being considered or whether a day falls on a public holiday or not might also have an impact. While calculating the count of days where the weather data was high in each of the sets created, it was also counted how many of those days were weekends and how many were public holidays. The reasoning is to see if those days with high-water consumption depended on the day of the week or whether the day was a public holiday. Furthermore, this method makes the conclusions drawn from this study stronger and indicates that the differences observed are largely due to the external weather data and not which day of the week it is.

3.6 Charging Water Load Prediction for a TES-AC of a Commercial Building with MLP

3.6.1 Overview

This research includes many of the typical steps that are required to solve complex machine learning problems. The objective is to predict the water charge load required to be chilled at night during off-peak hours so it can be discharged to the building during the day. The application is quite crucial, and predictions need to provide an adequate amount of accuracy, or the model will not be useful.

Every TES-AC system might be different to some extent and each one might have different sensor types and data, so in order to generalize the solution more, none of the sensor data from the TES-AC were used. The model developed only relied on external data that can be retrieved by anyone. The data used to make the predictions consisted of the weather data based on the location of the building the TES-AC is used in, the data informing which day of the week it is and whether that day is a weekend or a public holiday, and finally the occupancy data.

Occupancy data were available for the historical data used to train the model, however, the occupancy in the future is not known. Therefore, this approach does not predict the water charge directly, as it needs to predict the occupancy before it can feed that prediction as an input to predict the water charge. While using a predicted value for the input of the main prediction might be making the problem more complicated, after thorough experimentation with the model and different parameters, it was noticed that the model was making better predictions if the occupancy data was included and therefore a second model to predict occupancy for the next day was also developed.

3.6.2 Data extraction

The data was analyzed carefully to understand the different types of data available and to understand which data was being collected. The main target was on the water data to understand how much water the TES-AC was chilling every day as that is the main focus. The TES-AC consisted of twenty water tanks, each of the same size and material and completely identical in every aspect. However, not all the tanks are used at the same time and the technical staff managing the TES-AC change the usage according to their needs. The data included sensor data indicating the water volume in each tank for a given time. The data was recorded every fifteen minutes and stored accordingly.

Before working on extracting the data however, it needed to be preprocessed and cleared of issues. It is very unlikely for a dataset collected from sensors to not have problematic instances in it. Using the wide array of data manipulation libraries in Python like NumPy and Pandas the bad data were removed from the dataset. This included removing the data that did not have values or had wrong data types instead of actual numbers. Despite this step removing some of the data from the dataset, it was necessary and crucial.

The next step was to calculate how much water the TES-AC was using every day and to do so it was important to understand how the staff was using the chiller on a daily basis. As per information acquired directly from the company, the chiller runs for two hours every day during the off-peak hours early in the morning before the occupants arrive and when the electricity is cheaper than usual. During those two hours the chiller will cool a certain volume of water and store it in some of the tanks. During the rest of the day the chilled water will be dispersed throughout the building and the heated water coming back from the building enters the tanks once more. If there is not enough chilled water in the tanks to last the day, the staff are forced to use the chiller again during standard working hours when the electricity demand is higher, raising their costs.

Given this context, it can be deduced that the water volume will increase in the water tanks if new chilled water is entered into it or returned heated water. On the other hand, when water volume does decrease it is because water is being sent to the chiller to either cool or disperse to the building. It is to be noted that this research ignored the fact that a small amount of water might be decreasing due to natural evaporation and assumed all water lost is due to either of the above cases. This TES-AC is well insulated and natural evaporation is very minimal and the water mostly gets recycled.

To calculate the water that is being chilled every day and used, code was written to calculate the amount of water that decreases the water volume reading for the sensor. This was assumed as water being sent to the building as chilled water; therefore, it was water that needed to be chilled. In the situations where the staff did not add enough chilled water in the tanks and the chiller gets used, the new chilled water does not return to the tanks but is sent directly from the chiller to the building.

Therefore, in those situations the chiller would decrease the water in the tanks to chill the returned heated water and send it again to the building, making it safe to assume that whenever the water volume in the tanks decreases, it is because this water is being chilled for usage and that makes it count towards the water volume used every day. This calculation only ran on the twenty-two hours where the main charging load is not happening, to ignore the initial charged load volume as it will interfere with the values. For example, if the initial water volume is also calculated, it will be calculated twice as it is discharged during the day. Another issue arises if that water volume discharged was not fully used. By only calculating the amount of water that leaves the tanks during the other twenty-two hours it can be calculated in a more accurate way and a more precise value can be used. This was the best way to know the amount of water used as the chiller did not have any specific sensors to measure how much water it chills. This calculation ran for each day and each tank, and the final data extracted included the date and the total amount of water used for that day.

3.6.2.1 Weather data extraction

As mentioned earlier the historical weather data was retrieved by scraping a weather website and storing the required values based on the location of the TES-AC. However, the method to retrieve the weather for the next day is slightly different, however. Using an open-source weather website an Application Programming (API) key is generated which is then used to make a GET request to the website to retrieve the weather information for the next day. The request returns a JSON output which is then parsed, and the needed information is extracted accordingly. This occurs every time a new prediction for the next day is required.

3.6.2.2 Days & holidays data extraction

Extracting the days of the week and public holidays was easier than the weather data. Python contains a datetime library and a calendar library that makes it easy and possible to determine what a specific date is. That data was added to the dataset and then the holidays library was used to retrieve the information if a specific date was a public holiday or not.

3.6.2.3 Merging data with occupancy

All of the data including water used per day, weather temperature, humidity, atmospheric pressure, name of the day, and whether that day was a public holiday or not were all merged together based on the date as that was the common factor. In doing so, any records that did not have the same date were removed from the dataset. The occupancy data was provided separately and simply included the date and the approximate number of people that were in the building for that day. The final dataset was then saved separately and ready for further preprocessing.

3.6.3 Preprocessing

The first step was to remove any empty values in the dataset which was done earlier. However, the step was repeated again after the rest of the data was added. The next step was to remove outlier values as they can negatively impact the training process. By checking some of the maximum and minimum values of the data it was apparent that there were a few outlier values that did not make much sense in relation to the rest of the data. These values might be due to sensor reading errors or machine faults. They are significantly fewer in number but will impact on the overall training process. A general rule of thumb was used to remove those outlier values by keeping only the values that were less than or equal to the mean value added to the standard deviation multiplied by three.

To further improve the dataset a one-hot encoding representation was used on the days of the week data, replacing strings corresponding to week names by a binary vector of zeros with a single element set to 1, which indicates the day of the week based on its position. This step can help in the training process and make it faster to train a more complex model. Furthermore, label encoding was used on the public holiday data to represent a day with a one if it is a public holiday and a zero if it is not. The weather data that was extracted had unit strings attached to it and therefore those strings were split to keep only the numbers and store them as appropriate floating numbers.

The following preprocessing step only took place after experimentation with the water volume data and trying to solve it as a regression problem by predicting a specific water volume to be charged. However, this method was not very effective and did not make much sense as predicting an exact water volume is not very realistic. Instead, providing a water volume range is more realistic and provides the staff with a close range so that using their expertise they can determine the exact figure. This process would also make prediction easier as the model needs to predict a range rather than an exact number. To do this however, the problem needed to be converted to a classification problem rather than a regression problem and that required labels.

The water volume was labelled according to their values and split into ten unique labels, each indicating the water volume range. The labels started from Low_1 having the least water volume range and increased to Low_2 and Low_3. After that, Mid_1 was used and so on. After three variations of Low, Mid, and High there was one label for any water volume above those ranges and that was labelled ExtraHigh. By checking the water volume number in each row, the proper label was added, and the data was finalized. The final data was scaled using the min-max scaler to keep it uniform and easier to train.

The initial data before preprocessing contained 2473 records, and after removing outliers and rows that had missing values the dataset was reduced to 2418. As mentioned above various preprocessing techniques were implemented like one-hot encoding, label-encoding, and min-max scaling. The final dataset contained 12 features and one target variable. The features were namely the weather variables like temperate, humidity , and atmospheric pressure. Features detailing the day data included a variable representing every day of the week, a variable to check if a day is a public holiday, and finally if a day is a weekend. Occupancy was the last feature added to this dataset, and for the dataset used to train the occupancy model the water level column was removed and the occupancy variable became the target variable.

3.6.4 Final Model Data Preparation Diagram

Figure 3.4 shows a simple flowchart indicating the process through which the final data was gathered. Starting from raw sensor values that get converted to CSV files, to calculating the water used every day from those sensor readings, Python is then used to scrape the required weather data and Python libraries are used to calculate the day of the week based on date and whether a date is a public holiday or not. This is all merged and then preprocessing takes effect where outliers also get removed. Finally, the preprocessed data is merged with the sensor data to create the final dataset.

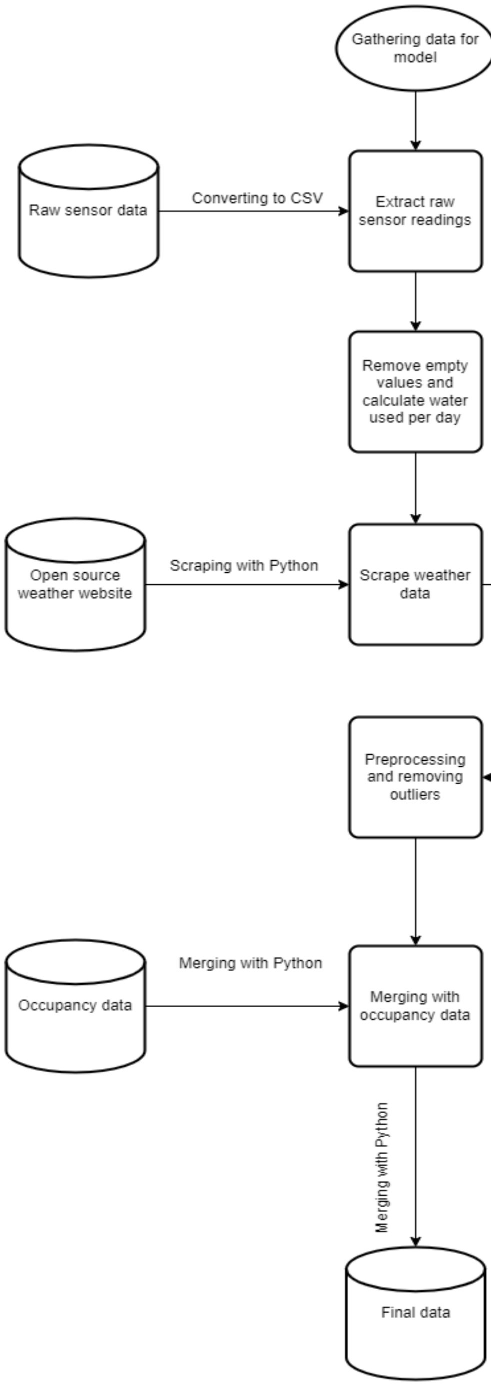

Figure 3.4 Flow Chart outlining the Process of Data Gathering

3.7 Final Model

3.7.1 General Approach

Every Machine Learning problem is unique and has different requirements and therefore the solutions might vary and by extension the approach. However, for this research the general approach was to rely on external data only that are generally available anywhere and not rely on the specific sensors coming from the TES-AC. The main reason behind this is to allow this research to have a higher reproducibility chance and to make the solution more general and more applicable elsewhere. Relying on specific sensor data coming from the TES-AC would only allow similar TES-AC models to apply this solution. Regardless, sensor data from the TES-AC are applicable to predict maintenance related values that might be useful to predict machine component failure, or anomaly detection in sensor readings. Regarding the water volume that will be required to chill and get used by the building for the next day, external factors are important. The external weather affecting the surrounding environment of the building might have an impact on how hard the TES-AC has to work that day to maintain optimal indoor temperatures. This research focuses on a TES-AC that is used to cool an office building with a small shopping complex occupying the lower grounds. The occupancy changes based on which day of the week it is and whether it is a public holiday or not. Therefore, knowing which day of the week it is, and whether that day is a public holiday or not and finally the occupancy number are all crucial for this research.

Finding a suitable and reliable model based on these factors is not an easy task and the model would need to discover a complex pattern to produce reliable predictions. Neural networks have been proven to find complex patterns that other linear machine learning models do not discover. Multi-layer perceptron models are a good choice for this type of problem. In preliminary stages of this research, when the problem was to predict an exact water volume, a Multilayer perceptron regressor was used as the model of choice, however, that was eventually replaced with a Multilayer perceptron classifier after the problem was re-defined as a classification problem.

Linear machine learning models and kernel methods have also been tested briefly on the data, but their results were not satisfactory despite their training time being very short and fast to test. The pattern between the input data and the output is not very straightforward and therefore a deep learning neural network model is more appropriate in this case.

3.7.2 Dataset Imbalance and Oversampling

The dataset contained 10 labels, of which 3 of them occupied 79% of the dataset while the remaining 7 labels occupied only 21% of the dataset. This indicated an imbalanced dataset that would result in the model mostly favoring predictions to the more dominant labels. To overcome this issue an oversampling approach was taken. Oversampling is a common technique used when there are labels or classes that are a minority but predicting them is important and they cannot be overlooked. The approach essentially duplicates examples of the minority labels in the dataset to make them occur more frequently without compromising the integrity of the data.

Prior to oversampling the data, 15% of the dataset was randomly removed to represent the test set on which the data would be finally evaluated on. The remaining dataset was resampled to increase the instances of the minority labels before the training process.

3.7.3 Model Configuration

A very important part of any machine learning model is the configuration of the hyperparameters. Hyperparameters differ based on the chosen algorithm and in the case of this research the MLP classifier implemented in the widely used machine learning library scikit-learn was used. The details of how the algorithm works and an in-depth discussion of each hyperparameter both fall outside the scope of this work, and therefore will not be elaborated upon further. This research develops a deep learning MLP classifier that provides decent predictions to the water charging load in a TES-AC and evaluates how these predictions could be useful for facility managers using TES-ACs.

There were 5 main hyperparameters that were fine-tuned until acceptable predictions were accomplished. One was epochs, which is the maximum number of iterations that the solver would run before it would stop. However, if convergence occurred before that, the model would stop training. The convergence criteria used was either when the maximum number of iterations is reached which was set to a maximum number of 60,000 or when there has been no improvement of more than 1e-4 in the score for 10 consecutive epochs. The hidden layer size is another hyperparameter that was focused on, and it is one of the most important hyperparameters to be fine-tuned in any neural network. However, finding the optimal hidden layer size is extremely tricky and time consuming.

The three other hyperparameters were the activation function for the hidden layer, the solver type and finally the alpha value. To avoid manually changing the value of the hyperparameters and training the models separately, which would be very time-consuming, a grid search was used instead. A grid search takes in a range of values for each hyperparameter and trains the model several times with all the different combinations from the list provided and returns the best hyperparameters found using a scoring metric specified.

In an effort to come up with the best parameters a wide range of values were given for each hyperparameter. The maximum iteration number was set to 60,000 to give enough time for complex networks to converge. The hidden layer sizes were given a range starting from (2,1) till (300,1) indicating 2 units in just one layer to 300 units in one layer. Moreover, two hidden layers with 2 units to 300 units were also tested, denoted by hidden layer sizes (2,2) to (300,2). All three different solvers were tried including the adam solver, sgd and the lbfgs solver. The activation function had 4 different variations, of which 3 were tested which were logistic, tanh and relu functions. Finally, the given range was used for the alpha value or learning rate (0.1,0.32,1.0,1e-3,1e-4,1e-5,1e-6,1e-7,1e-8,1e-9,1e-10).

The scoring metric used for the search evaluation was the weighted precision and 4 cross validations were used for each combination of parameters. The training process was extremely long, and the best parameters were noted down for further usage. Finally, after the grid search found the best parameters, these were used as the final hyperparameters for each model. The best parameters were a hidden layer size consisting of a single layer of 250 units, the tanh activation function, a learning rate of 0.01 and the LBFGS solver.

3.7.4 Occupancy Detection Model

To train the water charge load models, occupancy was used as one of the features during the training process. However, unlike the other features it is not possible to get the value for the next day until the day has already passed. All the weather features can be obtained from a public API and the day features are easily obtainable since the names of the days or the public holidays will not change. Occupancy on the other hand needs to be predicted first for every new day. Similarly, a machine model needs to be developed to predict the occupancy.

The features used for this model were the same as the water charging load model with the exclusion of the water volume data. Therefore, to train the model the features included the weather data, the days data and the previous occupancy data to compare against. This was modelled as a regression problem to predict the number of occupants for the next day. The same preprocessing of data was applied to the data of this model and the same min-max scaling technique was used.

Following the same model tuning method used for the other two models, the grid search algorithm was used to determine the best parameters from a list of values given. The same range of values was used except for the hidden layer size where the maximum increased to (500,1) and (500,2) respectively. The maximum iterations were also set to 20,000 runs.

After the grid search was completed, the best parameters consisted of a hidden layer size consisting of a single layer of 310 units, the LBFGS solver, and a learning rate of 1e-5.

3.8 User-Friendly Application integrating the developed ML Model

3.8.1 Gathering Design Guidelines for the Application

The methodology taken by this research can be viewed in the research framework in Figure 3.5. There were two different groups of participants, where the initial group consisted of experts in the construction industry, and the latter group involved University students who are pursuing Engineering degrees. A qualitative content analysis is carried out initially by 15 experts to understand the features that will be useful regarding the deep learning-based TES-AC application prototype that would include the deep learning model, making it a deep-learning based TES-AC application.. After the application is structured based on the suggested features according to the analysis, a further analysis is carried out to evaluate the user-satisfaction, usability, and interactivity of the application by 35 participants. The participants got a demonstration of the application, and all information they received was in English Language. No personal information was collected from the participants, and they all were informed about the reasons for the study being conducted before they took part in it. The study had minimal risk and all the participants were adults i.e., 18 years and older. The study was verified to be conducted by the institutional ethics committee.

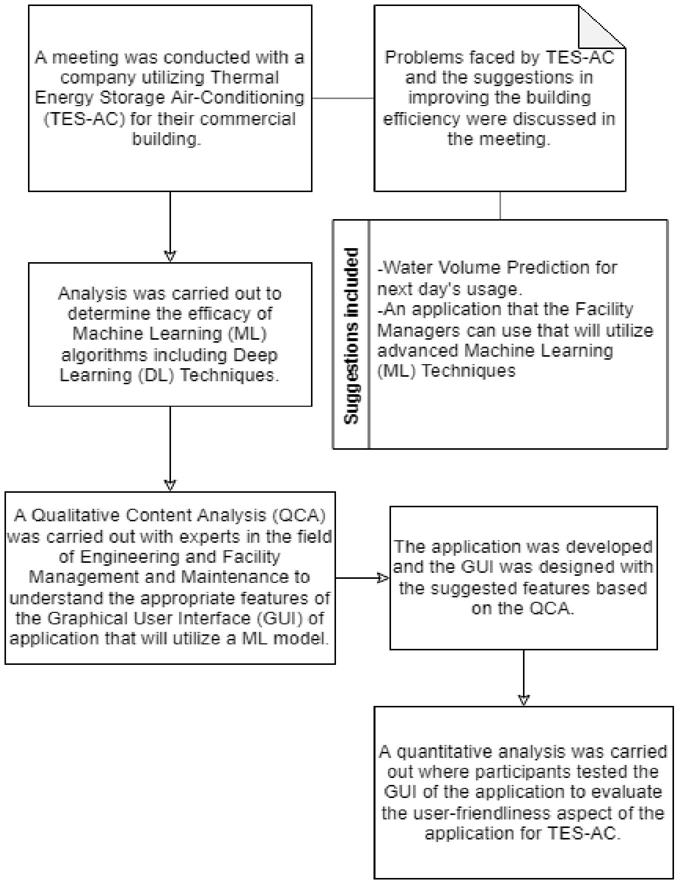

Figure 3.5 Methodology Framework to Gather Design Guidelines

The following questions were asked in the survey questionnaire for the experts as shown in Table 3.1. The questions were in Multiple-Choice-Question (MCQ) format in Google Form for its availability. The MCQ format was chosen so the experts can point what they prefer within options instead of completely giving them a blank canvas. These questions helped to understand the desirable features and outlook of the application such as whether they want a horizontal or vertical navigation bar. There were also questions to understand whether the experts will find it useful if deep learning is deployed in predictive maintenance of FMM. Then they were also asked how they would like to view predictions for charging load, statistics related to efficiency and whether they wanted a “Tips” tab. The experts were also asked regarding the Import feature to upload the sensor data related to TES-AC for charging load prediction and the Export feature to retrieve all the information from the application in a PDF file to view the information.

Table 3.1 Survey questionnaire to understand opinion of experts.

No.	Question description
Q1	Do you suggest a Login feature for the application so not just anybody gets to view your information?
Q2	For the overall outlook of the application, which option do you suggest will help you to concentrate on your daily activities?
Q3	A navigation bar for the application will allow you to switch to different windows within the application. For the application, do you suggest a horizontal navigation bar or a vertical one?
Q4	This application will be based on a deep learning model for water prediction of Thermal Energy Storage Air-Conditioning (TES AC). Knowing the volume of water needed for the demand of the next day helps improve the building efficiency. Do you believe it will help the facility managers to know the water prediction for the tank?
Q5	Would you want to view the deep learning model-based water volume prediction in a graphical form or just a numerical value?
Q6	A tasking feature will allow you to add tasks and show the completed ones. For better management of TES-AC related tasks, would you suggest the application to have an in-built tasking feature?
Q7	The main reason of water volume prediction is to optimize the energy efficiency of the building. Besides the water volume prediction of the chiller plant, do you also want to view the energy efficiency of your building?
Q8	Do you think displaying the current weather temperature inside the application is useful?
Q9	A lack of interest in upgrading in utilizing deep learning methods are mainly related to many models requiring constant real-time input of sensor data that have specific requirements. Do you suggest that more enterprises will be interested to utilize such advanced deep learning methods if they do not require to change their equipment?
Q10	Would you suggest the application to have an import feature so the .csv dataset files can be used to predict the water volume?
Q11	Do you suggest letting the Facility Managers control the settings for the overall outlook of the application to have a customization aspect?
Q12	Do you think it will be useful to also have an export feature to export the charts and information to a .pdf file for viewing?
Q13	In this TES-AC application, do you think adding a "Tips" tab with helpful information regarding maintenance, or using the application or what certain values depict will make the app better?

Then following questions as shown in Table 3.2 were asked to measure the user-interaction aspect of the application to the participants who were pursuing engineering since they might choose to become facility managers. The questions were in a linear scale where 1 denoted least satisfaction and 5 denoted most satisfaction and were available on Google Form. The questions were designed to understand how they like the overall look of the application, whether they find a feature easy-to-use.

Table 3.2 Survey questionnaire to evaluate the user-interaction of the application.

No.	**Question description**
Q1	Do you like the ambience of the application?
Q2	Do you find the login feature to access the application to be complicated?
Q3	Do you find the overall controls of the application, such as navigating, easy-to-use?
Q4	Do you find the form of water volume prediction easy to understand by looking at the application's graphical output?
Q5	Do you find the efficiency graphical output to be useful?
Q6	Do you like the customization aspect of the application to control the general settings?
Q7	Do you find changing the control settings of the application easy-to-use?
Q8	Do you find the tasking feature easy-to-use?
Q9	Do you think the "Tips" tab is useful for the users?
Q10	Do you think displaying the current weather temperature is useful?
Q11	Do you think the "Import/Export" tab is a necessary feature for the application?

3.8.2 Application Overview

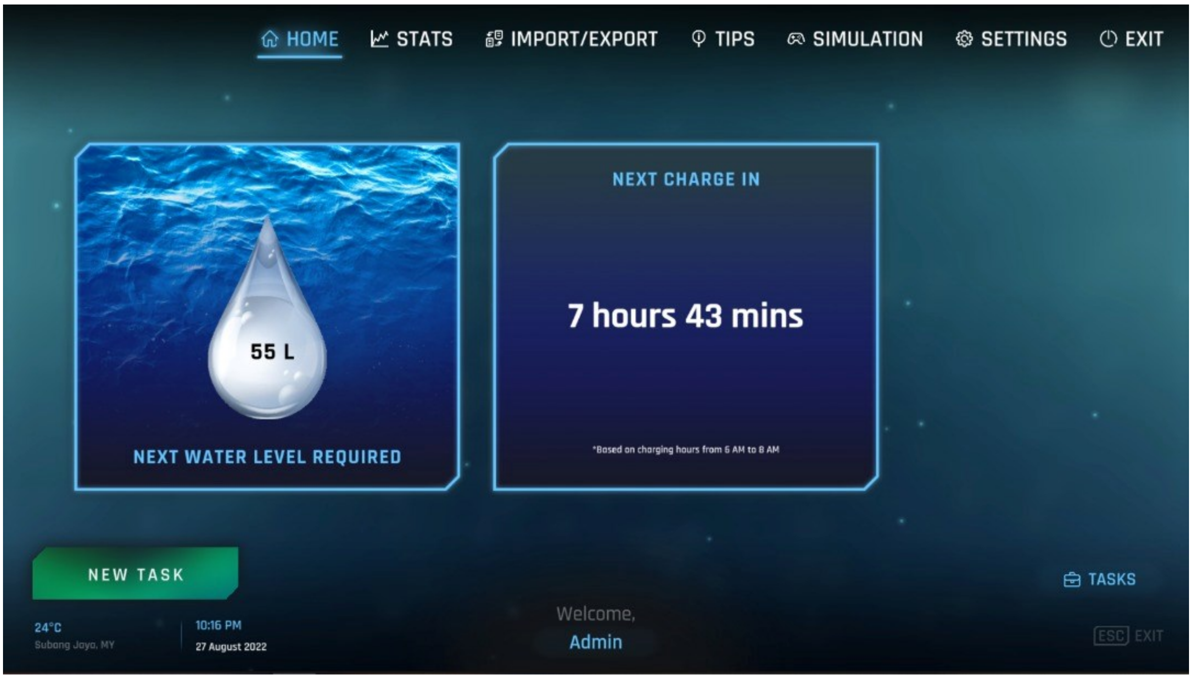

Figure 3.6 (a) Application snippets

Figure 3.6 (b) Application snippets

The application has been designed in an untraditional way to make it easier to use and to keep it more interesting. While most maintenance applications would have a very simple design that does not pay attention to details and just places controls and information in front of the user, this application design focused on making an impactful design. The user interface is very easy to use with buttons and text being very clear. The whole application is designed using a science fiction like theme which makes it more appealing to younger audiences who are most likely to be using this application. It reflects a futuristic design to uplift the mood of the user and relies on visuals and graphics to keep it interesting to look at and boost creativity.

As seen in Figure 3.6 (top), the design of the application relies on a simple but informative interface. The user can easily access the most crucial information and it is easy to navigate the rest of the application. Proper graphics and visuals are used to convey the meaning of the information without the user having to look through manuals to understand what each component of the interface stands for. Figure 3.6 (bottom) shows how statistics are displayed in the application, using simple graphics that look better than traditional charts but also provide very rich information. A top navigation bar makes it easy to access the different main components of the application while the bottom bar displays information like the time, date, and weather information.

Ideally, an application like this could be further improved by automating most of the processes discussed above. This was not possible in this research as access to new data halted but also because there was no way to get real-time sensor data from the TES-AC. A suggested solution would be using some cloud service as a medium to send sensor data from the plant and retrieve it from the application, resulting in the machine learning model being constantly updated and improved. This could in turn lead to a fully automated prediction and even water charging process. This, however, was not the focus of this research, as this research sought to explore using machine learning in this field and prove how it can be of useful impact.

3.9 Potential application of the developed model on a larger scale

3.9.1 Overview

With climate change and global warming, the time is due to make environment-friendly decisions especially in building infrastructure. Due to poor development decisions, urban areas, besides being densely populated, create a heat island effect as buildings continuously absorb and re-emit heat. Drastic increases in urban island heat are contributing negatively to our environment, increasing temperature and humidity, and eventually negatively impacting human health. New developments are contemplating greener choices to make cities more habitable and sustainable. Some corporations are remodelling their buildings to positively contribute to the environment. As flooding and heat waves become a concern, the sponge city concept is presently being considered for developments in coastal areas to absorb flooding as they continue to receive increasing levels of rainfall. Climate action has become a focal point in research to combat natural disasters due to climate change. Additionally, an energy crisis is also being felt which is why research needs to be conducted on using renewable energy sources and incorporating them into urban regeneration of especially vulnerable areas such as coastal cities. Buildings account for around one-fifth of global energy consumption due to inefficient Air-Conditioning (AC) and through appropriate research, this energy and climate crisis can be addressed with innovation in this sector.

The developed MLP model can be integrated into a potential idea that might help in improving this issue. Using the predictive power of the model, TES-ACs can be used more efficiently, reducing the workload of facility managers and helping in fully automating the process. Rainwater harvesting techniques can then be installed with IoT sensors to absorb rainwater from the rooftop and store it in underground water tanks. This water could then be reused to operate the TES-AC, topping up any water lost during its operation. By having sensors installed and automating the prediction and charging load process, this could turn into a fully automated closed system.

On a bigger and more ambitious scale, if big commercial buildings and factories adopt this technique, then the rainwater harvested would amount to a big volume which might potentially reduce the risk of flooding, especially in coastal areas. Furthermore, by utilizing the more efficient TES-AC plants those buildings can drastically reduce heat emissions and save money on energy costs.

3.9.2 Feasibility Study

3.9.2.1 Proposed Concept

The proposed concept combines different aspects together to solve more than one problem together. The idea is ambitious but could have significant advantages and is therefore discussed. In coastal areas when heavy rainfall occurs it causes heavy flooding which affects the entire city, causing infrastructure damage and loss of life. Rainwater harvesting techniques are one of the solutions that could reduce flooding by absorbing huge amounts of water and preventing them from flooding the streets. The big buildings would make the biggest difference in the volume of water absorbed due to their size and scale. At the same time the big buildings are responsible for a major part of the heat emissions contributing to the urban heat effect and increasing CO2 emissions.

Thermal-Energy-Storage-Air-Conditions are a great alternative for these buildings as it tries to shift the operation hours of the chillers to only operate during low-peak hours and to avoid using the chillers the whole day, which reduces carbon emissions and electricity costs. However, predicting the volume of water needed for next day's operation is tricky and not cooling enough water for the next day poses problems for the facility managers. By utilizing the strong predictive power of neural networks, a model could be deployed to predict the water volume needed to charge for the next day, making TES-AC plants more efficient and more attractive as a solution to implement in big buildings.

In the case of water-cooled TES-AC plants, water is a key resource and is usually supplied from the traditional external sources. However, if a building is harvesting rainwater, then the TES-AC plant can use that harvested water for its need, or at least reduce the need for external water by a great degree. Finally, by capitalizing on the use of IoT sensors throughout the system a fully automated system can be developed that automatically monitors the water flow through the system and automatically harvests rainwater when there is space in the storage tanks and also automatically supplies water to the TES-AC for its operation. Similarly, it could automatically predict the water volume needed to be chilled for the next day and can ease the workload of facility managers allowing them to focus more on managing the rest of the building.

The proposed concept can be visualized in the diagram below:

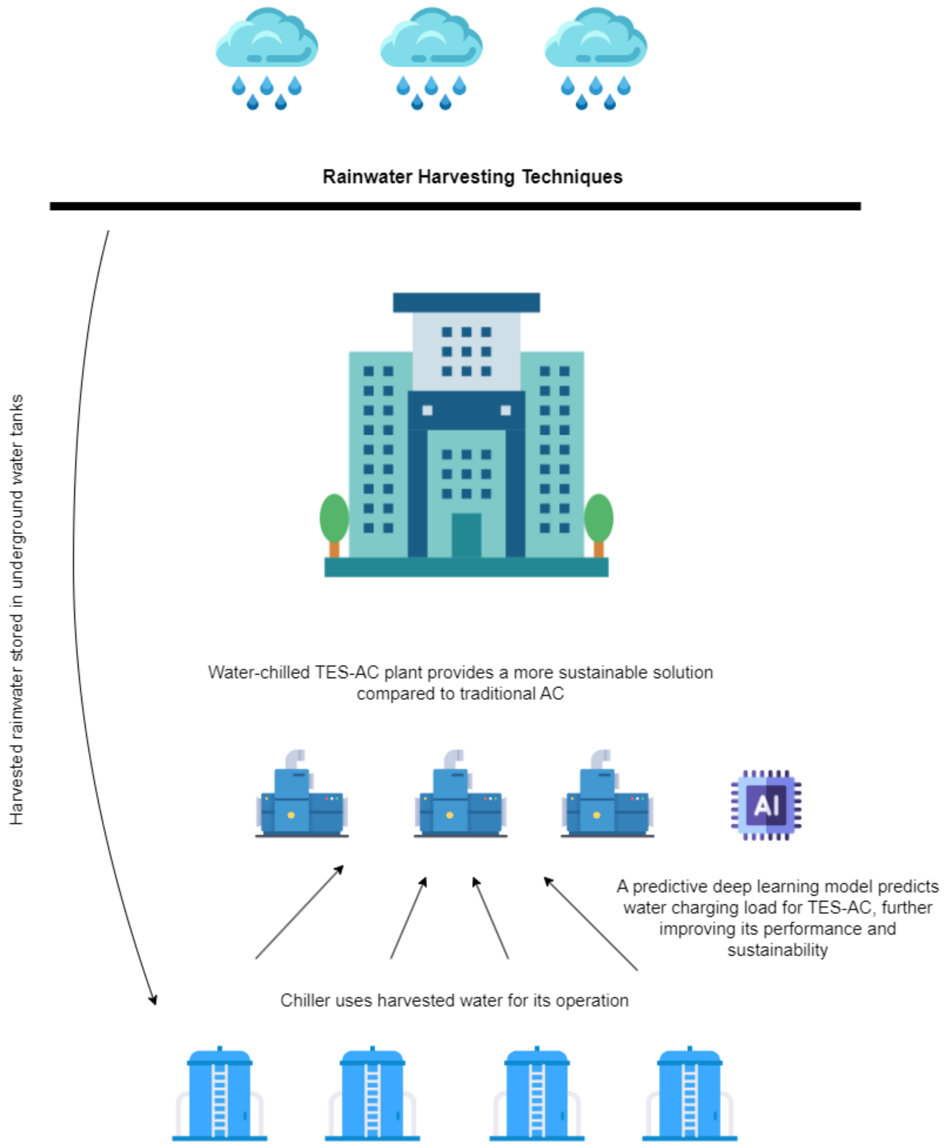

Figure 3.7 Proposed Concept

3.9.2 Methodology for the Feasibility Study

This section discusses a survey that was undertaken to explore the feasibility of the proposed concept of commercial multipurpose building incorporating TES-AC with the developed MLP model, and rainwater harvesting, and whether it is achievable or not. A total number of xx experts in different fields such as engineering, facility managers, and computer science were asked a set of questions that explained to them the proposed concept and questioned them about different aspects of the plan. The questionnaire was developed on Qualtrics Software with English Language and shared to the participants. All aspects of collecting data were conducted online for ease of access and to reduce paper waste. The study consisted of international participants who took part in the survey voluntarily and the study helped understand the opinion of experts from different parts of the world and the study was approved by the Ethics Committee of the University of Nottingham Malaysia. Measures to safeguard stored data of the participants include encryption protocol, pseudonymization procedure, and anonymization of data. By analyzing their responses and suggestions a conclusion is reached on whether this idea would require further investigation and research, in hopes that more work will be done exploring such ideas so that innovation can be advanced more in our buildings.

The questionnaire involved enquiring with the participants about their demographics and expertise, besides providing a description of the study. Then the participants were required to fill out the survey which consisted of Multiple-Choice Questions (MCQs), and Likert scale-based questions. The analysis was conducted with Microsoft Excel, SPSS software, and Qualtrics software. The questions asked are provided below in Table 3.3.

Table 3.3 Survey questionnaire to understand feasibility of a proposed concept.

No.	**Question description**	**Question Type**
Q1	Based on your experience, what is the common problem in chiller plant that can impact their performance and efficiency?	MCQ (Multiple picks)
Q2	Does your organization use chiller plants?	Yes/No/Not sure
Q3	Are you aware of Thermal Energy Storage Air Conditioners (TES-AC)?	Yes/No/Slightly
Q4	This question aims to evaluate the importance of predicting the water charging load for TES-ACs. Please score each sentence	Likert scale on six statements

	below from 1 to 5 to rate the degree of agreement on the following from your experience.	
Q5	What external data can be used to predict the water charging load in order to avoid relying on the specific sensor data of the TES-AC?	Free text field
Q6	This question is related to predicting water charging load in TES-AC and its effect on carbon emissions. Please score the sentence below from 1 to 5 to rate the degree of agreement on the following from your experience.	Single Likert scale
Q7	Do you think using harvested water to supply the TES-AC facility will help reduce costs compared to pumping water from external sources is important?	Less important/Important/Very important
Q8	Are you aware of rainwater harvesting techniques?	Yes/No/Slightly
Q9	Do you think the cost involved in implementing rainwater harvesting techniques and machine learning prediction on TES-AC water charging load is worth it compared to the benefits?	Yes/No/Might be
Q10	Do you think if multiple commercial buildings or factories adopt a harvesting water technique it might potentially reduce the risk of flooding during heavy rainfall?	Yes/No/Maybe
Q11	What are the other advantages in using harvested water to supply the TES-AC facility?	MCQ (Multiple picks)
Q12	What are the disadvantages of rainwater harvesting?	MCQ (Multiple picks)
Q13	Do you think using underground water storage tanks to store harvested rainwater in commercial buildings is feasible?	Yes/No/Maybe
Q14	What are the other challenges in implementing rainwater harvesting techniques and machine learning prediction on TES-AC water charging load?	MCQ (Multiple picks)
Q15	How can we support the implementation of the water harvesting techniques and machine learning prediction on TES-AC water charging load?	MCQ (Multiple picks)

3.10 Summary

This section included the steps taken to conduct this research in detail. It explained how the TES-AC works and how optimizing it can be formulated into a Machine Learning problem. The problem is broken down into smaller problems that are each solved in different ways. There are various Machine Learning algorithms and trying them all out is not efficient nor sensible. The initial step tried algorithms on regression (sensor reading prediction) and classification (cooler condition). Since the final model involved classification, and the input features were numerical data (the initial step), the outcome of that initial step was useful. Besides, MLP was also a good option from the intensive literature review. Based on those conclusions the MLP was the chosen algorithm for the problem. Equally important to the choice of algorithm is the dataset used. Raw sensor data from the TES-AC was not usable initially and therefore careful analysis and study was required to understand what each part of the data does and how it relates to the overall problem.

During the study it was concluded that heavily relying on sensor data for prediction would provide a non-generalized solution as different TES-ACs might have different sensors. However, considering how the entire system is essential to an AC, the external weather and occupancy of the building might play a more important role. Weather data and information related to the type of day it is alongside occupancy data were all extracted, calculated and processed as the main input training data. This method proved to be reliable and produced good results after the necessary steps were taken to optimize the hyperparameters while training the model.

The final model was tested on unseen testing data and the results were positive which indicates that a potential solution was found. However, using a machine learning model for facility managers requires a user-friendly interface without too many complications or technical details. Sample prototype interfaces were designed, and facility management experts were interviewed to determine the best features and design practices to follow when developing such a software. All these design guidelines were used as a base blueprint to develop a simple maintenance software that will integrate the trained model into it that functions as a more complete facility management software.

Finally, a feasibility study discussing a proposed concept where a commercial building facility will operate using TES-AC with the developed MLP model and rainwater harvesting technique is conducted with international experts. The survey collected data that was useful to understand the scope of the research and to understand the potential applications where sustainable energy can be used to benefit the environment and facility management industry with computational intelligence. This step essentially highlights the research scope and possible future directions.

Chapter 4 Results and Discussions

4.1 Introduction

This section introduces the topics discussed. Section 4.2 discusses the analysis of the Machine Learning algorithms that have been used for this research on the online dataset. It will briefly mention the evaluation of prediction accuracy and other metrics of different algorithms in graphical form. Furthermore, section 4.3 will discuss the results that show the impact of weather data over water consumption in TES-AC. Section 4.4 discusses the performance of the final model developed to predict the water charging load of TES-AC. Finally, section 4.5 discusses the questionnaire response of the best design practices to use when developing a facility management software with the trained model integrated into it. Section 4.6 discusses the feasibility study for an innovative building with TES-AC and Section 4.7 contains the summary of the chapter.

4.2 Analysis of ML algorithms on an online hydraulic rig dataset

Machine Learning algorithms were analysed on a hydraulic rig dataset from an online source. Both classification and regression algorithms were tested and the assets and liabilities of each were outlined. Feature scaling was performed on the data and the scaled data was analysed. The goal is to determine which algorithms would be best to use in the industry dataset based on their performance analysis on the online dataset of hydraulic rig for the classification problem, and the regression problem.

4.2.1 Findings

Overall, in this research, the classification problem was solved using ten different approaches. A very important metric to measure would be the time it takes for the model to run or also known as fitting time, which could be counted by measuring the time it takes the model to fit on the dataset and the time it takes to predict which is called prediction time. Measuring the time taken for the model to fit on a new training set and the prediction is important for decision making when it comes to deciding when to run the model. If the model takes too long to fit and uses a lot of resources then maybe a different approach could be used. Furthermore, if the prediction takes a long time to run then it might be suitable to run the prediction well before the time in which the output would be needed. The good results obtained can partially be explained because the data has only 2205 instances, and also the labels in the data tend to be consecutive which makes the prediction problem easier. Despite that, some algorithms performed better than the others and would be more suitable to be used in this research to solve related classification problems. Accuracy is the main metric used to evaluate classification models and is counted simply by calculating the total number of correct predictions over the total number of predictions made.

The Gaussian Process classifier and the MLP with an LBFGS solver and a (100,) hidden layer configuration (one hidden layer and 100 nodes), both had the highest prediction accuracy score, however, it is clear that the MLP is the better performer because of the huge difference in the fitting time. The Gaussian classifier needed 106.001 seconds to fit a model with 2205 instances. The MLP however, with the proper configuration for the problem took only 0.814 seconds to come up with the same result. Table 4.1 shows the comparison of prediction accuracy scores with fitting and prediction time of the classification algorithms used to predict the cooler condition.

Table 4.1 Comparison for Classification Algorithms

Algorithm	**Comparison for Classification**		
	Accuracy	***Fitting Time (s)***	***Prediction Time (s)***
Logistic Regression	0.9894	0.978	0.000000 e0
k-NN	0.9668	0.004	3.100000 e-02
Gaussian	0.9985	106.001	4.280000 e-1
Decision Tree	0.9864	0.012	1.000000 e-03
MLP with LBFGS (5,2)	0.4320	0.039	1.000000 e-03
MLP with LBFGS	0.9985	0.814	6.000000 e-

Algorithm	Comparison for Classification		
	Accuracy	*Fitting Time (s)*	*Prediction Time (s)*
(100,)			03
MLP with SGD (5,2)	0.4199	1.759	2.000000 e-03
MLP with SGD (100,)	0.9955	1.149	2.000000 e-03
MLP with Adam (5,2)	0.9743	4.147	2.000000 e-03
MLP with Adam (100,)	0.9970	1.116	3.000000 e-03

According to the analysis of the six different approaches, LSTM has the potential of having accurate data predictions, but it tends to be on the slower side of fitting the model, especially as the LSTM's complexity increases as seen by the stacked LSTM example. The MLP however, had a very good prediction result but maintained a very short fitting time which can be a crucial decision fact in this research as a real-life HVAC dataset will be very big and predictions cannot be done too slowly.

As seen in Figure 4.1, the different regression models used to solve this problem had their prediction results plotted on a scatter plot. The blue dots represent the actual values while the orange dots represent the training data predicted values and the grey dots represent the testing data predicted values. The outlier values are only of the actual value, and they can be visibly seen as the blue dots which are out of range. The outlier values have not been predicted using any of the approaches because Robust scaling does not deal with outliers and data was not standardized for MLP Regressor. Visually, the outlier values can be interpreted in an easier way along with training predictions and testing predictions, but it is also important to note the MSE and RMSE scores to evaluate their performance. Table 4.2 shows the RMSE scores of both training and test sets with fitting times.

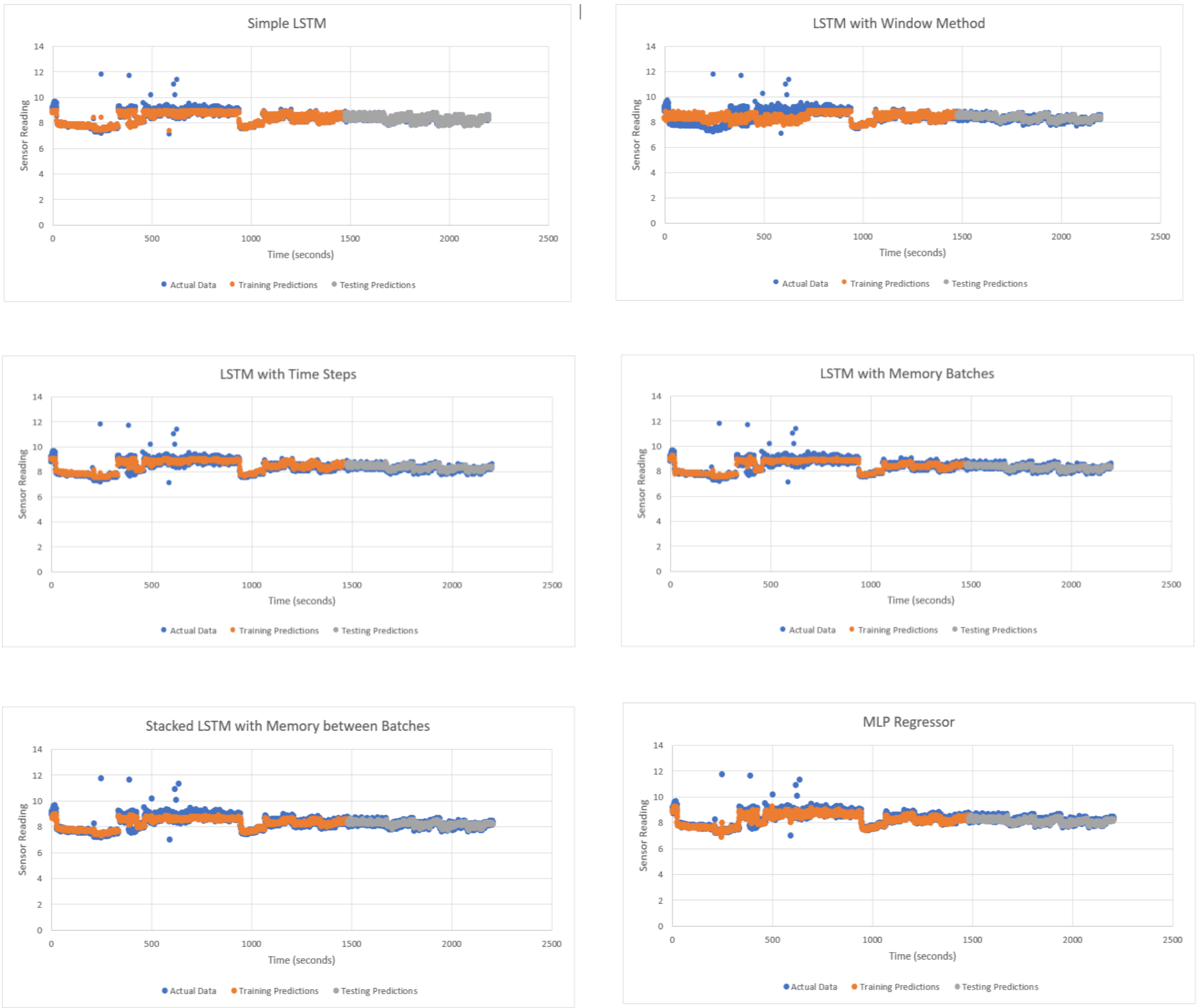

Figure 4.1 Scatter plots of all the regression approaches, showing true data, training predictions and testing predictions

Table 4.2 Comparison of used regression approaches

Algorithm	Metrics		
	Fitting Time (s)	Training RMSE	Testing RMSE
Simple LSTM	218.658	0.3215	0.230

LSTM with window method	257.362	0.2962	0.2029
LSTM with time steps	296.61	0.2959	0.2004
LSTM with memory batches	283.461	0.2959	0.1752
Stacked LSTM with Memory between Batches	454.393	0.2913	0.1995
MLP Regressor	11.359	0.3028	0.1780

4.2.2 Discussion

According to the analysis of both the regression and the classification problems, some conclusions were deduced; see Table 4.2. For the classification problem most of the approaches had high prediction accuracy. Two models that included the Gaussian Process classifier and the MLP with LBFGS solver with a hidden layer of (100,) scored the highest prediction accuracy which was 0.9985. However, it can be seen that the MLP will be the better option as it exhibited a much lower prediction time of 0.006s and therefore will be much faster to use than the Gaussian Process Classifier with 0.428s of fitting time. Moreover, MLPs can be configured in different ways to fit different datasets which makes it a scalable, fast, and efficient approach.

For the regression problem, some of the LSTM networks performed really well, especially the LSTM with memory batches as the Rounded Mean Squared Error (RMSE) for the test set was 0.1752. However, the fitting time was still much faster on the MLP Regressor (fitting time: 11.359s, RMSE for test set: 0.1780) despite not having the same accuracy as the LSTM with memory batches (fitting time: 283.461s, RMSE for test set: 0.1780). LSTM requires more epochs to run to be more accurate which tends to be expensive on the fitting time. In this case, the accuracy difference is not so significant to sacrifice the additional fitting time and therefore MLP regressor is the better option. Therefore, as per the analysis the MLP seems a more suitable approach for both classification and regression problems. MLP remains to be a particularly good option for its flexibility, accuracy, and speed but LSTM is also a good approach and could be configured in multiple ways that might be more suitable for certain datasets. However, a limitation is that only the cooler condition of the system was investigated, though traditionally for a complete solution, all the components need to be discussed.

For the classification problem, MLP was tried with three different solvers 'ccl', 'lbfgs', 'sgd', and with two different combinations of hidden layers (5,2), (100,). MLP with LBFGS solver with a (100,) hidden layer appeared to be the best performing one amongst the ML algorithms for the classification problem. MLP with LBFGS (100,) and Gaussian Process had the highest prediction accuracy of 0.9985, but MLP with LBFGS (100,) had lower prediction time and fitting time compared to the other algorithms including Gaussian Process. The Gaussian Process had a very high fitting time which can be impractical for some applications. For the Regression problem, LSTM, a type of artificial Recurrent Neural Network (RNN), was tried with five different approaches which include Simple LSTM, LSTM with Window Method, LSTM with Time Steps, LSTM with Memory Batches and Stacked LSTM with Memory between Memory Batches.

Although LSTM had good prediction accuracy, it had a slower fitting time when the complexity increases which can be seen in Stacked LSTM with Memory between Memory Batches (fitting time: 454.393s). MLP with (100,) hidden layer had proved to be better performing in the regression problem than the five different approaches of LSTM with a fitting time of 11.359s, and an RMSE score of 0.1780 for the test set which means the prediction accuracy is quite good. Based on the analysis, MLP has proved to be useful for both classification and regression problems for the online dataset and should be explored more in the future to utilize it in the form of a deep learning model for predictive maintenance. The next step of this research includes utilizing MLP according to the findings from this study for predictive maintenance of a Thermal-Energy-Storage Chiller Plant.

Table 4.3 Pros and Cons of Machine Learning Algorithms from the Analysis

	Algorithms	**Pros**	**Cons**
Classification	Logistic Regression	High accuracy	Solver LBFGS required higher number of iterations
	Decision Tree	High accuracy	Biased to training set

	k-Nearest Neighbors	Very fast fitting time	Accuracy high, but not as high compared to others
	Gaussian Process	Very accurate	The slowest approach
	MLP Classifier	Very flexible Most accurate (alongside Gaussian)	Need to experiment to find best hidden layer structure
Regression	Simple LSTM	Easy to implement with average results	Does not represent the time series properly
	LSTM window method	Higher accuracy than the simple LSTM	Increased fitting time due to increased lookbacks
	LSTM with Time Steps	More accurate on larger datasets	Slow fitting time on small datasets
	LSTM Memory with Memory Batches	Accurate LSTM with better fitting time than stacked LSTM that uses memory	Requires a lot of training epochs to be accurate, which makes it slow.
	Stacked LSTM with Memory between Batches	Allow for a deep learning architecture to maximise accuracy	Requires a lot of training epochs to be accurate, which makes it slow.
	MLP Regressor	High accuracy, flexible and fast	Need to experiment to find best hidden layer structure

4.3 External Factors Impact on TES-AC

It has been proven that spring-summer warm temperatures and snow-free ground surfaces may induce significant increases in water consumption, both indoors and outdoors [38]. Additionally, this research depends on the theory that the hotter it gets outside, the harder an Air Conditioner (AC) system has to work to keep the indoor air cool [2]. Another hypothesis mentions that humidity and temperature affect the performance of air-conditioning systems as humidity cancels out the cooling effect making the indoor feel warmer than it is [39].

According to the theories mentioned in the literature review, the external weather factors would affect the water consumption of the TES-AC system though a TES-AC differs from a conventional AC as TES-AC depends on water volume as a factor for charging load. Moreover, with relatively elevated humidity, the body's ability to lose heat through perspiration and evaporation would be reduced which can be factored in whilst considering the water consumption of TES-AC systems as it might have an effect [40]. This research does not try to refute claims that other external factors also affect the water consumption in TES-AC according to the theories mentioned. However, it is trying to show that weather data provides one main set of external factors that do have an impact on the water consumption of a TES-AC system. This work considers the metrics of temperature, humidity, and atmospheric pressure for analysing the effect on water consumption of the TES chiller plant.

4.3.1 Determining the relationship of external factors on TES-AC

Each one of the different weather data types was tested separately but using the same procedure. As discussed earlier, the data gets sorted by the chosen weather metric in descending order and then the top 25% of the data and the bottom 25% of the data are split and kept separately. With regards to this research, the data in between these two ranges was ignored as we are more interested in the extreme weather values.

Starting with the most common weather metric, temperature, it was observed that in the top 25% of the data which is equivalent to the days with the highest temperatures, the water consumption was high a total of 42 days or 6.95% of the time. Table 4.3 shows the overall analysis. The percentage was calculated based on how many days manifested high water consumption over the total number of days in the top 25%, which in this case is 604 days. It was also calculated how many days out of the high-water consumption days were either weekends or public holidays. A total of 11 days out of 42 were weekends (26.19%) and just one day was a public holiday (2.38%). On the opposite side where the temperatures were at their lowest, we have again 604 days to compare with. A total of 36 days had high water consumption (5.96%) of which 6 days were weekends (16.67%) and 2 days were public holidays (5.56%). It is to be noted that the highest temperature was around 31 degrees Celsius, and the lowest temperature was 21 degrees Celsius.

Table 4.4: Analysis of Temperature Effect on Water Consumption of TES-AC

Temperature							
	High water consumption days	High water consumption days (%)	Weekends	Weekends (%)	Public Holidays	Public Holidays (%)	Ratio of high water consumption days to total number of high water consumption days
Top 25%	42	6.95	11	26.19	1	2.38	25.45
Bottom 25%	36	5.96	6	16.67	2	5.56	21.82

Humidity was considered for comparison next, and the data was sorted in an equivalent way as shown in Table 4.4. This metric is calculated as a percentage of how much humidity is in the air with 100% being the maximum value in the data and 0% being the minimum value. At the top 25% of the data where the humidity values were the highest a total of 35 days had high water consumption (5.79%) of which 6 were weekends (17.14%) and 2 were public holidays (5.71%). On the other hand, at the bottom 25% of the data where the humidity values were the lowest a total of 47 days had high water consumption (7.78%) of which 13 days were weekends (27.66%) and 3 days were public holidays (6.38%). The total number of days at the top 25% and the bottom 25% were the same as temperature, with

604 days each. The table depicts how many days had high water consumption in the higher range of temperatures and the lower range of the temperatures.

Table 4.5: Analysis of Humidity Effect on Water Consumption of TES-AC

Humidity							
	High water consumption days	High water consumption days (%)	Weekends	Weekends (%)	Public Holidays	Public Holidays (%)	Ratio of high water consumption days to total number of high water consumption days
Top 25%	35	5.79	6	17.14	2	5.71	21.21
Bottom 25%	47	7.78	13	27.66	3	6.38	28.48

Finally, the atmospheric pressure was the last variable to be investigated, and the data was sorted accordingly as shown in Table 4.5. The maximum atmospheric pressure was 1014 mbar, and the minimum was 1008.8 mbar. At the top 25% of the data a total of 47 days had high water consumption (7.78%) of which 12 days were weekends (25.53%) and 1 day was a public holiday (2.13%). At the bottom 25% of the data a total of 44 days had high water consumption (7.28%) out of which 11 were weekends (25%) and 1 day was a public holiday (2.27%).

Table 4.6: Analysis of Atmospheric Pressure Effect on Water Consumption of TES-AC

Atmospheric Pressure							
	High water consumption days	High water consumption days (%)	Weekends	Weekends (%)	Public Holidays	Public Holidays (%)	Ratio of high water consumption days to total number of high water consumption days
Top 25%	47	7.78	12	25.53	1	2.13	28.48
Bottom 25%	44	7.28	11	25	1	2.27	26.67

It is to be noted that out of the 2418 days in the dataset, only a total of 165 days had high consumption (6.82%) out of which 38 days were weekends (23.03%) and 6 days were public holidays (3.64%). Considering that high water consumption days do not occur frequently, it makes sense to calculate the percentage of high-water consumption days in relation to the total number of days (including non-extreme days) in which the water consumption was high, to get a clearer idea about the impact. This gives a better understanding of how much each metric affects the days with high water consumption. For the temperature metric, the top 25% of the data had 25.45% of the total number of days (including non-extreme days) with high water consumption, while the bottom 25% had 21.82% of the total number of days.

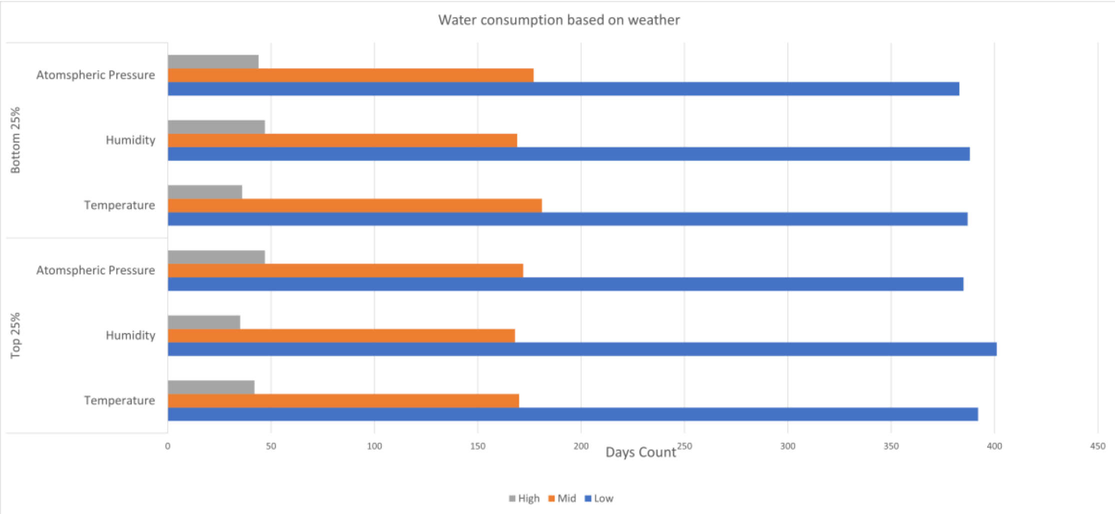

Figure 4.2 Graphical display of the relation of water consumption by TES-AC chiller with weather metrics

Similarly for humidity the top 25% had 21.21% of the total days and the bottom 25% had 28.48% of the total days. Finally, the atmospheric pressure had 28.48% of the total days in the top 25% and 26.67% in the bottom 25%. Figure 4.2 shows in graphical form the water consumption comparison in relation to the weather metrics of temperature, humidity, and atmospheric pressure.

4.3.2 Discussion

The results displayed some predicted outcomes and some unexpected outcomes. There are limitations to this study that will be discussed at the end of this section. However, the analysis of each weather metric and how it impacts the water consumption is as follows.

4.3.2.1 Temperature

As one of the first weather metrics that typically comes to mind, temperature was expected to have an impact on water consumption. As shown above, at the top 25% of the data where the temperatures were the highest and most extreme, there was a total of 42 days observed with high water consumption which amounted to 6.95% of the days in the top 25%. However, given that high water consumption days do not occur very frequently, it is wiser to compare with the full totality of high consumption days. From this perspective, the 42 days represent 25.45% of all days with high water consumption. On the other hand, at the bottom 25% of the data, there were 36 days with high-water consumption, which is equivalent to 21.82% of the total data. That means that the higher temperatures resulted in a 3.63% increase in water consumption days. The percentage might seem small but when considering the fact that high water consumption days are not frequent, the difference is not insignificant.

Out of the high-water consumption days in the higher temperatures, 11 days or 26.19% of those days were weekends, which shows that the difference is more reliant on the temperature and not on whether the day was a weekend or not. A similar observation could be made about the high-water consumption days in the lower temperatures, where 6 days or 16.67% were weekends. The public holidays are insignificant and do not seem to be having an effect.

4.3.2.2 Humidity

Out of the three metrics analyzed, humidity had the biggest impact on water consumption. However, unlike initially predicted, the water consumption seemed to increase as the humidity decreased. The exact reason humidity could have this sort of effect requires more research to understand the underlying reasons. As noticed in the table, out of the top 25% values with the highest humidity 35 days or 21.21% of the entire high water consumption days were present. Surprisingly, in the bottom 25% of the data 47 days or 28.48% were high water consumption days. That means that in the days with the lower humidity values there was 7.27% more water consumption. This suggests that humidity has roughly twice as much of an effect on TES-AC water consumption compared to the weather temperature.

Keeping in line with how weekends and public holidays factor into the results, it was seen that out of the 35 days of high-water consumption in the top 25% of the data, 6 were weekends (25.53%) and for the bottom 25% there were 13 days falling on weekends (27.66%). Similar to the temperature results, public holidays were much scarcer and did not appear to have had a noticeable effect.

4.3.2.3 Atmospheric Pressure

The weakest result in the three metrics analyzed pertains to atmospheric pressure. The difference between high water consumption days between the top 25% and the bottom 25% was only 3 days amounting to an increase of 1.82% in the set of days with the higher atmospheric pressure. However, this does not necessarily imply that this is a metric that should be ignored when trying to factor in features for a Machine Learning solution.

In order to figure out if atmospheric pressure is relevant, it is important to look at the maximum and minimum values in the dataset. The maximum atmospheric pressure observed was 1014 mbar while the minimum was 1008.8 mbar. The difference between both extremes is relatively small and therefore additional data needs to be collected, covering a wider range, before any conclusions can be reached about the usefulness of this feature.

4.3.3 Effect of weekends on water consumption

By looking at the tables and results, one might put forth the idea that the real reason there is any difference in water consumption is the presence of more weekends in the data that has more water consumption. For example, it can be observed across all three metrics that when there are more days with high water consumption, there is always a larger number of weekends. While this research is not denying that weekends could be a factor contributing to the amount of water consumed, it also points to a simpler explanation.

A week consists of 7 days and the probability of any day being a weekend is 0.29. Therefore, when the weather affects the water consumption and leads to more days with high water consumption, it is only natural that there will be more high-consumption days as weekends, since for every new day with high water consumption because of the weather, there is a 0.29 chance of that day being a weekend. This is consistent with the fact that weather changes, conditioned on what day of the week it is, tend to be relatively small. The weather is unpredictable and can change whether it is in the middle of the week or on the weekend. Therefore, as more days are having high water consumption, more of those days will be weekends. The number of public holidays on the other hand tends to be small, and yet it will be expected to be larger if the high-water consumption days are more frequent, but this increase is likely to be practically negligible.

4.4 Using Trained MLP for Charging Water Load Prediction of TES-AC

4.4.1 Water Charging Load Models

First the model was evaluated by predicting the water charging load for the next day. When evaluating any classification model there are several metrics that could be considered, and it usually depends on the problem. Precision is calculated by dividing the number of true positives (TP) with the total number of TP and false positives (FP). Recall is calculated by dividing the TP with the total of TP and false negatives (FN). Each one of these metrics might be more useful than the other depending on the scenario, however, the model was evaluated using a combination of both precision and recall known as the f1-score. The f1-score considers both precision and recall and is a good metric to evaluate a classification model on.

There are 2 typical versions of the f1-score in this multi-class context, depending on the averaging technique used. The simple average simply sums all of the f1-scores (one for each label) and divides this by the number of labels, without considering how many occurrences of each label there are. This method of averaging is called the macro-average value. A better way to calculate the average f1-score would be to consider the weight of each label which is called the support value. The more a label occurs in the data the higher support value it gets, and the weighted average considers the weight of each label to provide more reliable evaluations. Accuracy, on the other hand, is a metric that measures the overall correctness of the model's predictions across all classes in a classification problem.

Table 4.7 Evaluation Metrics for the Developed Model for Charging Water Load Prediction

Model	**Precision**		**Recall**		**F1-Score**	
Main Data	0.93	0.96	0.93	0.93	0.92	0.94
	Macro Avg.	**Weighted Avg.**	**Macro Avg.**	**Weighted Avg.**	**Macro Avg.**	**Weighted Avg.**

The evaluation metrics of the model can be seen in Table 4.6. The model scored 93% macro average precision, and 96% weighted average precision. It scored a 93% macro average recall value and weighted average recall value. Finally, it scored 92% macro average f1-score and 94% weighted average f1-score. It is to be noted that these metrics are based on the predictions done on the 15% of the dataset that was taken out initially for testing purposes. This makes these results the most unbiased and reliable ones to use, and all the other metrics obtained while training were not included in this paper as they were used only to refine the model further.

It has to be noted however that the prediction provides a label for the facility managers that gives them a small range of values to choose from. This method will not provide them with an exact volume to charge but should get them close enough to it.

Figure 4.3 shows a stacked bar chart indicating the predictions made by the model. Each bar indicates one of the labels and the stacks inside are divided based on the labels that got predicted as the label on the x-axis. As seen in the chart, the model predicted nearly perfectly for most of the labels, except for the label Low_2. Overall, the prediction accuracy of the model is considerably good, and the results are promising.

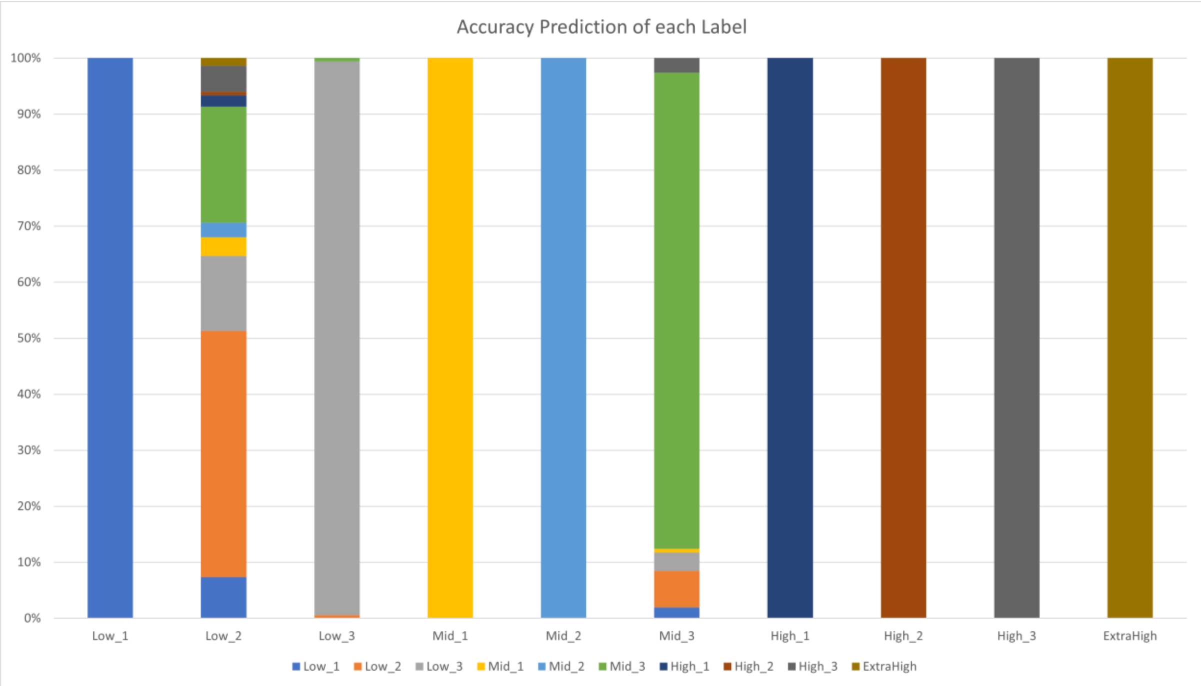

Figure 4.3 Stacked Bar Chart indicating the Accuracy Prediction

4.4.1.1 Hyperparameter Sensitivity Analysis

To measure the sensitivity of the hyperparameters and how much impact each of them have on the performance of the model, their scores on a given run can be compared to understand how changing each of those hyperparameters could have an impact on the model's performance. The main hyperparameters analysed here are the learning rate value or alpha value, the hidden layer size, the activation function, and solver. The research ran many runs so comparing all of those runs is not possible since a different combination of hyperparameters values were used in each run, however, one of the runs were used for this analysis and it was the run that produced the best performing model. For each hyperparameter being compared the rest of the hyperparameter will have the same value to only assess the impact of the hyperparameter being changed.

Alpha Value

The learning rate or alpha value is one of the most important hyperparameters in training a model and changes to it usually affect the performance drastically. The best performing model had a value of 0.01 for the alpha value, a hidden layer size of (250,1), tanh activation function and lbfgs as a solver. For this particular run alpha value was also tried with 0.32 and 0.001. The metric value used to score the performance is the weighted f1-score, the same metric used to evaluate the final result. The comparison is done on the runs where the other hyperparameters were the same values as the ones that produced the best model, meaning hidden layer size is (250,1), solver is lbfgs, and activation function is tanh. When the alpha value was 0.32, the score was 0.829, when alpha value was 0.01 the score was 0.94 and when alpha value was 0.001 the score was 0.921. The results show that changing alpha value with a big margin can cause a noticeable difference in performance. A simple scatter chart displays the results in Figure 4.4.

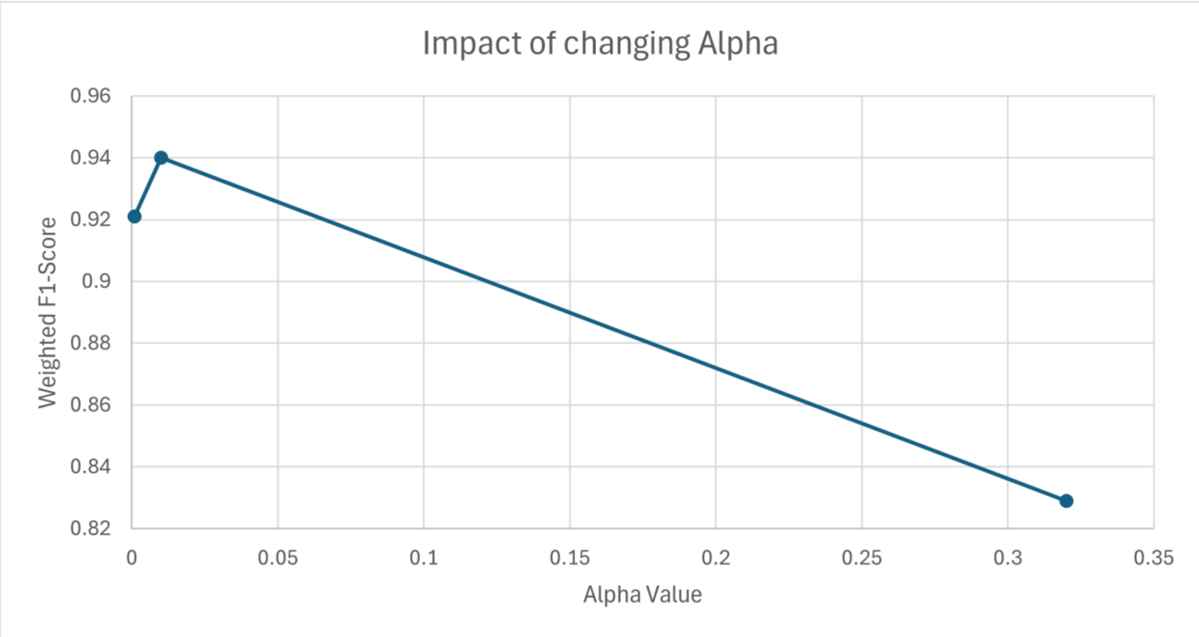

Figure 4.4 Scatter chart showing Model Performance vary when Alpha value is changed.

Hidden Layer Size

Hidden layer size is another crucial hyperparameter in training any neural network. From the same run, there were three values tried which were (200,1), (250,1), and (300,1). The comparison is done based on the existing values of hyperparameters that performed the best model, which means alpha value is 0.01, solver is lbfgs, and activation function is tanh. The model had a weighted f1-score of 0.898 when hidden layer size was (200,1), a score of 0.94 when the hidden layer size was (250,1), and a score of 0.932 when the hidden layer size was (300,1). Figure 4.5 shows a simple bar chart displaying the variations in performance as hidden layer size is changed.

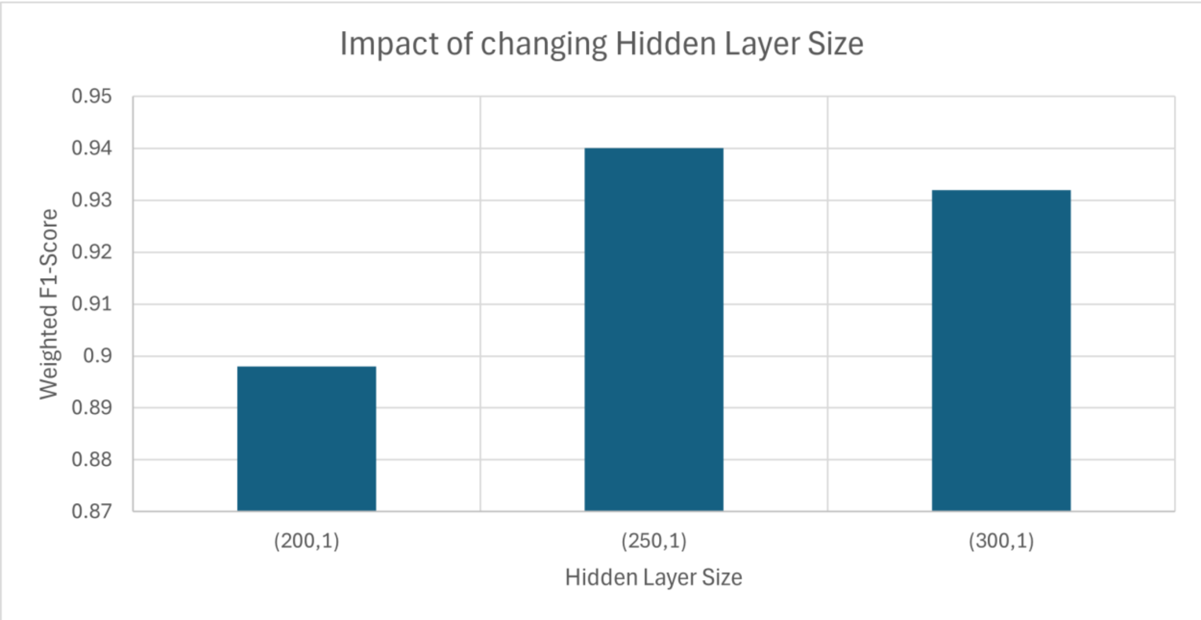

Figure 4.5 Bar Chart showing the variation in Model Performance as Hidden Layer size is changed

Solver

The solver used can also cause the model performance to change since the training method changes with the solver. The three solvers used were lbfgs, adam, and sgd. Similar to the previous two hyperparameters analysed, the comparison was done by keeping the other hyperparameters consistent with the values that produced the best model, meaning alpha value is 0.01, hidden layer size is (250,1), and activation function is tanh. When the solver was lbfgs the weighted f1-score was 0.94, when it was adam the score was 0.856, and when it was sgd the score was 0.8165. Figure 4.6 shows the bar chart with the result.

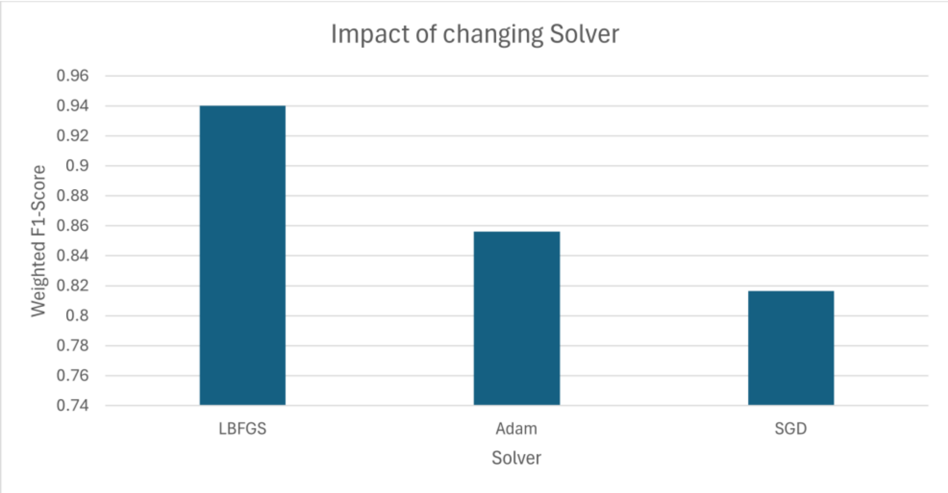

Figure 4.6 Bar chart showing the variation in Model Performance with different solvers

Activation Function

The last hyperparameter analysed is the activation function used, which can also cause changes in model performance based on which one is used. The three activation functions used were tanh, logistic, and relu. In a similar way, the comparison was done by keeping the other hyperparameters consistent with the values that produced the best model., which means alpha value is 0.01, hidden layer size is (250,1), and solver is lbfgs. When the activation function was relu the weighted f1-score was 0.883, when tanh was used it was 0.94, and when it was logistic the score was 0.78. Figure 4.7 shows a bar chart with the result.

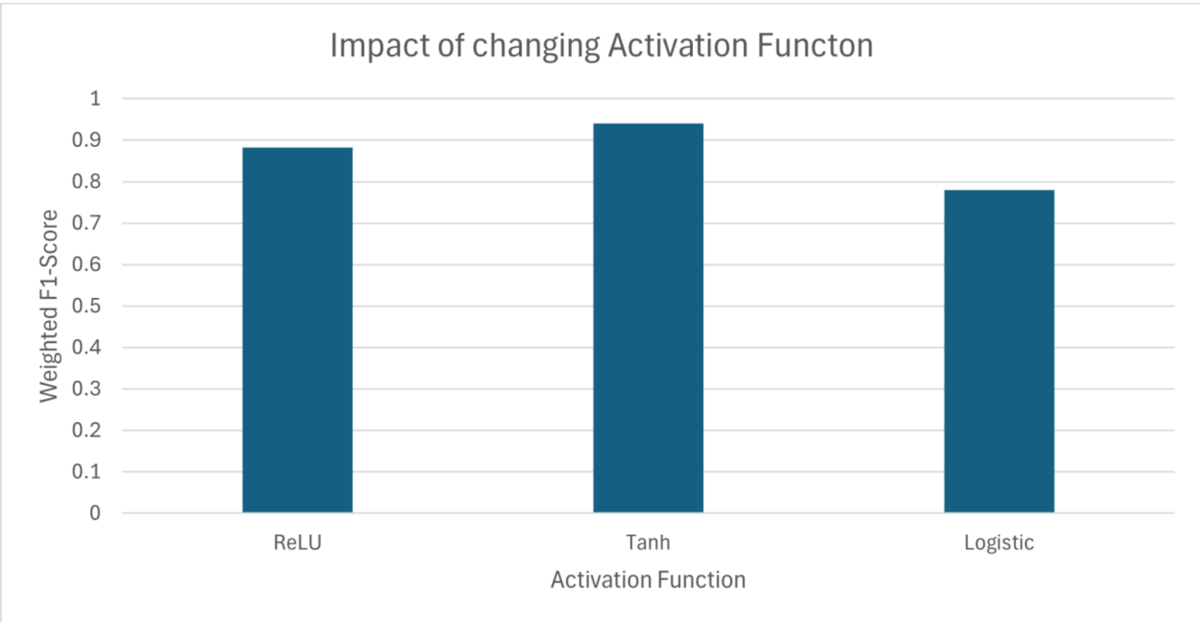

Figure 4.7 Bar Chart showing the variation in model performance with different Activation functions

Based on the above analysis it can be noticed that some hyperparameters had bigger impact than the others, and that is what is usually called as the sensitivity of hyperparameters. The model might be more sensitive to changes in some hyperparameters compared to others. It can be deduced that this model was the most sensitive to the solver being used and the alpha value, as changing these hyperparameters produced the biggest difference in performance. This could be followed by the activation function and then the hidden layer size. Overall, all four hyperparameters play an important role in the performance of the model and should all be treated carefully, however, some hyperparameters were more volatile and caused a bigger difference in performance compared to the rest.

4.4.2 Occupancy Model Evaluation

The occupancy model was evaluated in a different way since it was a regression prediction and not a classification. Regression is tricky to evaluate because in many cases the evaluation metrics might not be giving a good result, but the prediction could actually still be useful and therefore the model is suitable for usage. Therefore, for regression problems the margin of error is measured. There are two main metrics to measure the error which are the mean squared error (MSE) and the root mean squared error (RMSE).

RMSE is used to evaluate this model as it returns the average deviation between the prediction and the target in the same units as the values in the dataset. Given that the occupancy number is in the thousands, the margin of error is acceptable as long as it is in the hundreds. After training and evaluating the model, the RMSE was found to be 160, which is acceptable, considering the fact that the occupancy number is usually between 2000 and 3000. Figure 4.4 shows a scatter plot depicting the actual points in green and the predicted points in purple. It can be seen that the model still manages to get close predictions even when the actual values deviate from the normal average and it does manage to get close predictions to the outlier values as well.

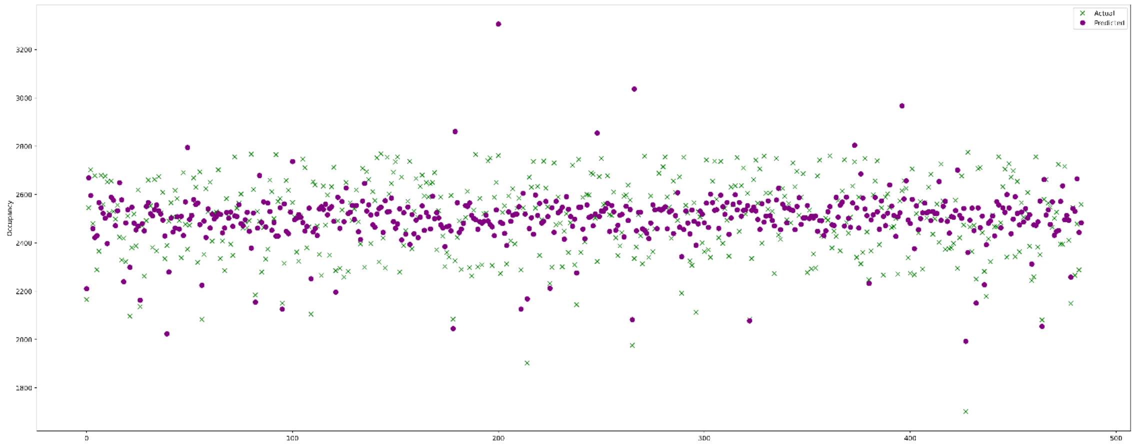

Figure 4.8 Scatter Plot of the Actual and Predicted Values for the Occupancy Detection

4.4.3 Discussion

This research presented a machine learning solution that aims to predict the water charge load that will be required to cool a commercial building the next day. The research focused on predicting the load using external data that is found everywhere and not tied down to a specific sensor type or depending on the model of TES-AC used. The research utilized the power of MLP neural networks in finding complex patterns in data and developed two models that followed a similar design to predict the final output.

The problem was divided into smaller problems to make solving it less complex and to provide a more reliable result. The output of this research could be very beneficial for facility managers handling TES-AC systems as it can greatly reduce their energy consumption. One of the main issues that TES-ACs face is not knowing how much water will be needed for the next day, and as such more or less water might be charged and stored in the water tanks. Storing less water means they have to use the chiller during on-peak hours and increase their energy consumption and storing more means they would have wasted energy cooling more water than they needed. However, a similar solution to the one proposed in this research can provide a more accurate way of knowing what range of water volume the facility managers need to charge for that day which would reduce the instances where the water charged is too low or too high.

4.4.3.1 Limitations

The proposed solution provided satisfactory predictions however it is not a perfect solution but a step in the right direction. One of the main limitations of the proposed model is that it depended on a large amount of data to make predictions. When trained with anything less than a year's data the results were unsatisfactory and therefore more data was needed. This might not always be viable as some TES-AC facilities have not been running for many years, therefore making this solution infeasible for them. The model would need further fine-tuning and improvements to be able to make reliable predictions using less data to train.

Another limitation is that the data was evaluated using the grid search cross-validation method only. Other network parameterizations and hyperparameter search procedures, more extensive search ranges, and finer granularities, could be considered in future work, in order to obtain even better parameter configurations.

The trained model could not be applied in practice because the TES-AC unit was sold before the study concluded. Nevertheless, the model underwent testing with unseen water usage data, ensuring the assessment of prediction accuracy in a suitable manner. Although additional data from the TES-AC would have served as extra test data, it does not diminish the fact that the model was already evaluated using previously unseen data. However, the limitation arises from the model not being tested in practical scenarios and its impact on operational efficiency. For instance, had the model been implemented, it could have quantified the cost savings compared to not using it. This information, unfortunately, could not be derived from historical data and would have been best obtained through practical usage. However, there was no guarantee that the company would agree to conduct practical tests or share financial information.

4.4.3.2 Future Directions

In the future this research could be further improved by allowing the designed model to train using smaller datasets, so that it can get trained using a few months only instead of years. A more thorough hyperparameter search can also be conducted using different types of algorithms like global stochastic optimization methods and with much bigger range values. In addition to that, other external features could be added to the data to improve the training process and provide better predictions. Furthermore, if the model could be improved to remove the reliance on occupancy data it would be a better solution, as the model would not need to rely on a predicted value to make a prediction.

4.5 Deploying the MLP model into an Application for Facility Managers

According to the QCA, for a user-friendly GUI, the features to include based on experts in the field in the application are displayed in Figure 4.9 and 4.10. The experts were asked to fill up a survey to understand their desirable features in a deep learning-based facility management application. As shown in Figure 4.9, the tree map demonstrates the desired features. The participants for the application feature evaluation involved experts aged from 34-60 years (average age 51.8 years), and 14 were males and 1 female. Among 15 experts, 9 were facility managers, 5 were from Civil Engineering and 1 was from Architectural Engineering.

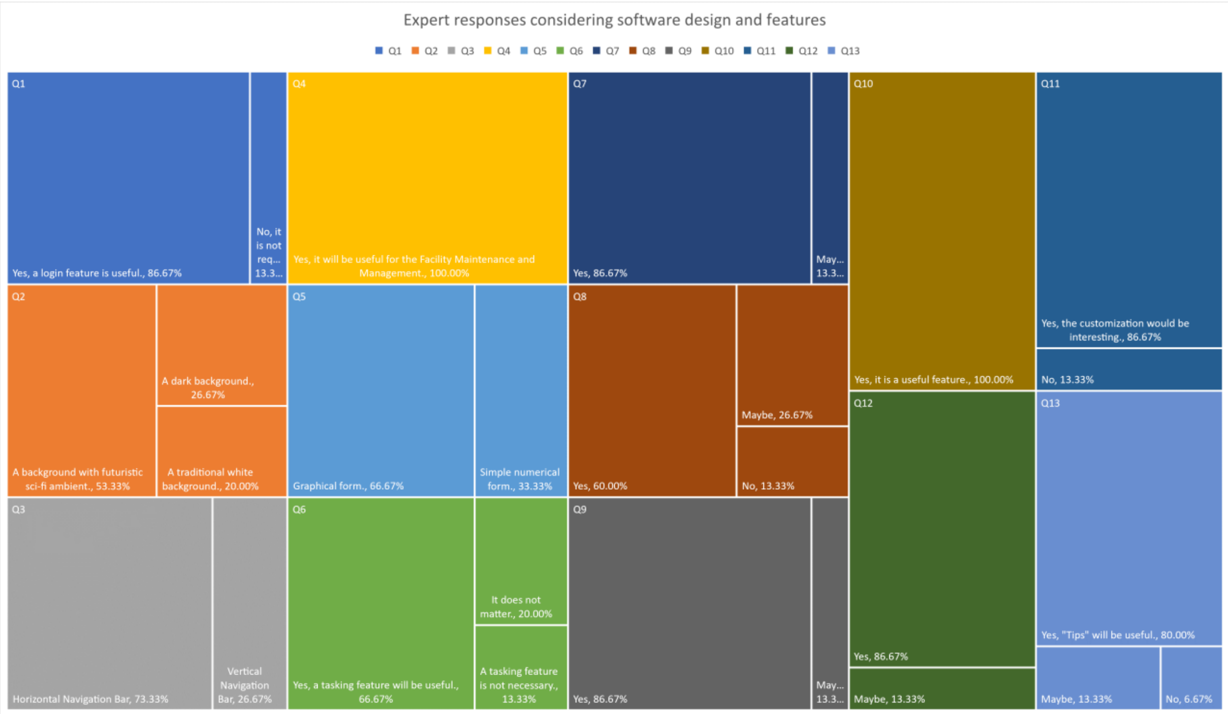

Figure 4.9 Feedback from the experts considering software design and features

Out of the participants, 86.67% of participants suggested a login feature, 53.33% suggested a futuristic sci-fi background whereas 26.67% wanted a dark background. A total of 73.33% of expert participants wanted a horizontal navigation bar. However, all participants mentioned knowing the charging load required will be useful, and 66.67% wanted to view the information in a graphical form and suggested including a tasking feature. 86.67% participants also mentioned that viewing energy efficiency statistics will be useful, 60% participants said that displaying weather data within the application will be beneficial. When asked if more enterprises will be interested in utilizing advanced technologies such as deep learning if they do not require changing or upgrading their equipment, no participants said no, and 86.67% said that more enterprises will be interested. All the participants wanted an import .csv file feature. 86.67% participants mentioned that customization of the application would be interesting. Regarding exporting the information displayed in the application in a pdf file, 86.67% participants suggested it whereas 13.33% said maybe it will be useful. 80% of participants mentioned including a “Tips” tab as it will be useful for staff.

Among the participants who evaluated the developed application, they were mostly of Civil Engineering background i.e., 20 (68.57%), 5 participants were from Mechanical Engineering background, and 4 participants were from Electrical Engineering background. The age range of participants was between 19-32 years with an average age of 24.66 years. The participants were selected to be young individuals as they will be going for jobs and will handle the chores, hence their feedback regarding the application interaction was important. As mentioned earlier, the survey was based on a linear scale of 1-5 where 5 exhibited most satisfaction, and 1 exhibited the least satisfaction. The graphical form of the feedback is shown in Figure 4.10.

Out of the participants, 19 participants i.e., 54.29% showed the most satisfaction, i.e., scale 5 regarding the ambience of the application, and 12 participants i.e., 34.29% chose scale 4. Regarding the login feature, no participants found it complicated and found the application controls easy-to-use. 33 participants i.e., 94.29% chose scale 5 as they found the water volume prediction easy to understand. A total of 29 participants i.e., 82.86% found the graphical efficiency output to be useful, and 30 participants (85.71%) liked the customization aspect of the application. Out of the 35 participants, 25 participants (71.42%) chose scale 5 for changing the controls of the application, and 27 participants (77.14%) found the tasking feature easy-to-use. Regarding the display of tips for facility management of TES-AC, 19 participants i.e., 54.29% chose a scale of 5. A total of 22 participants, which is 62.86% found the displaying of current weather information within the application to be useful. However, 17 participants (48.57%) found that the Import/Export feature to be a necessity for the application as they chose a scale of 5.

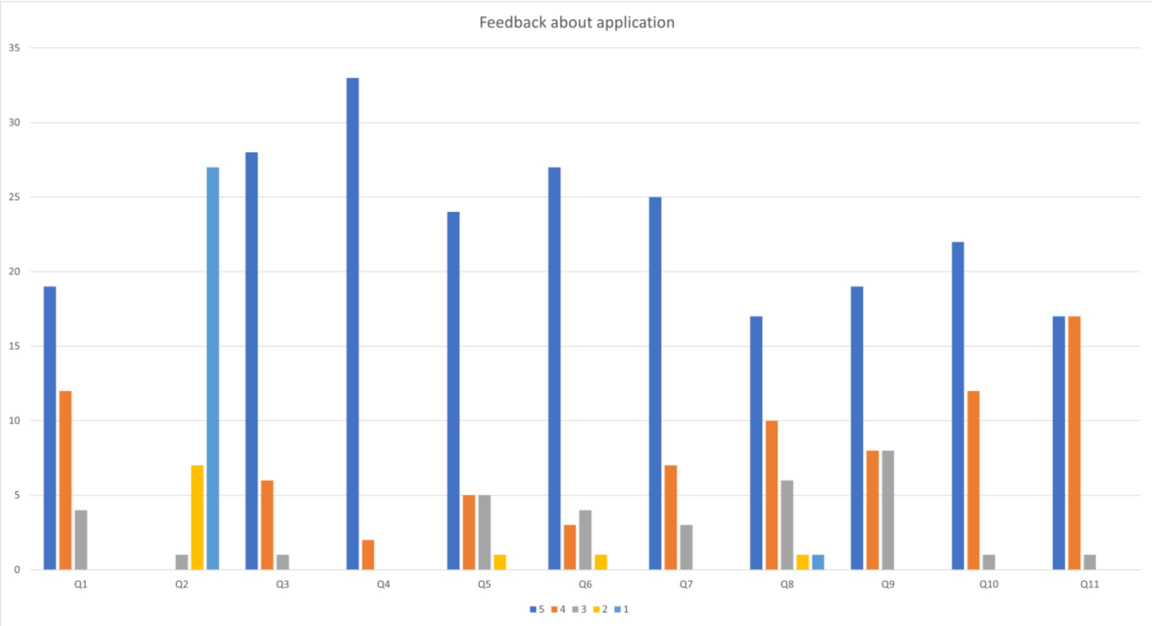

Figure 4.10 Feedback from the participants on the application

4.5.1 Discussion

The facility managers clearly factored the need for a user-friendly application that can predict the charging load required for the next day's use for the commercial building. As charging load prediction will utilize deep learning, the application needs to be developed with the aspect of user-friendly human-computer-interaction. The experts in the facility management field chose certain features to be included in the application. They pointed out that they want a dark futuristic interface for the application which may be because it causes less stress on the eyes. A login feature was suggested by 86.67% as it is an installed desktop application, and it may be useful in data protection. Since 53.33% experts suggested a futuristic sci-fi background and 26.67% experts wanted a dark background, the application was developed with a dark futuristic interface. 73.33% participants wanted a horizontal navigation bar to access the tabs which can be because it is a desktop application, and it is easier to navigate with a horizontal bar. Most of the participants suggested demonstrating energy efficiency statistics and 60% experts suggested displaying weather data within the application for accessibility reasons. A "Tips" tab was also included according to the suggestion.

When the application was tested for the human-computer-interaction aspect by the participants, the overall feedback was positive. This shows initially gathering design guidelines for an advanced application from experts and then developing it is a good approach as it meets the necessary requirements. Among the participants, 88.57% were satisfied with the interface, and 85.71% liked the customization aspect. Also, most of the participants indicated high satisfaction in the user-friendly aspect in switching tabs, using the application, viewing the predicted charging load and statistics. The participants also appreciated the tasking feature and the accessibility of getting to know the "Tips". Based on the analysis after the demonstration of the application developed, it had the necessary features for the GUI and the analysis, these design guidelines demonstrated a satisfactory output.

4.5.1.1 Limitation

The prototype application takes a unique approach in how it was designed, which resulted in positive feedback, however, it might also result in negative feedback. While most people preferred this type of interface, some users might not be very satisfied with the futuristic design and might prefer a simpler black and white interface. This application design would not be very suitable if the users who will be using it prefer the old and traditional way of application designs. It requires the users to be more open to change and be willing to adapt.

4.5.1.2 Future Direction

The application could be further enhanced by turning it into a website that could be accessed from anywhere so that there is no need to install the application every time on the computers. This allows for better productivity and allows the staff to use the application from home. Moreover, the application could be developed as a phone application which allows the users to have access to it anywhere and at any time. However, developing either of these would be time-consuming, or require professionals to develop it.

4.6 Feasibility Study for an Innovative Building with TES-AC and Rainwater Harvesting

The survey collected responses from a diverse group of 21 participants, with the majority falling within the age range of 25-39 (76.19%), while a smaller portion were in the age ranges of 18-24 (9.52%) and 40-60 (14.29%). The survey captured respondents from various countries. The highest representation was from Bangladesh (28.57%), followed by Malaysia and Saudi Arabia (19.05% each). Other countries represented were Egypt, UAE (14.29% each), and Australia, USA, and Canada (4.76% each). The average work experience of the respondents was 2.24 years, with a standard deviation of 0.43. The majority (76.19%) had 1-5 years of work experience, while a smaller portion (23.81%) had over 10 years of experience.

The respondents had diverse job titles, with the most common being Civil Engineer (28.57%), followed by Facility Manager (23.81%) and Project Manager, and Industrial Researcher (9.52% each). Other job titles included Mechanical Engineer, ML Ops Engineer, Machine Learning Engineer, Maintenance Manager, Operations Engineer, Chief Engineer, and Account Manager (4.76% each). This diverse demographic ensures a comprehensive perspective on chiller plants and related topics.

The respondents identified inadequate maintenance (42.50%) as the most common problem impacting the performance and efficiency of chiller plants. Other significant problems included inefficient chiller performance (27.50%) and insufficient cooling capacity (12.50%). A majority of the respondents (57.14%) confirmed that their organizations use chiller plants, while some were uncertain (19.05%) and a smaller portion indicated non-usage (23.81%). Most respondents (57.14%) indicated awareness of Thermal Energy Storage Air Conditioners (TES-AC), while a smaller portion (42.86%) claimed only slight awareness.

From the responses, it can be concluded that the respondents generally agreed on the importance of predicting the water charging load for TES-ACs. The statements related to enhancing operational efficiency, optimizing energy usage, enabling effective resource planning, and aiding in maintenance management received average ratings above 3.00 on a scale of 1 to 5. They also suggested various external data sources for predicting the water charging load of TES-ACs, including occupancy, weather conditions, building load, and maintenance schedules. These sources can provide valuable insights to avoid relying solely on specific sensor data from the TES-ACs. Moreover, they believed that predicting the water charging load in TES-ACs would have a positive impact on reducing carbon emissions, with an average rating of 3.33 out of 5.

Most respondents (80.95%) considered it important to use harvested water to supply TES-AC facilities, highlighting its potential to reduce costs compared to pumping water from external sources. Also, most of them (71.43%) were aware of rainwater harvesting techniques, indicating a certain level of familiarity with this approach. The cost involved in implementing rainwater harvesting techniques and machine learning prediction on TES-AC water charging load was deemed worthwhile by a majority (57.14%) of respondents, with 28.57% suggesting that it might be worth it. The opinions were divided regarding the potential reduction of flood risks during heavy rainfall through the adoption of water harvesting techniques by multiple commercial buildings or factories. While 57.14% indicated that it might have a positive effect, 19.05% were uncertain and 23.81% expressed skepticism.

Respondents recognized several advantages of using harvested water for TES-AC facilities, including environmental benefits, cost savings, and the provision of water during drought periods. The identified disadvantages of rainwater harvesting included high initial costs, storage limits, and the unpredictability of collection amounts. Some respondents also mentioned the need for expensive filtration systems. The feasibility of using underground water storage tanks for rainwater harvesting in commercial buildings was seen as a possibility by 57.14% of the respondents, while 28.57% were uncertain. The respondents highlighted challenges such as data availability and quality, integration with existing systems, maintenance and monitoring, and stakeholder acceptance and adoption when implementing rainwater harvesting techniques and machine learning prediction for TES-AC water charging load. Finally, to support the implementation of water harvesting techniques and machine learning prediction for TES-AC water charging load, respondents suggested investing in research and development, providing infrastructure and technology support, and encouraging collaboration and partnerships.

We can explore the relationship between the importance of predicting water charging load for TES-ACs and the respondents' awareness of TES-AC. Performing an independent samples t-test, we find that respondents who are aware of TES-ACs ($M = 3.29$) perceive a significantly higher importance of predicting water charging load compared to those who are not aware ($M = 2.50$), $t(20) = 2.23$, $p < 0.05$. This suggests that awareness of TES-ACs may influence the perception of the importance of predictive modeling for water charging load. We can examine the relationship between the importance of using harvested water and the respondents' opinion on the cost-benefit analysis of rainwater harvesting techniques and machine learning prediction. Performing a one-way ANOVA, we find a significant difference in the mean importance ratings between the three groups ($F(2, 18) = 4.25$, $p < 0.05$). Post-hoc analysis using Tukey's HSD test reveals that respondents who consider it less important ($M = 1.75$) differ significantly from those who find it important ($M = 2.53$) or believe it might be worth it ($M = 2.92$). This indicates that the perceived importance of using harvested water is related to the opinion on the cost-benefit analysis.

4.7 Summary

From the first step when the common ML algorithms were compared for cooler condition prediction accuracy, Multilayer Perceptron (MLP) proved to be a suitable algorithm for HVAC related dataset for both classification and regression. In section 4.2, the findings from analysing several ML algorithms were discussed along with the pros and cons of using each. In the second step in section 4.3, whether there are external factors that impact the TES-AC chiller were determined and according to the findings, weather factors such as temperature, humidity and atmospheric pressure, occupancy, and the day of the week had an effect on the TES-AC charging load requirements.

The next step involved developing an MLP model for predicting charging water load needed for operating a TES-AC of a commercial building. The findings in section 4.4 showed the model proved to be efficient with an average accuracy of 93.4%. Furthermore section 4.4 carried out an extensive discussion about the MLP model and it can be mentioned that it has potential to significantly assist facility managers and optimize building energy consumption. The following step involved gathering design guidelines for deploying the developed MLP model in a user-friendly application that the facility managers can use, and section 4.5 evaluates the application design guidelines to be user-friendly and for facility managers to find it useful.

Finally, the feasibility study conducted with the experts provided an overview on the future directions of this research and explored the scopes of the research findings. The expert findings highlighted the importance of using innovative techniques to battle climate crisis and contribute positively to the environment.

Chapter 5 Conclusion

The first objective to find the most suitable ML algorithm to use for HVAC dataset in predicting cooler condition was achieved by comparing common ML algorithms where MLP was proven to be the most suitable in the context. The second objective was to determine external factors that impact TES-AC chillers. Based on the results and the discussion, these results have shown evidence that external weather data has an impact on the water consumption of TES-AC. However, some of the weather metrics have more impact than others. According to the results, humidity had the biggest impact on the water consumption followed by temperature and finally atmospheric pressure. Incorporating weather data as features in a machine learning solution to forecast the chiller's water charging load for the following day appears to be a sensible approach that could potentially yield satisfactory results.

The research does not by any means reject any other external factors as having an impact on water consumption, however, weather does have a significant effect. Including weekends and public holiday data could still be beneficial, mainly because weekends seem to increase with water consumption and that could be helpful for deep learning models. Deep learning models have the ability to find patterns in complex data with complex relationships. By including weather data alongside weekends and public holidays, a solid foundation for a deep learning model to predict the water charge for the next day might be achieved.

It also must be noted that this research was conducted on a chiller in Malaysia, where the difference in temperatures between the maximum and minimum over 2418 days was only 10 degrees Celsius. Based on the findings, this research suggests that data in cities or countries that have more significant differences in weather data could yield more obvious results and show the impact of weather data more clearly. For example, many cities in Europe would have average temperatures of 25 degrees Celsius in the summer, and temperatures as low as –2 degrees Celsius (or lower) in the winter. With more obvious temperature changes, water consumption values might vary across a broader range and might be easier to analyse if research is conducted in such areas.

TES-ACs can be very beneficial to the environment in the long run, however, there are concerns when it comes to operating them as the way in which they are used could either save a lot of money or increase the costs substantially. Many stakeholders are hesitant to make the shift to TES-AC because they cannot guarantee its operational efficiency and are looking for short-term solutions. Deep learning has been used to solve many complex real-life problems and optimizing TES-ACs should be one of them. The more efficient operation of TES-ACs will not only reduce costs in many commercial buildings but will also contribute positively to the environment. In a time where the global climate crisis is at its peak, the need for technological innovations to ease the burden on our planet should be clear.

The third objective was to develop an ML model with MLP to aid facility managers in forecasting the daily water charging load required for operations in a commercial building, relying solely on external factors, and subsequently assessing the model's performance. The research demonstrated that by running a thorough grid search on an MLP neural network and using only external data like weather data, days data, and occupancy data it is possible to develop a well performing deep learning model to predict the water charging load of TES-AC. The model had an average accuracy of 93.4%. The achieved prediction accuracy opens the door to deploying such a model in practical, real-world scenarios. Accurate forecasting of water charging loads holds the potential for significant energy savings by mitigating the risks associated with both overcharging and undercharging. Manual estimation of the charging load often leads to these inefficiencies. The precise prediction offered by the model could revolutionize the operational efficiency of TES-ACs. This improvement extends to the reduction of undesirable heat emissions resulting from chiller overuse, ultimately curbing energy consumption. This not only alleviates stress on the energy grid but also translates into cost savings for the operator.

Moreover, the prospect of lowering energy costs serves as a compelling incentive for a wider adoption of TES-ACs among stakeholders. This broader adoption, in turn, could have a substantial positive impact on the environment. The cumulative effect of reduced energy consumption and improved operational efficiency contributes to a greener approach, making TES-ACs an attractive and environmentally friendly choice.

Improving on this research can result in robust deep learning neural networks that can adapt to many TES-ACs and provide accurate predictions that eventually leads to the usage of machine learning in TES-ACs, a standard which would eventually result in more people shifting to TES-ACs to reduce their costs and resulting in a green choice of ACs. The research outlined how MLP networks can be useful to predict the water charging load, but the work is far from over. More research is needed to further improve such models and to find more features that can help in these predictions.

The fourth objective is to research a suitable way to deploy the developed MLP model in a user-friendly application for the facility managers to use to benefit from the powerful predictions of ML. This research objective determines the appropriate features to be integrated with a user-friendly GUI for the application for facility management and maintenance of TES-AC that can be used by facility managers and deduces the validity of the human-computer interaction aspect of the application. Furthermore, this study contributes to being a possible approach for gathering design guidelines for an advanced application as the expert suggestions demonstrate satisfaction from the users when included into the application. By using the deep learning-based application, facility managers will be able to prepare in advance regarding the charging load, handle maintenance schedule, allocate tasks, and even prepare for maintenance with suggested tips increasing labor and building efficiency. Also, the design guidelines collected for the deep learning-based application for facility management and maintenance of TES-AC will be beneficial for future researchers and developers who wish to apply computational intelligence for assisting facility managers make better management decisions through a user-friendly software.

Finally, a feasibility study discussing a proposed concept where a commercial building facility will operate using TES-AC with the developed MLP model and rainwater harvesting technique is conducted with international experts. The survey collected data that was useful to understand the scope of the research and to understand the potential applications where sustainable energy can be used to benefit the environment and facility management industry with computational intelligence. This step essentially highlights the research scope and its possible future directions.

It can also be seen that the awareness of TES-ACs influences the perceived importance of predictive modeling for water charging load. The importance of using harvested water is related to opinions on the cost-benefit analysis, indicating that those who consider it less important have different views compared to those who find it important or believe it might be worth it. The idea showed potential but had drawbacks that are important to address. This work addressed an idea and received feedback that should encourage further research to investigate a potential solution. While there are risks, the benefits could be very trivial, especially when the climate crisis is at its peak.

As with any research endeavor, this study has its set of limitations and areas that warrant enhancement. Several improvements could enhance the precision and applicability of this research. For instance, training a model on a TES-AC located in a country characterized by substantial weather variations could offer deeper insights into the influence of weather conditions on water consumption in TES-ACs. Exploring these differences may lead to a more nuanced understanding of the model's performance across diverse climates.

Furthermore, an avenue for refinement lies in the practical application of a trained model for predictions over a specific timeframe. This would involve comparing energy costs when utilizing the model against scenarios where the model is not employed. Such a comparative analysis could yield valuable insights, allowing for the quantification of the actual impact of using the predictive model. Determining the cost-effectiveness and operational benefits of the model in a real-world setting would enhance its practical utility and inform stakeholders about the tangible advantages of adopting such predictive technologies.

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