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Data-Driven Energy-Efficiency and Comfort Optimisation in Indoor Environments

Giacomo Segala

Advisor

Dr. Domenico Siracusa

Fondazione Bruno Kessler, Università degli Studi di Trento

Co-Advisor

Dr. Roberto Doriguzzi-Corin

Fondazione Bruno Kessler

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Abstract

Climate change, uncertainties in energy prices, and the Covid-19 pandemic have significantly reshaped building management, highlighting the need for energy-efficient, safe, and comfortable indoor environments. With advancements in Internet of Things (IoT) sensors and Artificial Intelligence (AI) techniques, optimising building performance now includes forecasting key parameters and intelligently controlling Heating, Ventilation and Air Conditioning (HVAC) systems. However, existing studies often lack practical applicability in real-world scenarios, typically relying on extensive data collection or tailored physical/mathematical models, with limited focus on deployment, scalability, and long-term performance.

This thesis addresses the problem from a different angle, proposing an adaptive and practical AI-based solution for energy-efficient comfort optimisation in indoor environments. The designed approach continuously learns from the monitored environment through collected data and requires minimal human effort for configuration and maintenance. The contributions are as follows: i) a method for accurately predicting key parameters using a limited window of data, with a dynamic mechanism to keep the AI model current with environmental changes and operational in a short time frame, and ii) a novel algorithm called EECO for automated and intelligent HVAC control, driven by continuous short-term decisions based on long-term predictions to balance thermal comfort and energy consumption, with no need for preliminary knowledge of the local environment.

Evaluation results demonstrate that the proposed approach achieves high prediction accuracy, ensures desired thermal comfort, and reduces the energy footprint by up to approximately 16% in a real-world environment, in addition to potentially saving on operating costs.

Keywords

[Thermal Comfort; Energy Efficiency; Artificial Intelligence; Automated HVAC Control]

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Acronyms

AI Artificial Intelligence.

ANN Artificial Neural Network.

API Application Programming Interface.

BDExp Business Development Experience.

BEMS Building Energy Management Systems.

CNN Convolutional Neural Network.

CO_2 Carbon Dioxide.

DCV Demand-Controlled Ventilation.

DL Deep Learning.

EECO Energy-Efficient Comfort Optimisation.

ESCO Energy Service Company.

GEM Genius Energy Manager.

HVAC Heating, Ventilation and Air Conditioning.

IAQ Indoor Air Quality.

IoT Internet of Things.

LSTM Long Short-Term Memory.

MLP Multi-Layer Perceptron.

MPC Model Predictive Control.

NLP Natural Language Processing.

PM Particulate Matter.

PMV Predicted Mean Vote.

ppm parts per million.

RMSE Root Mean Squared Error.

SP Set Point.

VOC Volatile Organic Compound.

VRV Variable Refrigerant Volume.

Never say never, because limits, like fears, are often just an illusion. (Michael Jordan)

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Chapter 1

Introduction

1.1 Scenario and Motivation

Buildings take a central role in global energy dynamics, contributing to 30% of the world's total energy consumption and accounting for approximately 26% of global energy-related emissions [1]. Since 2015, these emissions have exhibited a consistent growth trend, increasing at an average rate of 1% annually [2]. A significant portion of this energy consumption is primarily due to heating and cooling demands across industrial, commercial and residential sectors. Notably, Heating, Ventilation and Air Conditioning (HVAC) systems alone account for 32% of energy use in residential buildings and 47% in the tertiary sector [3]. In light of challenges posed by climate change and the escalating energy prices, the demand for energy-efficient buildings has become increasingly crucial over the past decade.

The Covid-19 pandemic in 2020 slightly reshaped this scenario, highlighting the critical need for safe and healthy living and working environment beyond mere building energy efficiency. As a result, sustainable buildings have become essential not only for addressing environmental concerns but also for economic and public health reasons. This shift in perspective has highlighted the importance of ensuring thermal comfort in response to changing occupancy patterns and indoor environmental conditions while reducing energy consumption. Governments, regulatory agencies and public bodies have been actively promoting policies and measures aimed at achieving healthy and energy-efficient buildings. A prominent example is the Directive (2018/844) [4] developed by the European Parliament, which underlines the importance of guaranteeing sustainable environments through enhanced energy performance. Additionally, the adoption of green building certifications such as LEED (Leadership in Energy and Environmental Design) and BREEAM (Building Research Establishment Environmental Assessment Method) has grown significantly, drawing the interest of managers and owners to introduce innovative technologies that reduce environmental impact while improving occupant well-being.

The increased interest in sustainability, combined with advancements in technology, has facilitated the deployment of advanced software solutions commonly known as Building Energy Management Systems (BEMS) in buildings. They support facility managers and owners of modern and existing buildings in meeting the increasingly stringent requirements for energy efficiency and thermal comfort [5]. Originally designed for real-time monitoring of energy and environmental parameters, the integration of cutting-edge technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) into modern BEMS has become increasingly relevant in shaping the future of building management. By leveraging large amounts of data collected from indoor environments through a wide range of sensors and communication protocols (e.g., Modbus in industrial sites, BACnet in tertiary buildings), these systems offer a range of functionalities aimed at optimising building performance. Key features typically include predictive analytics, anomaly detection and advanced control algorithms. This allows for dynamic adjustment of heating, ventilation, and air conditioning (HVAC) systems, chillers, or other energy-hungry systems, resulting in more informed decision-making and enhanced control of local devices. For instance, AI algorithms can effectively predict energy demand and environmental parameters based on current and historical data collected from IoT sensors, using this information for providing relevant feedback for optimal control.

In such scenario, research and development of new intelligent and innovative technologies within BEMS are fundamental to achieve sustainable, efficient and healthy environments. This ongoing innovation holds the potential to significantly reduce the environmental footprint of both modern and existing buildings, contributing to global efforts to mitigate climate change and improving thermal comfort for people.

1.2 Research Challenges

Optimising indoor environments involves a wide range of tasks, each presenting unique research challenges. Our research has been focused on two critical tasks of building optimisation: forecasting of key parameters and optimising HVAC devices.

One of the key aspects of building optimisation is the ability to predict the future behavior of key parameters within the environment. The literature extensively studies solutions for predictive analytics, proposing different AI techniques with the aim to accurately forecast the variables of interest (e.g., indoor temperature, CO_2 levels, energy consumption). To cope with this task, research studies typically rely on a large amount of data, requiring potential extensive data collection locally to train AI models. For instance, Kallio et.al. [6] addressed the forecasting of indoor CO_2 levels using data collected throughout a whole year from different environments. Similar approaches are adopted in other studies focusing on different variables. A major challenge in this area lies in developing an approach that minimises the prediction error without compromising the practical applicability. This primarily involves ensuring rapid system deployment and maintaining high accuracy over time, which is particularly crucial from a business perspective.

Another primary task in optimising indoor environments is the intelligent control of HVAC devices. As discussed earlier, recent years have seen a focus on rational energy usage while optimising indoor comfort levels. Understanding the behaviour of key parameters within the indoor environment in response to specific HVAC configurations is crucial for this task. Solutions proposed in the literature typically employ physical or mathematical models tailored to the monitored environment, requiring significant manual effort to model different aspects (e.g., layout, materials, location, installed HVAC machinery). These approaches also need potential ongoing adjustments to account for changes within the monitored environment, posing clear challenges for facility managers or owners overseeing a large number of buildings. Additionally, simulated or calculated models might not accurately replicate the behaviour of real-world environments, which can be affected by unexpected events. Given the large amount of data regularly collected from buildings through IoT sensors, the research challenge is to propose innovative and actionable data-driven approaches. These should ensure scalability, ease of maintenance and long-term performance, enabling a direct assessment of HVAC control decisions' impact in real scenarios. This aligns with a priority in this research area: the validation of AI-based control solutions in real-world environments, as underlined by Ngarambe et.al. [7].

In summary, the optimisation of indoor environments involves forecasting key parameters and intelligently controlling HVAC systems, with the additional challenge of potentially ensuring interoperability between these two operations. Both forecasting and optimisation present unique challenges that require innovative solutions to ensure accuracy, ease applicability, and scalability.

1.3 Contributions and Outline of the Thesis

This thesis aims to provide a tangible contribution to building sustainability. In line with current research directions, the overall objective is to improve occupant comfort while minimising the energy footprint caused by heating and cooling operations. Unlike existing studies, this thesis presents a practical approach that is readily applicable in real-world scenarios. The proposed solution continuously adapts to the monitored environment through collected data and requires minimal human effort for deployment and long-term performance. This bridges the gap between theoretical research and practical application, which often misses in the literature.

Considering the complexity of the topic, a systematic approach is used, breaking the problem into multiple steps. Initially, we direct our focus towards forecasting energy and environmental parameters. Accurate predictions of indoor environments over time are crucial for mitigating potential critical issues and making informed decisions. This is achieved by using a sliding window of recent historical data to keep the AI model current with environmental changes over time. This predictive capability is integrated within an intelligent algorithm capable of automatically selecting the HVAC configuration strategy that optimises thermal comfort while minimising energy consumption. Specifically, the forecasting approach is used to continuously evaluate the environmental and energy impact of a set of possible device configurations (ON/OFF, set point) for the near future, learning and adapting to changes within the environment based on collected data.

In addition to simulations, the final solution is validated through experiments conducted in a real-world scenario. Specifically, it has been tested within the warehouse of a small production plant belonging to an International retail company located in northern Italy, a direct customer of Energenius. This real-world validation demonstrates the effectiveness of the designed forecasting approach and AI-based control algorithm, as the environmental responses reflect predicted impacts studied during the decision-making process.

From a practical perspective, the main contributions of this thesis are twofold:

1. A practical approach for accurately predicting key parameters within indoor environments using a limited window of collected data, thus avoiding extensive data collection periods. The AI model remains updated over time through an adaptive mechanism called mobile window, resulting in a potential zero-touch solution for forecasting desired parameters in indoor environments.

2. A novel algorithm, named EECO, to intelligently control HVAC devices in an automated way. The goal is to optimise thermal comfort while minimising energy consumption within indoor environments. The designed solution continuously learns from the monitored environment to select an efficient HVAC configuration through short-term decisions based on long-term predictions of the environment, with no need for any preliminary information (e.g., installed HVAC devices, layout, and materials) or intervention of expert personnel.

At a high level, this research can significantly reduce the carbon footprint of buildings caused by HVAC systems, improve occupant comfort, and lower the operating costs required to maintain thermal comfort, meeting growing demands in the industry. The final solution's potential applicability to any building equipped with a control system that collects environmental and energy consumption data and interfaces with local HVAC devices opens new business opportunities for Energenius, as discussed in this thesis.

1.4 Structure of the Thesis

The remainder of this thesis is organised as follows:

- In Chapter 2, we present an overview of existing research focused on optimising building performance in terms of energy efficiency and environmental sustainability. This Chapter highlights the potential for advancing Building Energy Management Systems (BEMS) capabilities through innovative technologies such as Internet of Things (IoT) and Artificial Intelligence (AI), while also identifying high-level gaps in the literature that this thesis aims to address.

- In Chapter 3, we delve into the problem of forecasting key parameters in indoor environments. In contrast to purely performance-oriented solutions commonly proposed in the literature, we tackle the problem from a different angle, proposing a practical and adaptive approach capable of achieving comparable prediction accuracy using a limited amount of data over time.

- In Chapter 4, we address the intelligent control of HVAC devices for optimising indoor environments. We introduce EECO, a practical and automated solution that requires no prior information of the local environment (e.g., installed HVAC devices, building features) nor the intervention of expert personnel. This solution continuously selects an efficient HVAC configuration in terms of ON/OFF and set point to ensure the desired thermal comfort while minimising energy consumption.

- In Chapter 5, we analyse the business impact derived from the research contributions of this thesis, particularly as applied in the business domain of Energenius, the host company. This analysis aims to demonstrate how the research outcomes (i.e., the forecasting and optimisation approaches) can positively impact business operations and create new opportunities.

- Chapter 6 provides conclusions, summarising the key findings of this research. It also highlights open issues and challenges that require further investigation.

Chapter 2

State of the Art

This chapter presents an overview of existing research dedicated to improving building management from environmental and energy perspectives. This research area aims to advance the functionalities of Building Energy Management Systems (BEMS) by leveraging innovative technologies such as Internet of Things (IoT) and Artificial Intelligence (AI). By integrating and enabling interoperability between these advanced technologies, the research seeks to optimise building operations, improve energy efficiency, and create more sustainable and comfortable indoor environments, in line with with the recent needs outlined in Chapter 1.

The deployment of IoT-enabled smart sensors and meters for regular data collection takes a central role in developing advanced solutions for efficient building management. By harnessing the power of IoT, these sensors and meters provide real-time data that is crucial for developing intelligent functionalities within buildings (e.g., optimising energy usage, enhancing indoor comfort, facility management [8]). As investigated by Jia et.al. [8], a typical IoT-based solution consists of three layers, in particular: i) the perception layer, responsible for sensing and data collection; ii) the network layer, responsible for data transportation through a wide range of communication protocols (e.g., Modbus, BACnet, Zigbee, MQTT); iii) the application layer, which offers intelligent data management and processing.

Mataloto et.al. [9] exemplify this approach by proposing an IoT open-source layered platform to monitor indoor environments. The data collected through the platform is not only used to provide critical feedback for cost reduction but also to facilitate direct control and interaction with existing lighting, heating and cooling systems. This highlights the multiple benefits of adopting advanced software solutions such as BEMS. However, in their case, the local devices are managed through automation rules that are manually defined by users based on their own analysis of the collected data. This manual approach, while useful, has clear limitations in scalability and accuracy, especially when dealing with large and complex datasets. The challenge remains to move beyond manual operations towards more automated and intelligent control solutions.

Similarly, Marinakis et.al. [10] attempt to address this issue by developing an IoT-based solution that integrates heterogeneous real-time and predicted data (e.g., energy production, energy prices, weather data, end-users' behaviour) to generate daily and weekly action plans for building occupants. This approach promotes energy efficiency and enhances indoor comfort, highlighting the advantages of IoT-based solutions in BEMS for integrating and correlating raw data from different sources to provide actionable insights. However, while their system offer suggestions for improved building management, it does not automate the control of local devices (e.g., Heating, Ventilation and Air Conditioning (HVAC) units), leaving the task of execution to human operators.

Finally, scalability, in terms of both sensors and environments, is a key feature for BEMS in order to manage multiple indoor environments or buildings effectively. In this regard, Terroso-Saenz et.al. [11] address this need by proposing an IoT platform for the management and analysis of energy data. Their solution is validated in a real-world pilot with several buildings and involving many sensors, highlighting the importance of scaling and adapting to different scenarios.

Alongside IoT technologies, Artificial Intelligence (AI) is fundamental for extracting valuable information from collected data. AI introduces innovative approaches to develop smart BEMS, enabling the generation of useful knowledge (e.g., occupancy behavior, fault detection, energy usage patterns) to enhance building control [12]. This approach aims to overcome the limitations of manual data analysis, which might overlook patterns, correlations, and trends that AI models can efficiently detect. For instance, forecasting the occupancy behaviour might be crucial for building energy simulations, innovative control strategies, and management practices. Yuan et.al. [13] emphasize this aspect, proposing a machine learning approach for detecting occupancy patterns and forecasting building occupancy, with the aim to optimise the use of renewable energy sources.

As we delve into next sections, forecasting the indoor parameters through AI-based solutions is crucial for building optimisation. Commonly predicted parameters in building environments include energy consumption [14–16], indoor temperature [17, 18] or indoor CO_2 levels [6, 19–21]. A number of deep learning architectures, including Convolutional Neural Network (CNN), Multi-Layer Perceptron (MLP), and Long Short-Term Memory (LSTM), are explored, considering different input variables. As discussed in Chapter 3, these solutions typically require extensive data collection before model training and deployment, with limited attention to periodic updates. These limitations could be addressed by adopting a potential zero-touch forecasting approach for indoor environments, which autonomously updates AI models and generates predictions, thus reducing the need for manual intervention.

AI also supports the detection of abnormal energy consumption patterns and faults in HVAC systems. In the first case, different research works are proposed in the literature. For instance, Himeur et.al. [22] demonstrate the effective interoperability between IoT and AI. The authors collect power consumption data from different appliances, along with occupancy patterns. They employ a micro-moment paradigm to label power consumption datasets, discriminating among different categories. Finally, a deep neural network architecture is used to identify abnormal consumption classes in an automated way. Regarding HVAC devices, BEMS typically include extensive building operational data from local systems, hence providing the opportunity to develop robust, data-driven solutions for anomaly detection applied on building energy data. Fan et.al. [23] highlight this research direction, proposing an autoencoder-based ensemble method for anomaly detection. They discuss the advantages of AI techniques, with a particular attention for autoencoders (i.e., a type of artificial neural network), for analysing complex, high-dimensional energy data and detecting critical behaviours.

While AI-driven methods provide valuable insights for improving building performance, they often require manual analysis to derive actionable steps for mitigating potential issues. A more advanced approach involves integrating AI-based systems that not only analyse data intelligently (e.g., to optimise indoor comfort while minimising energy consumption) but also directly control local devices in real-time. This automation reduces the need for human intervention, allowing facility managers to lower operating costs, simplify building management, and improve overall system efficiency. In recent years, numerous research efforts have focused on balancing energy consumption in HVAC systems with maintaining optimal indoor comfort for occupants, often interfacing directly with local devices. Different AI-based methodologies have been explored to achieve this balance, which will be explored in detail in Chapter 4. However, many of these approaches rely on ad-hoc physical or mathematical models (e.g., [24–29]), which require significant manual effort for both short-term deployment and long-term maintenance, especially when managing multiple sites. Additionally, some methods depend on simulated environments (e.g., [26, 28–31]), presenting challenges in scaling and ease of implementation in real-world scenarios. Further details on the state-of-the-art solution for forecasting and optimising indoor environments are discussed in Chapter 3 and 4, respectively.

Recent advancements in in IoT and AI research have driven the development of different commercially available solutions aimed at optimising buildings and indoor environments from an energy and/or environmental perspective. Some of these solutions, briefly introduced in Chapter 5, include EnergyCAP SmartAnalytics [32], Enterprise Data Xchange (EDX) [33], Powerhouse Dynamics' SiteSage [34], Spacewell Energy Platform (Dexma) [35] and Energis.Cloud [36]. These platforms are proposed in the market and primarily focus on automated data analysis, providing actionable insights into indoor environmental conditions and energy usage. However, while these systems offer valuable information, most still require manual intervention for operational decision-making or strategy implementation. Although some tools provide direct control over HVAC systems, they often involve manual scheduling or static rules of HVAC operations. Additionally, they often lack the ability to automatically balance energy consumption with occupant comfort, a key factor for achieving optimal performance. The potential for further improvement lies in enhancing the automation across all stages, from data collection and advanced data analytics to the development of intelligent algorithms that dynamically optimise both energy efficiency and occupant comfort, while autonomously controlling HVAC devices. Integrating real-time predictive capabilities combined with automated control of local devices would reduce manual effort, improve building management and promote sustainability.

In conclusion, the integration of AI and IoT enable BEMS to transform raw data into predictive and actionable information, resulting in reliable and intelligent building management. The synergistic use of these technologies facilitates advanced functionalities (e.g., forecasting, optimisation) that enhance energy efficiency, optimise building operations, and ensure sustainable and comfortable indoor environments in an automated way.

Chapter 3

Forecasting Environmental and Energy Parameters

Accurately forecasting changes in environmental parameters and energy consumption is crucial for optimising building management. Predictive information allows building managers and owners to anticipate and respond to fluctuations in indoor conditions, either through manual operations or advanced solutions that optimise HVAC systems. Effective forecasting enables proactive decision-making, which can lead to significant energy savings, improved thermal comfort, and enhanced occupant health and productivity. The ability to predict these changes is increasingly important as buildings grow in complexity and requirements in terms of energy efficiency and indoor comfort become more stringent, as discussed in Chapter 1.

In this chapter, we explore this topic from a different angle, proposing a practical and adaptive methodology for predicting environmental parameters and energy consumption in indoor environments. Initially, we delve into forecasting a single variable, which helps us to break down the considered problem into multiple steps. Given its significant impact on IAQ, especially highlighted during the Covid-19 pandemic, and its notable interest in research literature, we direct attention to indoor CO_2 levels (Section 3.3). Subsequently, we extend the designed methodology to predict multiple variables of interest within the indoor environment, including temperature, humidity, as well as energy consumption due to HVAC devices (Section 3.4).

This chapter is mainly based on our published paper "Segala, G.; Doriguzzi-Corin, R.; Peroni, C.; Gazzini, T.; Siracusa, D. *A Practical and Adaptive Approach to Predicting Indoor CO_2*. Appl. Sci. 2021, 11, 10771." [37].

3.1 Motivation

While solutions proposed in the literature mainly focus on maximising prediction accuracy through different AI techniques, a purely performance-oriented approach (i.e., which primarily focuses on prediction accuracy) might limit the applicability of such solutions in real-world scenarios. High performance typically requires a significant amount of data collected over extended periods (both in forecasting environmental parameters such as CO_2 [6, 19–21] and energy consumption [14–16]) or complex input variables from expensive, cutting-edge sensors [21, 38], which are not always readily available. This scenario typically necessitates data collection over many days or even months before training AI models, resulting in lengthy wait times for full system deployment and making it unattractive from a business perspective.

Additionally, the challenges of periodically updating AI models to account for changes in the monitored environment are often overlooked. These challenges include adapting to variations in environmental parameters due to changes in human activity or natural seasonal fluctuations, which are essential for ensuring accurate predictions throughout the year. Hence, while maximising prediction accuracy is important, it is equally crucial to develop practical and adaptable solutions that can be quickly deployed and maintained in dynamic real-world environments.

3.2 Main Contribution

This research study places particular emphasis on the proposed methodology tailored for practical applicability in real-world scenarios, an aspect often lacking in current research. Combining the practical constraints while maintaining the requirement of accurate predictions, we provide the following contributions:

- A Deep Learning solution based on 1D Convolutional Neural Network (CNN) for predicting key parameters within indoor environments. The designed AI model can be trained with a small amount of recent data collected over a short time frame, hence guaranteeing high prediction accuracy after few days from the beginning of the data collection, with no need for model pre-training.
- A model update mechanism based on a mobile window that keeps the predictions consistent with any environmental changes. This approach potentially provides a zero-touch forecasting method that can effectively adapt to real-world scenarios. This adaptability ensures that the system remains responsive to variations in the environment, maintaining prediction accuracy throughout different conditions and periods of the year.

3.3 Single Output Variable: CO_2

CO_2 is one of the main pollutants that most affects IAQ in buildings, due to its strong correlation with human presence. Medical and scientific studies have underlined how high levels of CO_2 not only affect cognition [39] and well-being of people, significantly reducing comfort perception in indoor environments, but might contribute to Covid-19 infection [40]. In this regard, National and European regulations define specific thresholds to maintain IAQ standards, e.g., the Joint Research Center (JRC) of the European Commission [41] defines the limit of 1000 ppm. In this context, effectively forecasting CO_2 is crucial for implementing preventive actions and keeping its level as low as possible.

3.3.1 State of the Art

Due to the growing interest in IAQ, as mentioned in the previous sections, numerous research studies on forecasting indoor CO_2 levels have been published over the past decade. These studies explores different predictive models and techniques, with the aim to maximise prediction accuracy.

Skön et.al. [42] evaluate the use of relative humidity and temperature for modelling indoor CO_2 by means of a Multi-Layer Perceptron (MLP). Their objective is to avoid the deployment of expensive CO_2 sensors. Despite considering data collected over six months and extracting advanced statistical features (e.g., kurtosis, skewness) to maximise the information available for model training, the performance is poor. The same authors highlight the need for additional input variables. As a result, following studies focus on adding new input variables. For instance, in [19] outdoor temperature and humidity, alongside with supporting parameters such as date and time, are introduced to predict CO_2 using Random Forest. This study considers different training dataset sizes and number of trees, achieving better performance, but require a large dataset covering more than a year for training.

In contrast to previous studies, Khorram et.al. [20] integrate the historical data of CO_2 and time parameters (e.g., weekday, hour and minute) in their study. They explore two different scenarios using an ANN with three hidden layers: the first case considers all input variables, including the time information, while the second case only focuses on historical data of CO_2. The results indicate that time and date variables do not significantly improve prediction accuracy. Furthermore, the chosen approach relies on a large amount of data (corresponding to a time period of 242 days) for model training, with evaluation limited to a mere 10 hours following the training period. Similarly, Putra et.al. [43] evaluate a scenario using only CO_2 data as the input variable. In this case, the authors use CO_2 values with an hourly time granularity, restricting the analysis to working hours. The proposed neural network is trained on data collected over a single week (from Monday to Friday, excluding night periods), predicting CO_2 values for the following Monday and Tuesday. While their results show a good correlation between true and predicted values with limited training data, this study is constrained by clear limitations: it tests predictions for only a couple of days, hence limiting the performance overview of the proposed method, and requires a large time granularity (i.e., one hour) of data. Khazaei et.al. [44] provide a detailed analysis regarding the use of CO_2 as an input variable. Three different approaches are considered: the first case includes CO_2 as an input variable, the second case uses only humidity and indoor temperature while the third case partially uses CO_2 as input variable to forecast five future time-steps. Each approach corresponds to a different neural network training method (in this case, MLP). Similar to Skön et.al. [42], the authors highlight the importance of collecting CO_2 data through sensors for model training. Despite achieving good prediction accuracy with a small amount of training data, their evaluation is limited to just one week of data, similar to previous research studies [20, 43]. Furthermore, none of the aforementioned works consider updating the AI models over time.

In the literature, some research studies integrate the prediction of CO_2 as part of the broader task of forecasting Indoor Air Quality (IAQ), exploring different neural network architectures for this purpose. For instance, Sharma et.al. [38] employ an optimised Long Short-Term Memory (LSTM) to estimate and predict CO_2 and PM 2.5 in some university classrooms. Although their approach achieves good prediction accuracy, it relies on detailed variables (e.g., indoor NO_2, wind speed, wind direction, number of students) that require cutting-edge sensors, making the whole data collection system expensive from a business perspective. Similarly, Ahn et.al. [21] use a gated recurrent unit (GRU) network as deep learning technique to predict fine dust, light amount, VOC, CO_2, temperature and humidity by providing the past values of these variables as input. However, this architecture is computationally demanding, requiring more than a day and a half for training. Furthermore, it depends on data collected over more than six months, including complex variables.

In this study, we mainly reference the research work proposed by Kallio et.al. [6], which provides a detailed and comprehensive analysis of indoor CO_2 prediction. Unlike the other studies, the authors analyse the research problem from data collection architecture to the forecast results, further considering the challenges of using edge devices in such scenarios. They evaluate different AI techniques (Ridge, Decision Tree, Random Forest, MLP) in terms of both computational load and prediction accuracy, and assess the impact of input variables, the number of past values to use and the number of future values to predict. The authors underline the infeasibility of applying neural networks on edge devices due to their computational demands and suggest less computationally demanding techniques like Decision Trees. Despite the detailed overview of the problem, the proposed approach poses challenges for real-world application. Indeed, it requires a large amount of data collected over a whole year from different rooms to train models for predicting CO_2 within the monitored rooms in the so called "hard sections" (i.e., when CO_2 has a significant variation). As a result, it is necessary to collect data for an extended time period before training the AI models, providing important limitations from a business perspective.

Table 3.1 highlights the key points of each research work presented in this section. Compared to them, a major benefit of our approach is the automated model update mechanism, necessary to keep up with the changes of the environmental conditions, hence to cope with the dynamics of real-world application scenarios.

Table 3.1: Summary of State-of-the-Art solutions for predicting CO_2 levels.

Related work	**Dataset Size**	**Input Variables**	**AI Architecture**	**Automated Model Update**
Segala et.al. [37]	**Adaptive (Max 30 days)**	**Temperature, humidity, CO_2**	**1D CNN**	**Yes**
Kallio et.al. [6]	One year	CO_2, PIR, temperature and humidity	Ridge, Decision Tree, Random Forest, MLP	No
Vanus et.al. [19]	One year	Temperature, humidity, time, date	Random Forest	No
Khorram et.al. [20]	242 days	CO_2, weekday, hour, minute	ANN	No
Ahn et.al. [21]	Six months	Fine dust, light amount, VOC,CO_2, temperature and humidity	GRU	No
Sharma et.al. [38]	One week	Indoor NO_2, wind speed, wind direction, number of student	LSTM	No
Skön et.al. [42]	Six months	Temperature, humidity	MLP	No
Putra et.al. [43]	One week	CO_2	ANN	No
Khazaei et.al. [44]	One week	CO_2, humidity, temperature	MLP	No

3.3.2 Dataset

In this research work, we use the data provided and published by Kallio J. et al. [6]. The authors specifically published the dataset for further analysis of CO_2 predictions, making it highly-suitable for our objectives. The dataset includes data collected from 13 different rooms (e.g., offices, meeting rooms) by means of different commercial sensors at Technical Research Center of Finland (VTT) in 2019. The monitored variables are:

- Temperature [°C];

- Relative humidity [%];
- Air pressure [hPa];
- Carbon dioxide concentration [ppm];
- Activity level.

For this research work, as detailed in in Table 3.2, we use indoor temperature, humidity and CO_2. To preprocess the data, we use a script developed by Kallio J. et al. [6], which automatically aligns the timestamps of the sensor data collected from the same room. As reported in their paper, communication issues affected the sensors in five rooms during the data collection, resulting in over 10% incomplete samples (i.e., missing at least one among T, H or CO_2). The script addresses the issue by filling the gaps with the mean between the previous and next value. Additionally, the script includes methods to split the dataset into train and test data. However, we do not use this functionality because the script excludes periods of slow CO_2 variation during the split process, which would impact the validation of our solution under all conditions. Instead, we implement a custom method to split the data within a given mobile window into training set (70%) and validation set (30%) (as indicated in Table 3.2). As described in Section 3.3.3, we test the prediction on the first day after the time window.

3.3.3 Methodology

Neural Network Architecture

A 1-Dimensional CNN is used as deep learning architecture for forecasting. 1D CNN, which find application in NLP [45], in network security [46] and other domains, are able to automatically analyse and extract fine-grained features from a single spatial dimension (in our case, time) by means of convolution operations [47]. From a computational perspective, they guarantee good performance through a shallow structure and advanced features such as weight sharing, with the possibility of using a small amount of data for training the model [48] without significantly impacting the accuracy. In contrast to other types of neural networks (e.g., recurrent neural networks) proposed in the literature [21,38], 1D CNN are less computationally demanding [49], making them suitable for limited-power and resource-constrained devices.

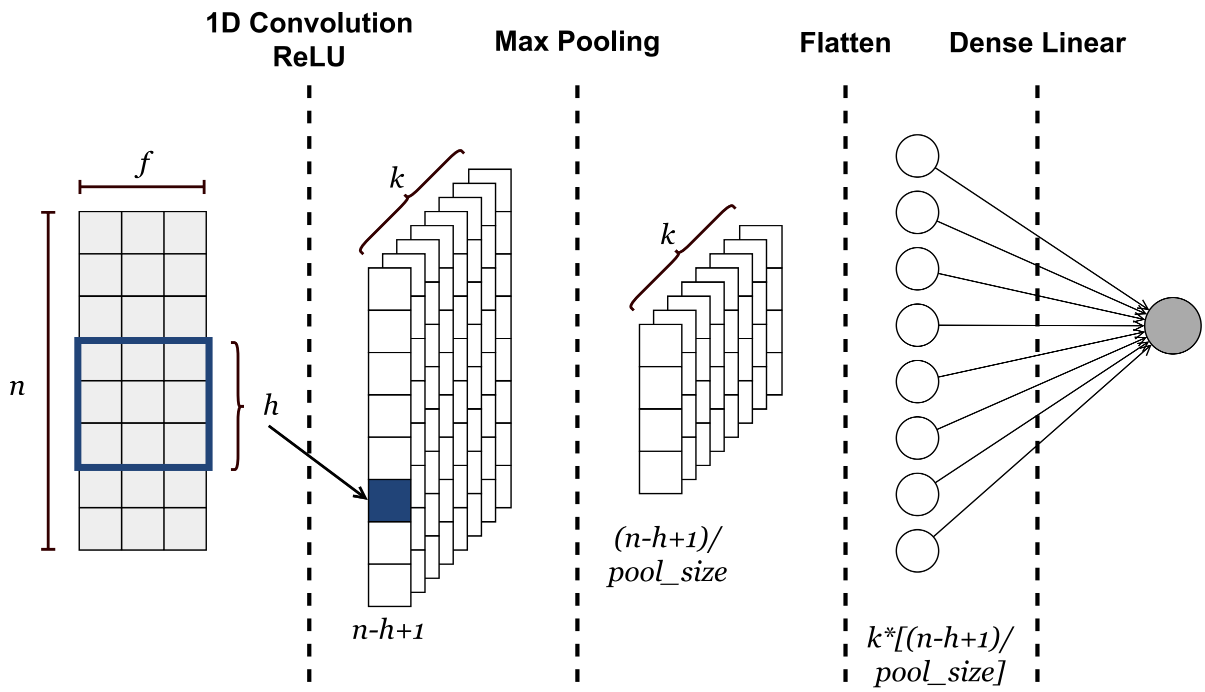


Figure 3.1: The designed neural network architecture for forecasting indoor CO_2.

The proposed CNN architecture, depicted in Figure 3.1, consists of the following layers:

- *Input layer.* Each sample includes the values of the input environmental variables (i.e., temperature, humidity and CO_2) covering a window of n quarters of an hour. Basically, a sample is a data matrix of size $n \times f$ where n is the number of quarters of an hour and f is the number of features. This approach leverages the temporal nature of environmental variables., as the values of temperature, humidity or CO_2 at close time intervals are correlated between each other. Before feeding the neural network, the input values are normalized by defining a maximum and minimum value for each variable.

- *1D Convolutional Layer.* This layer analyses and extracts features along time-dimensional axis of the input data. It outputs a matrix of size $(n - h + 1) \times k$, where each column is a feature vector extracted using convolutional filters or kernels. Each of the k kernels slides over the input matrix with a step equal to 1 and makes a convolution operation to extract the most significant local information. The common rectified linear activation function (i.e., $ReLU(x) = max\{0,x\}$) is used to extract non-linearity patterns from data.

- *Max Pooling layer.* This layer aims to learn the most valuable information from the extracted feature vectors by applying a subsampling operation to the output matrix from the CNN layer. A filter slides along each feature map according to a step given by the *stride* parameter and applies a maximum operation to a number of elements equal to the *pool size* parameter. The *stride* is set equal to *pool size*, providing an output matrix of size $[(n - h + 1)/pool\_size] \times k$.

- *Flatten layer.* This layer reshapes the input matrix into a one-dimensional feature vector which can be used to make predictions by the subsequent output layer.

- *Output layer.* This linear fully connected layer, consisting of a single neuron, predicts the CO_2 value for the next quarter hour.

Proposed Approach

The proposed approach is based on the use of a small amount of data collected over a short time frame to train the neural network model. This enables the system to become operational and provide accurate predictions shortly after its initial deployment, without requiring extensive data collection (e.g., over weeks or even months) or across different environments. In this regard, we introduce the concept of the mobile window, which refers to the amount of recent data used to train and update the model over time. This approach relies on the idea that only recent data include valuable information for modelling the local environment. In contrast, including outdated data from distant past periods might degrade prediction accuracy, potentially capturing conditions related e.g., to a another season of the year or different scenarios. Hence, the mobile window serves as a dynamic mechanism to keep the model up-to-date upon recent environmental changes. This capability is particularly valuable in dynamic environments where conditions can change rapidly, ensuring that the model remains accurate and reliable. The mobile window size is adjusted to achieve prediction accuracy within the 10-20 ppm range, hence ensuring an accurate control of HVAC systems, as indicated by previous studies [6].

The proposed approach seamlessly integrates with typical data collection procedures for IAQ monitoring. Furthermore, by leveraging a small amount of data and a lightweight neural network architecture (i.e., 1D CNN), this method can be effectively applied on edge devices to autonomously forecast local CO_2 levels. This results in a potential zero-touch indoor CO_2 prediction approach, making it highly efficient and practical for real-world application.

The main operations of our approach can be summarised as follows (Figure 3.2):

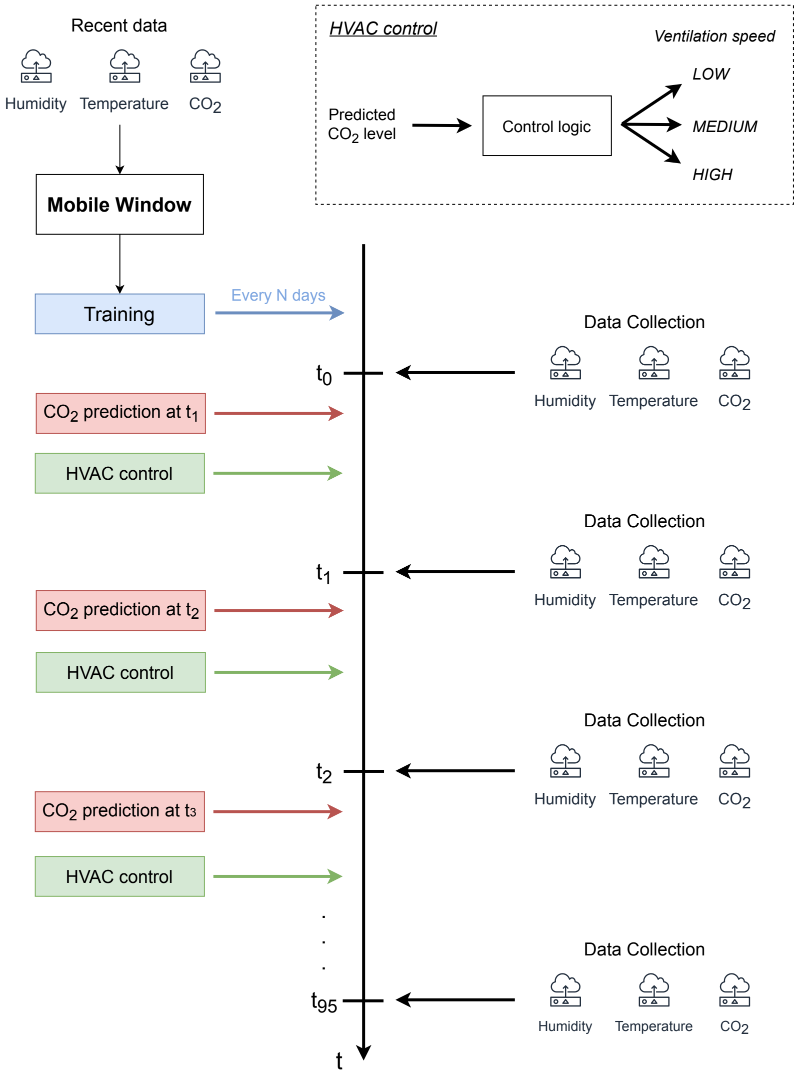


Figure 3.2: The sequence of operations for forecasting CO_2 levels at each quarter-hour interval (t_0, t_1, ..., t_{95}) throughout the day.

- Every quarter of an hour throughout the day t_0, t_1, ..., t_{95}, the environmental data (i.e., temperature, humidity, CO_2) are collected on the edge device through smart IoT sensors. This data collection frequency ensures a good balance among the accuracy of analysis, battery lifetime of sensors and storage capabilities of the edge device. Additionally, some industrial protocols (e.g., Modbus [50]) keep the channel busy during data reading operations. A quarter-hour granularity prevents the physical channel from being occupied at a high rate, enabling the edge device to perform other local tasks (e.g., actuation) without potential interference.

- Immediately after the data collection at every quarter hour t_0, t_1, ..., t_{95}, the system processes the collected data as samples. Specifically, the sample including the values of the environmental variables of the last n quarters of an hour is input to the Convolutional Neural Network to predict the CO_2 level of the next quarter hour. This process enables the system to regularly provide the forecast value of CO_2 for the next future, considering recent short-term environmental trends. The predicted value can be effectively used to regulate HVAC systems proactively to keep CO_2 levels under control. As noted by Pistochini et.al. [51], typical CO_2-based Demand-Controlled Ventilation (DCV) methods integrated into HVAC systems operate by either opening the damper at a fixed rate until the set point is reached, closing it when CO_2 levels fall below the minimum deadband, or by using a proportional-integral (PI) algorithm, or adjusting the damper position in function of CO_2 concentration.

- Every N days, a window of data spanning the past few days is used to update the neural network model. Initially, during the early stages of deployment, this window progressively increases to account for a larger amount of information with the aim to to improve the modelling of the environment as soon as possible. Basically, the adaptability of the mobile window allows the system to continuously refine its predictions, improving its performance over time in the start-up phase. Once the window achieves its optimal size, balancing prediction accuracy against computational demand, it slides over time to update the models, effectively becoming a mobile window (Figure 3.3). From a processing perspective, the data are handled as samples, which are then used to feed the 1D Convolutional Neural Network for training the model. This operation can be properly scheduled after the last data collection operation of the day (before t_0).

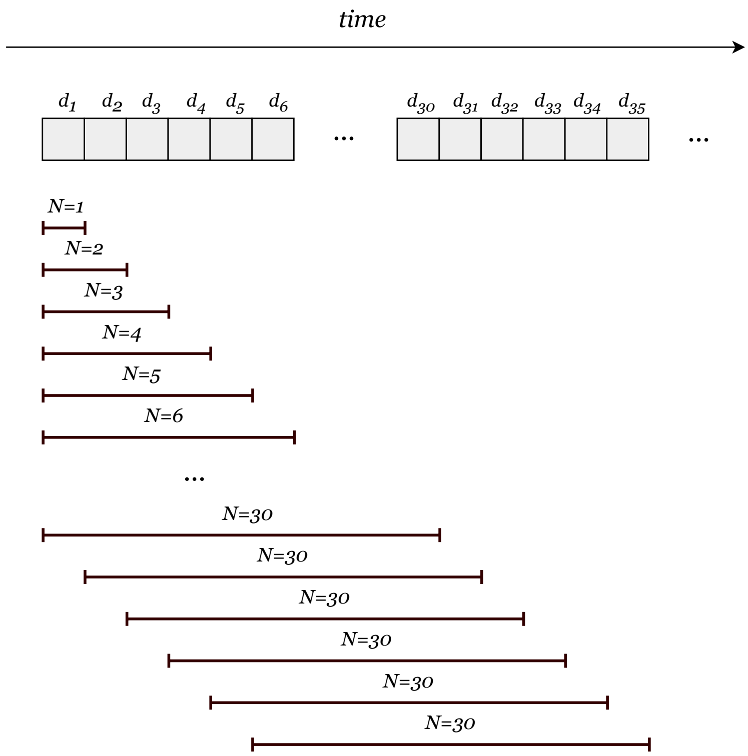


Figure 3.3: The behaviour of the mobile window during the initial system deployment.

3.3.4 Experimental Setup

In Table 3.2 we report the values of the main parameters used in the simulations.

Temperature, humidity and CO_2 of the dataset are used as input variables to predict future CO_2 levels. These variables take a central role for facility managers to have an overview of IAQ in their indoor environments. Integrating additional advanced sensors to monitor complex air pollutants

Table 3.2: Simulation parameters for the designed AI model for predicting CO_2 levels.

Parameter	**Value**
Environmental variables in input	Temperature, humidity, CO_2
Time granularity of data	15 minutes
Quarters of an hour in a sample	8
Number of kernel filters - Convolutional layer	64
Kernel size - Convolutional layer	3
Pool size - Max Pooling layer	2
Learning rate	0.001
Batch size	32
Optimizer	Adam
Loss function	Mean squared error
Validation split	0.3
Maximum number of epochs	5000
Patience	25

like particulate matters (PM1, PM2.5, PM10) or VOC significantly escalates the cost of the data collection system. Additionally, these variables depend not only on human activity but also on other agents, which can be considered of minor interest. As a result, we optimised the choice of the input variables, coherently with the rest of the proposed system. Their value range is reported in Table 3.3.

Table 3.3: Range of the input variables for predicting CO_2 levels.

Parameter	**Range**
Temperature	0-40 °C
Humidity	0-80 %
CO_2	350-5000 ppm

In [6], the data are characterized by a time granularity equal to one minute. However, the original values of the dataset have been aggregated every 15 minutes to simulate a typical data collection scenario.

We evaluated the main hyper-parameters of the 1D CNN in order to find the values that guarantee a good balance between model accuracy and computational demands. In this regard, we used RMSE as performance metric:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{3.1}$$

where y_i is the real CO_2, $\hat{y}_i$ is the predicted CO_2 and N is the number of total quarters of an hour.

We evaluated the performance of the system by varying the number of quarters of an hour per sample. We conducted experiments involving other relevant parameters such as: pool size, kernel size and number of convolutional filters. The results from these experiments are detailed in Figure 3.4:

- *Pool size* takes a central role in extracting the most relevant information from the feature vectors generated by the convolutional layer. According to Figure 3.4, we set it equal to 2, as global max pooling significantly impacted the accuracy.

- *Kernel size* is important to extract valuable information along the time dimension. The simulation results reported in Figure 3.4 show similar performance between different kernel sizes. Thus, we set it equal to 3, which is one of the standard values for CNN.

- *Number of convolutional filters* was set to 64. Indeed, as reported in Figure 3.4, we noticed that higher values (e.g., 128, 256) yielded comparable performance, especially when samples include a few quarters of hour. In this way, we provide more compact and lightweight models, reducing memory usage and guaranteeing faster computations, especially on limited-power and resource-constrained devices.

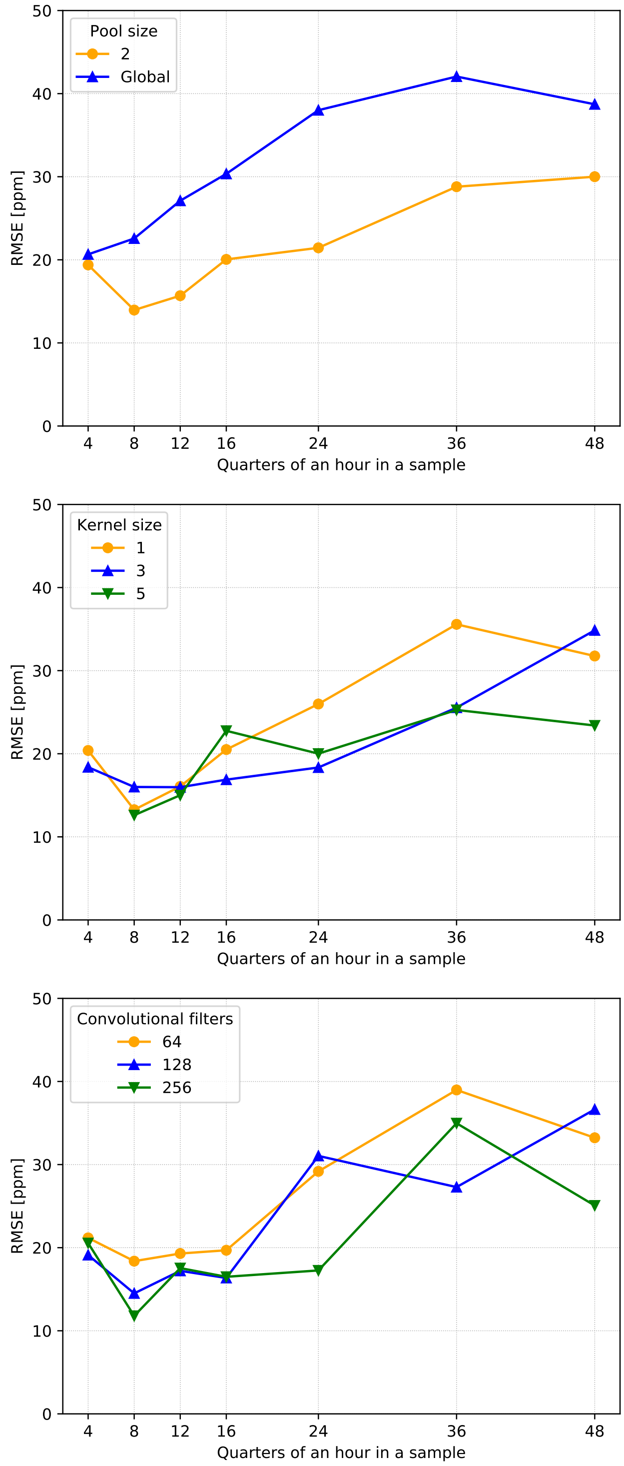


Figure 3.4: The behaviour of the model at different numbers of quarters of an hour per sample, with focus on the pool size (top), kernel size (center) and number of convolutional filters (bottom).

Other involved parameters are:

- *The learning rate* is set to 0.001, a value used in many complex and non-linear problems, which guarantees a good trade-off between convergence and computational time.
- *The batch size* is set to 32 to guarantee stability and to limit the memory footprint of the models.
- *Adam optimizer* [52] is used as optimisation algorithm.
- *RMSE* is used as the loss function during the training.
- *The validation split* is set equal to 0.3, as per common practice in studies on CO_2 prediction. Before the split, we shuffle the samples so that both training and validation sets contain samples which are spread across the whole time window. It is worth noting that we do not shuffle the time series within a single sample, as we want to preserve the chronological order of the consecutive quarters of hour.
- *Maximum number of epochs* set to 5000, combined with an early stopping patience parameter set to 25 epochs.

3.3.5 Results and Discussion

In this section, we present the outcomes of our experiments designed to evaluate the effectiveness of our proposed approach. Specifically, a couple of experiments have been conducted:

1. The first experiment aims to understand the impact of the mobile window, highlighting the practical and adaptive features of the proposed approach;
2. The second experiment assesses performance in predicting multiple days into the future, simulating model updates after N days.

Mobile Window

The mobile windows, which determines the amount of data user for training the AI model, is the most important hyper-parameter in our approach. For this reason, it needs to be deeply investigated in order to understand how its size affects the accuracy of the predictions.

To delve into the impact of different mobile window sizes, we use the simulation setup detailed in Section 3.3.4. Given a certain mobile window of N days, each of the 13 rooms in our dataset was subjected to analysis, picking up a random day per month to predict using the previous N days for training. Finally, the resulting performance metrics are averaged across all rooms, hence providing an overall performance for different sizes of the mobile window. This experimental approach enables us to simulate our methodology taking into account any possible period of the year (i.e., the deployment of the proposed system at any time of the year) as well as environments with different physical characteristics (i.e., volume and area), thus having a detailed overview of the performance of the proposed approach unlike other previous research works (e.g., [20, 43, 44]). As reported in Section 3.3.2, the dataset exhibits some missing values due to communication failures during the data collection. We recognise the potential impact of these gaps on the correctness of the predictions, hence we excluded from our experiments the days with holes in their data and in the previous N days used for training.

The experiment is executed on Raspberry Pi 4 Model B with 4 GB of memory, which plays the role of the edge device. This setup facilitates a realistic assessment of our approach's performance under practical constraints.

Figure 3.5 outlines the results of this experiment, demonstrating the benefits of the proposed approach. In the first place, it underlines the feasibility of deploying the system after just one day of data collection, without the need of any model pre-training or extensive data collection. Despite poor performance in the first days with RMSE values ranging between 30 and 50 ppm due to weak correlation between the days within the mobile window and the target day for prediction, the accuracy exhibits a significant improvement within a few days. Indeed, the model progressively learns complex features, improving its capacity to model dynamics and behaviours within the indoor environment. Within a week of data collection, the RMSE drastically decreases to around 15 ppm, ensuring precise control of HVAC systems in short time. As a result, during the initial deployment phase, the model can be regularly updated, progressively increasing the mobile window used for training in order to improve the performance as soon as possible from the beginning of data collection. After around a month, the RMSE is reduced until about 10 ppm, achieving prediction accuracy comparable to other literature studies employing larger datasets for training.

The results of this experiment highlight the benefits of the proposed approach:

1. During the first period of the system deployment, performance can be progressively improved by increasing the data within the mobile window, enabling the system to adapt and learn new features over time.

2. After just a month of data collection, the proposed approach achieves the best performance in terms of prediction accuracy. This amount of data proves sufficient to model the indoor environments accurately.

3. A 30-day window of data can effectively slides over time to update the model at a certain rate, effectively becoming a mobile window. This automated mechanism enables the model to guarantee accurate

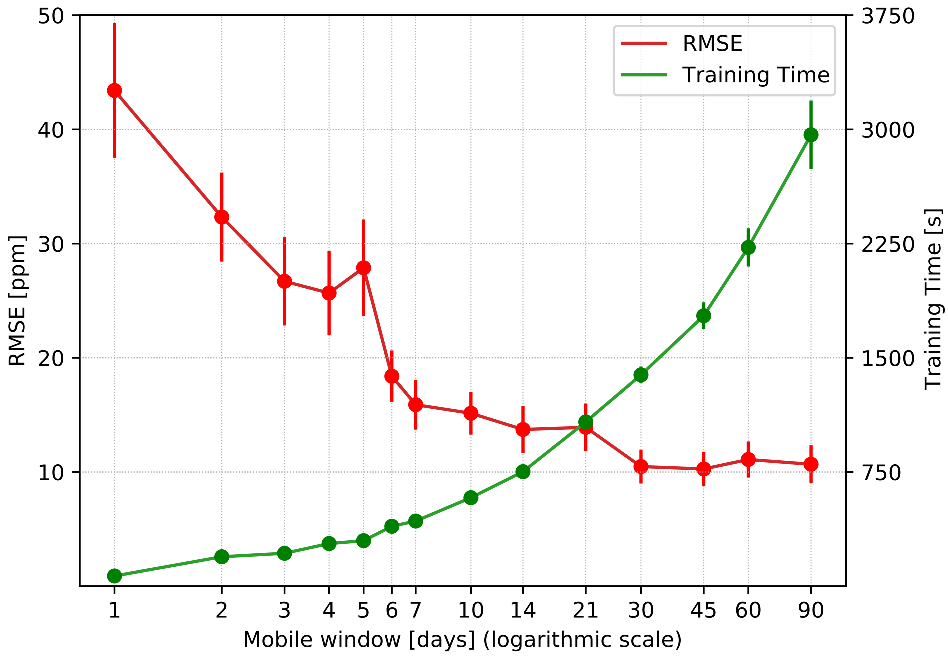


Figure 3.5: The behaviour of RMSE and training time as the mobile window increases.

long-term performance.

The plot in the figure also shows that mobile windows larger than 30 days do not bring any major improvements in terms of RMSE. On the other hand, as the training time grows exponentially, shorter time windows are preferred to prevent overloading the edge node and minimise interference with other (critical) processes executed on the same device. Additionally, with a time window size of 30 days, the model takes approximately 25 minutes to train. Thus, this operation can be scheduled when the device is idle or does not execute critical operations (e.g., overnight, when indoor environments are typically empty). Based on the above considerations, we can conclude that a 30-day mobile window allows a good trade-off between the computational demand and accuracy.

To illustrate a typical CO_2 trend in the dataset and visually assess forecast accuracy, Figures 3.6 and 3.7 present the predicted and actual CO_2 levels for one of the rooms described in Section 3.3.2, using a 30-day mobile window for training. As observed, CO_2 levels are typically lower in the summer compared to winter, likely due to increased ventilation as windows are often kept open, allowing for better air circulation. Nevertheless, in both cases, the predictive model demonstrates strong accuracy in capturing the overall trends.

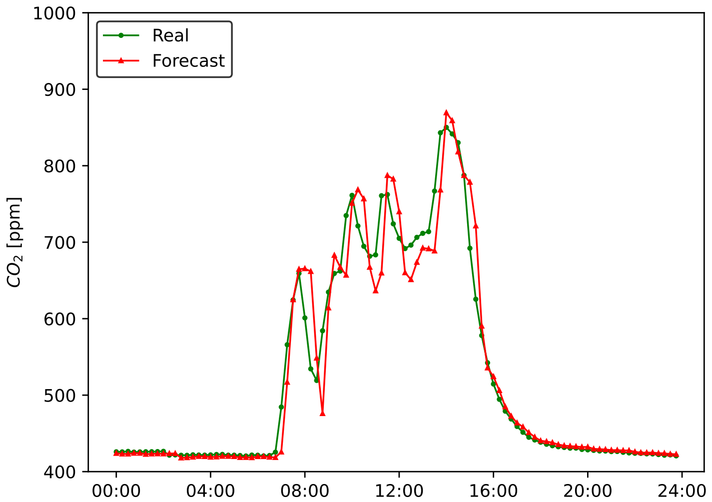


Figure 3.6: Predictions and actual CO_2 levels throughout a winter day in one of the rooms from the dataset.

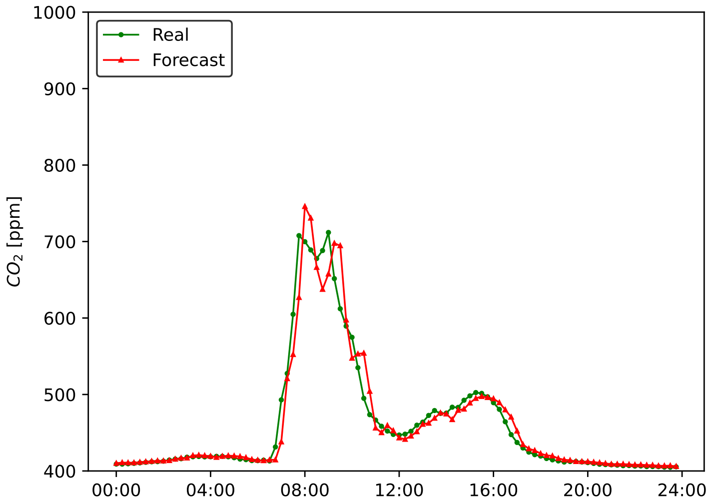


Figure 3.7: Predictions and actual CO_2 levels throughout a summer day in one of the rooms from the dataset.

Despite the above benefits, the proposed approach is affected by some limitations. First, as outlined in Figure 3.5, the RMSE during the first week is above the target threshold of 10-20 ppm. Although the performance of the system improves quickly, this warm-up phase can possibly lead to non-optimal regulations of HVAC systems. Second, the current version of the system is not resilient to missing values, as it requires a robust data collection system to work properly. This means that in the case of holes in the data (because of, e.g., communication issues, sensor failures), the future level of CO_2 cannot be predicted. In this regard, as further improvement of the system, we plan to solve this issue by implementing a mechanism that finds the largest time window with no holes in the past data, which would be used to perform the prediction of the CO_2 level. Here the challenge is to find a trade-off between the size and the age of the old window. Thus, we need a sufficiently large time window for a good prediction, but we do not want to go too far in the past to find such a large time window.

Model Update Rate

Based on our previous analysis, the model can be effectively updated on a daily basis. However, it is important to analyse whether the frequency of model updates can be reduced once the mobile window reaches the desired size. This prompts us to investigate how often the model should be re-trained to maintain the desired accuracy level. To this aim, we set the window size at a certain value and we evaluate the prediction error of our model when increasing the number of forecast days.

Figure 3.8 reports the results of this experiment, outlining a very slow increase in prediction error as the forecast horizon in terms of number of future days extends. This suggests that the indoor environmental behaviour remains relatively stable over weeks, demonstrating once again that data collection over extended time periods does not enhance indoor CO_2 predic-

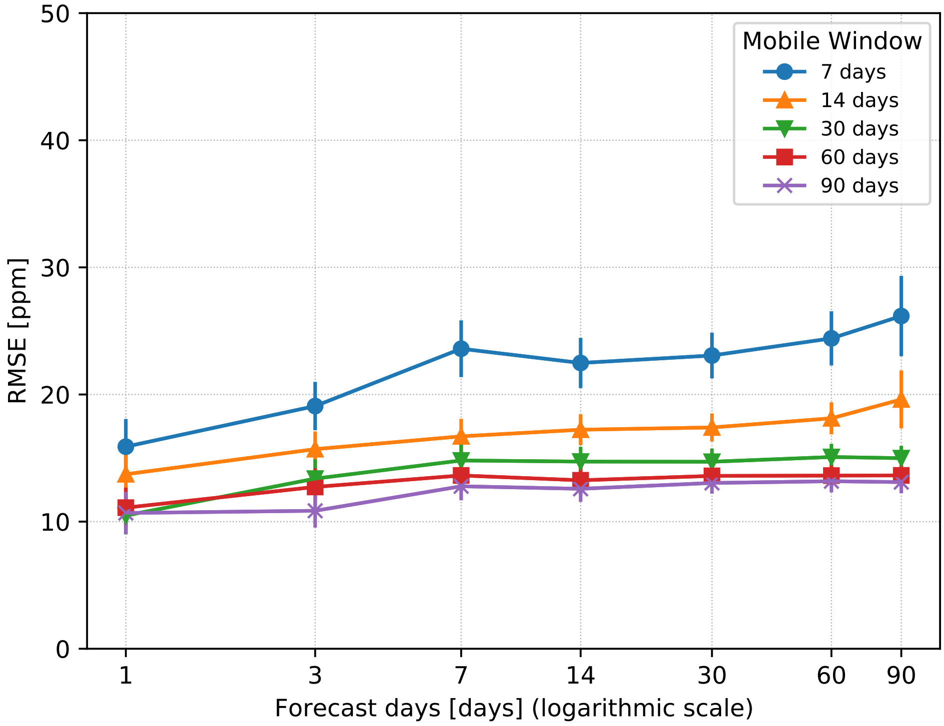


Figure 3.8: The behaviour of RMSE as a function of the forecast days.

tion accuracy in a significant way. Consequently, this allows for potentially less frequent model updates compared to a daily basis. For instance, the model could be effectively refreshed weekly e.g., in the scenario of retail stores, during the weekend when the store might be closed and the edge device is idle for most of the time. However, the best prediction accuracy is achieved with a daily model update. This can be properly scheduled at the end of the day, as defined by the previous experiment of the mobile window, when all the data of the previous N days are collected on the edge device.

3.4 Multiple Variables: Temperature, Humidity, CO_2 and Energy Consumption

Following the development of the forecasting approach based on the use of mobile window, we now aim to enhance the method for optimisation tasks. Our primary objective is to extend the AI model to predict changes within indoor environments from both environmental and energy perspectives. To address this task, we review and refine the designed architecture to forecast multiple variables, including indoor temperature, humidity, CO_2 and energy consumption due to HVAC devices. These predictions are based on a set of heterogeneous input variables that directly influence the evolution of key indoor environmental parameters and energy consumption, as we will discuss in Section 3.4.1. The ultimate goal is to use these predictions to intelligently and timely adjust HVAC systems through the EECO algorithm (discussed in Chapter 4), ensuring the desired comfort level is maintained with minimal energy consumption.

3.4.1 Input Variables

The variables used by the AI model to forecast changes within the considered environment can be categorised as follows (an overview is reported in Table 3.4):

- *HVAC parameters.* These include status (i.e., ON/OFF), Set Point (SP) (i.e., target temperature), fan speed and operating mode (i.e., heating or cooling) for each HVAC device installed in the environment. Such parameters are fundamental for modeling the indoor environment based on the operational settings of the HVAC systems. Data is collected through an electronic interface that enables our datalogger/master node to communicate through Modbus protocol [50] with the HVAC unit.

- *Outdoor environmental parameters*, which include temperature and humidity. Such variables significantly influence indoor environments, hence taking a central role in indoor climate control requirements and energy usage. This kind of information is retrieved from the OpenWeatherMap platform [53] through available APIs.

- *Indoor environmental parameters*, which include temperature, humidity and CO_2, and *energy consumption*. These variables are crucial for optimisation tasks, as they directly impact the trade-off between thermal comfort and energy footprint. Indoor temperature is sensed by thermostats connected to the HVAC devices, while humidity and CO_2 levels are monitored by an IoT ambient probe [54] installed within the environment, which sends raw data to its receiver. Additionally, energy consumption is monitored through a wireless energy meter [55] installed on the three-phase line powering the considered HVAC devices (i.e., Variable Refrigerant Volume (VRV) systems). This device communicates with its gateway [56] and provides data through the Modbus protocol [50]. The monitored energy consumption includes the overall energy demand of the VRV system (i.e., compressor and fans).

- *Supporting variables*. They basically include temporal features such as the day of the week and the hour of the day. This kind of information is important for the model to learn temporal patterns from historical data.

All the aforementioned input variables are collected every 15 minutes, except for the outdoor temperature and humidity, which are affected by a one-hour time granularity. In this case, a linear interpolation has been applied to fill the missing quarters of hour.

Table 3.4: Overview of the input variables for predicting indoor temperature, humidity, CO_2 and energy consumption due to HVAC devices.

Variable	**Type**	**Description**
ON/OFF	Categorical	ON/OFF of HVAC devices.
Set Point	Number	SP temperature [°C] of HVAC devices.
Fan Speed	Categorical	Fan speed of HVAC devices (1 = low, 2 = high, 3 = very high).
Operating Mode	Categorical	Operating mode of HVAC devices, i.e., cooling or heating.
Outdoor Temperature	Number	Outdoor temperature [°C] collected from the OpenWeatherMap platform [53].
Outdoor Humidity	Number	Outdoor humidity [%] collected from the OpenWeatherMap platform [53].
Indoor Temperature	Number	Indoor temperature [°C] sensed by the thermostats, which feed their readings to the installed HVAC devices. The mean value is used within the algorithm.
Indoor Humidity	Number	Indoor humidity [%] collected through an IoT sensor installed in the environment.
Indoor CO_2	Number	Indoor CO_2 [ppm] collected through an IoT sensor installed in the environment.
Energy Consumption	Number	Energy consumption [kWh] due to HVAC devices collected from a smart energy meter.
Day of the week	Number	Information on the day of the week.
Hour of the day	Number	Information on the hour of the day.

3.4.2 Methodology

A one-dimensional (in short 1D) CNN is a neural network model composed of one or more 1D convolutional layers. As previously reported in Section 3.3.3, 1D convolutions enable us to extract fine-grained information from one-dimensional data (such as indoor temperature, humidity, energy consumption) along the temporal dimension. Considering the strong performance achieved with CO_2 predictions, we use the same architecture for multi-variable predictions. Specifically, this approach aims to correlate heterogeneous data — including HVAC parameters and both outdoor and indoor environmental conditions — to accurately forecast future values of temperature, humidity, CO_2 levels, and energy consumption related to HVAC devices.

Neural Network Architecture

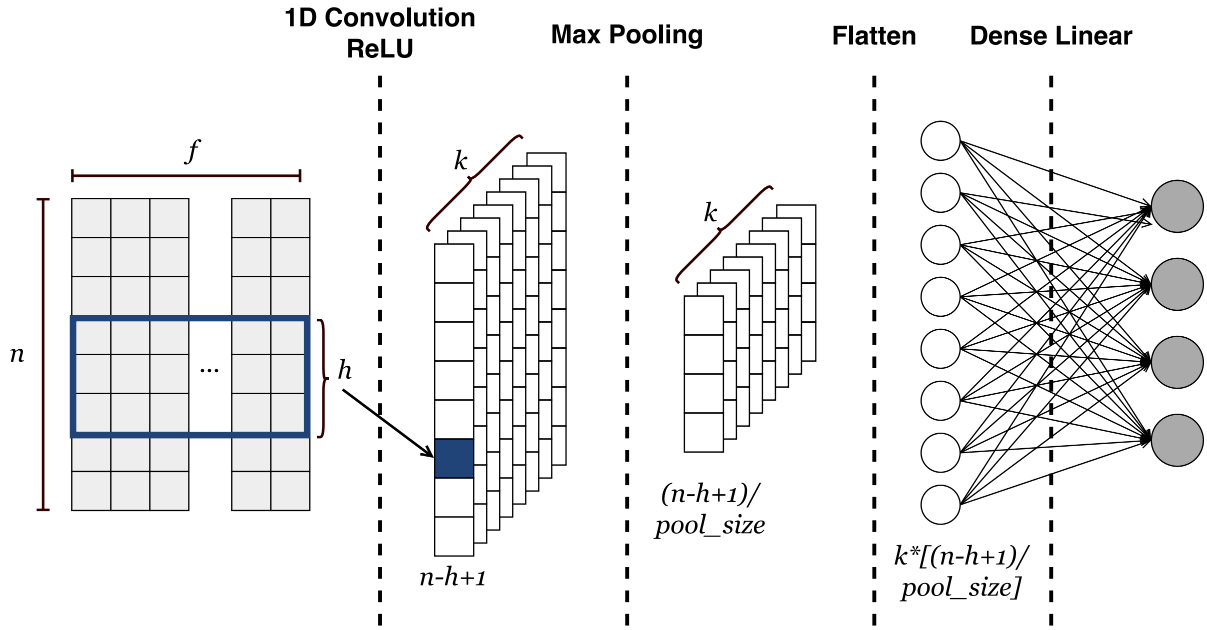


Figure 3.9: The designed neural network architecture for forecasting multiple variables.

The designed architecture consists of four layers, as sketched in Figure 3.9:

- *Input layer.* The first layer takes as input an $n \times f$ array, where n is the duration of the observation time window (expressed in quarters of an hour) and f is the number of features. That is, an input sample consists of the values of f variables (previously described in Section 3.4.1), including temperature, humidity and CO_2, energy consumption, HVAC operating parameters, collected during a time window of n quarters of an hour. Each sample is normalised along the temporal axis by using the nominal minimum and maximum values of each variable.

- *1D Convolutional Layer*. Each sample is operated by a convolutional layer with k filters, each filter of size $h \times f$, with h being the height and f the width of the input sample (i.e., the number of features). Each of these k kernels slides over the input matrix with a step of 1 to extract the temporal properties of the f features. This layer outputs a matrix of size $(n-h+1) \times k$, in which i-th column is a feature vector extracted by the i-th filter. The rectified linear activation function ($ReLU(x) = max\{0,x\}$) is used to break linearity in the model, as per convention for CNN.

- *Max Pooling layer*. The max-pooling operation downsamples the temporal properties extracted with the convolution by keeping only the largest values. This operation involves a filter that slides along each feature map with a pre-defined step (also called *stride*) and applies a maximum operator to a number of elements equal to the *pool size* parameter. As we set *stride* equal to *pool size*, the size of the resulting matrix is equal to $((n-h+1)/pool\_size) \cdot k$.

- *Flatten layer*. It reshapes the output of the max pooling operation into a one-dimensional feature vector.

- *Output layer*. The vector is processed by a final fully connected layer. The output of this layer is a vector of four elements, with the predictions of indoor temperature, humidity, CO_2 and energy consumption for the quarter of an hour that follows the input time window.

Model Training

Table 3.5 reports the values of the main hyper-parameters of the AI model. Considering the obtained performance, we use largely the same configuration reported in 3.3.4, differing only in a couple of parameters: we define different loss weights for the output variables with the aim to balance their contribution equally within the overall loss, and we reduce the maximum number of training epochs to 1000.

Table 3.5: Simulation parameters for the designed AI model for multi-variable prediction.

Parameter	**Value**
Time granularity of data	15 minutes
Quarters of an hour in a sample	8
Number of kernel filters - Convolutional layer	64
Kernel size - Convolutional layer	3
Pool size - Max Pooling layer	2
Learning rate	0.001
Batch size	32
Optimizer	Adam [52]
Loss function	Mean squared error
Validation split	0.3
Loss weights	co2: 0.1, indoor temperature: 100, indoor humidity: 1, energy: 1000
Maximum number of epochs	1000
Patience	25

Every day after midnight, we train the AI model by using a mobile window of data, as described in Section 3.3.3. This window consists of data collected over the past 30 days, handled in samples covering a window of eight quarters of an hour. The objective of this update mechanism leveraging the mobile window is twofold:

1. Enabling the model to learn the impact of actuations (ON/OFF, set point) on the indoor environment and energy consumption over the recent period. This allows the model to adapt to the most current conditions within the environment and improve prediction accuracy.

2. Keeping up with seasonal variations in environmental conditions. The same HVAC settings might lead to different effects on the environment, depending on factors such as outdoor weather and seasonal

changes. By continuously updating the model with recent data, we ensure it remains effective in adapting to these variations.

Overall, this strategy ensures that the AI model continuously learns and adapts to the monitored environment, providing reliable and accurate predictions that help optimise HVAC operations to improve energy efficiency and thermal comfort.

3.5 Preliminary Results

As outlined in Section 3.4, this predictive approach is integrated into EECO, an intelligent and automated algorithm designed to optimise HVAC systems, which we will discuss further. Before testing the EECO algorithm in a real environment during both winter and summer, we conducted a brief and preliminary analysis of the prediction accuracy to evaluate the reliability of the predictive engine. Specifically, we simulated few days using real data as input and analysed the resulting outputs.

In Figures 3.10 and 3.11 we illustrate the behaviour of the predicted variables (indoor temperature, energy consumption, indoor humidity and CO_2) for a typical winter and summer day, respectively. Although the predictions occasionally struggle to capture rapid or unexpected changes (e.g., during the late afternoon of the winter day), it is evident that the overall predicted trends closely align with the real behaviour. This consistency is a crucial aspect for optimisation tasks, as it ensures that the system can make informed adjustments based on reliable information. It is also worth noting that the accuracy of these predictions is further demonstrated in Section 4.7.4, where we validate the simulated environment by emulating real-world HVAC configurations across different days and comparing the corresponding predictions with the real values.

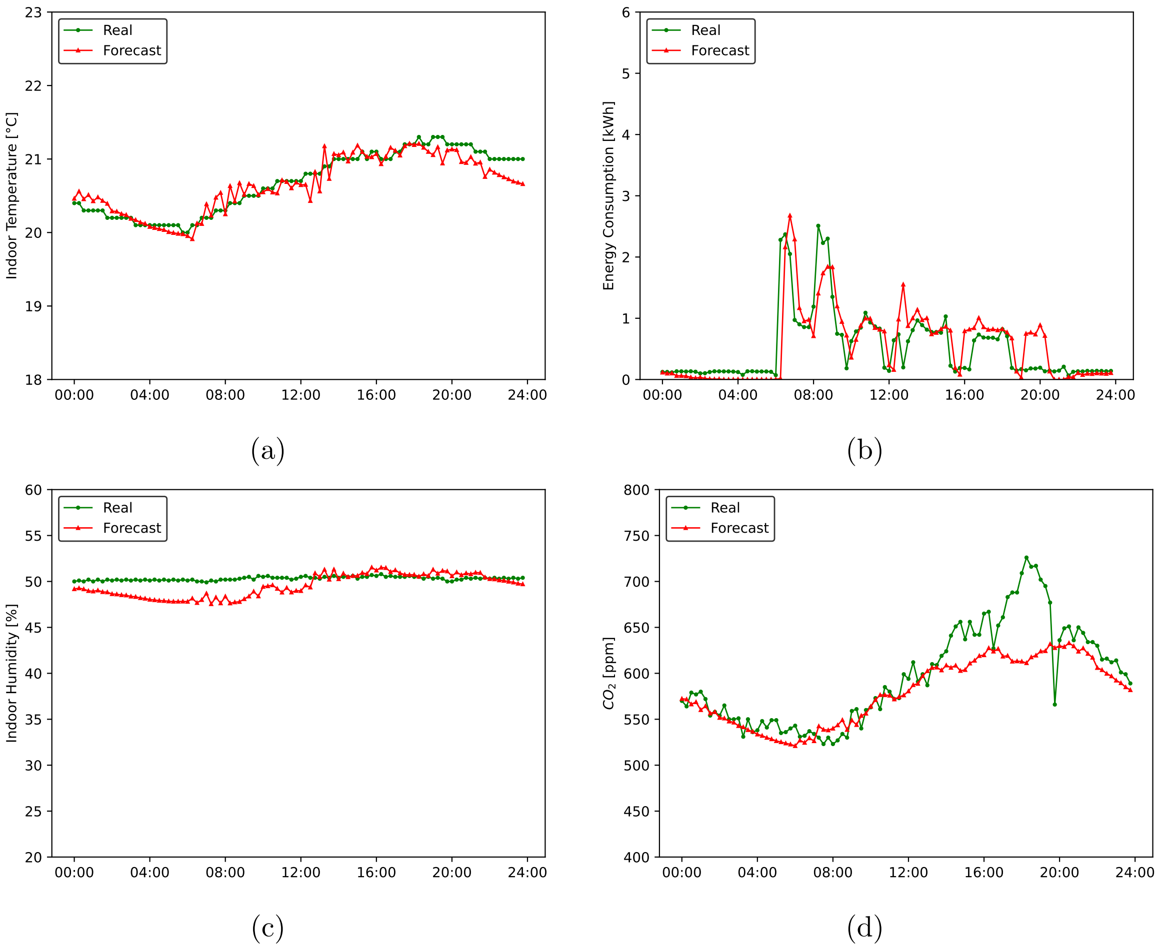


Figure 3.10: Predictions and real behaviour throughout a winter day (i.e., heating mode) for (a) indoor temperature, (b) energy consumption, (c) indoor humidity, and (d) CO_2 levels.

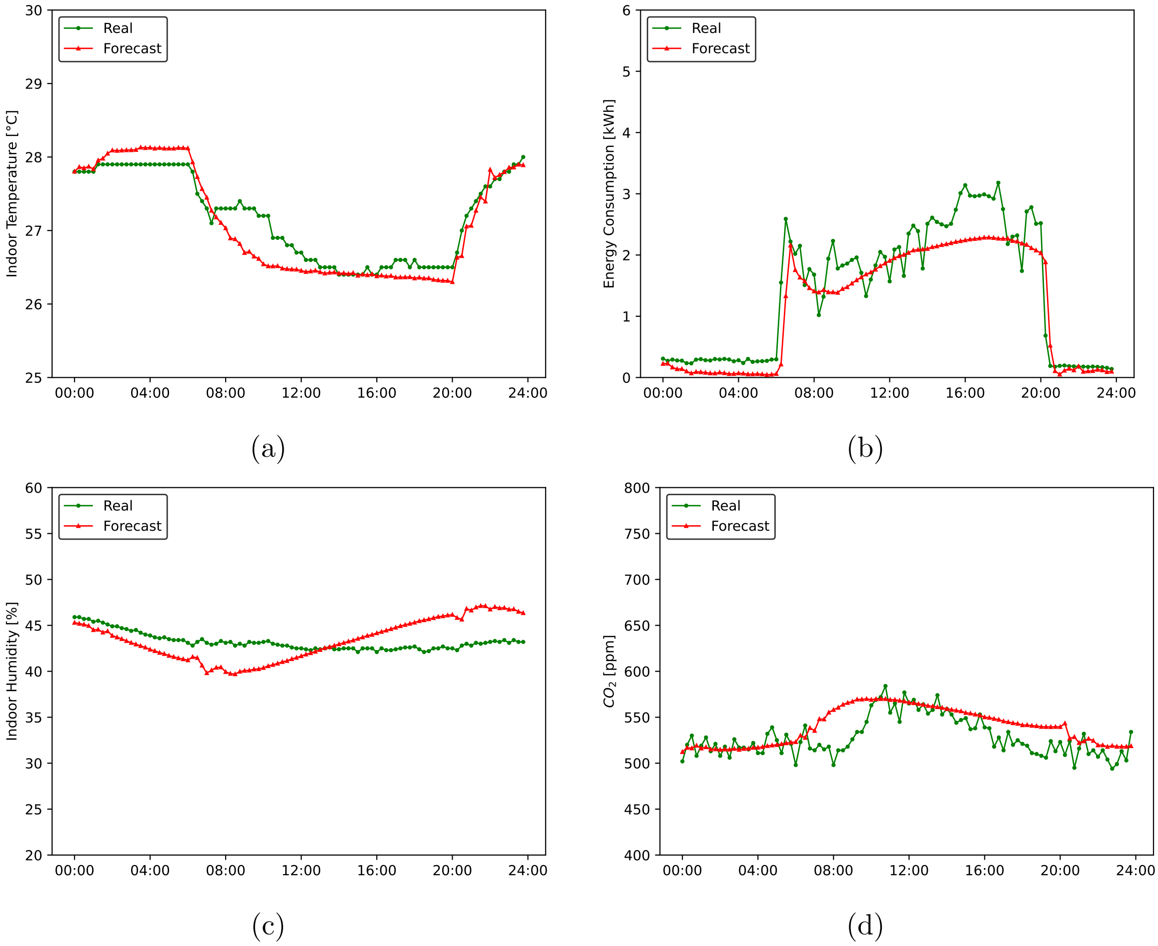


Figure 3.11: Predictions and real behaviour throughout a summer day (i.e., cooling mode) for (a) indoor temperature, (b) energy consumption, (c) indoor humidity, and (d) CO_2 levels.

3.6 Discussion and Summary

In this section, we have presented a practical approach for forecasting key parameters in indoor environments, with a particular focus on CO_2 levels. The proposed system uses a small amount of collected data and does not require model pre-training. It includes an adaptive mechanism based on a dynamic mobile window to keep the model up-to-date upon environmental changes. This approach guarantees rapid system deployment and high prediction accuracy in a short time frame, along with long-term performance.

Evaluation results for predicting CO_2 levels demonstrate the system's effectiveness on edge devices, providing a potential zero-touch solution for forecasting the desired parameters in indoor environments. Indeed, each edge device relies only on its own collected data, making the system setup and its general operation more practical in real-world scenarios.

The forecasting model for indoor environmental parameters and energy consumption has been deployed in a scenario using the well-known VRV system, commonly adopted in small environments such as retail stores (further details will be provided in Chapter 4). However, other types of HVAC systems, like hydronic systems, are also prevalent in larger and more complex buildings. While the modeling approach might be adapted for these systems, the complexity of the scenario increases. Hydronic HVAC systems typically consist of multiple devices, including heat pumps, chillers, valves, and water-based distribution networks, all of which introduce a greater number of variables in the model. These additional components not only influence the operational parameters of HVAC devices needed to optimise thermal comfort but also the overall energy consumption sources. Indeed, the interaction between different components, such as the balance between heat exchangers, circulating pumps and flow rates, directly affects both operational parameters and overall energy consumption. Therefore, adapting the forecasting model for hydronic systems requires a more comprehensive analysis, capable of integrating these dynamic processes. A promising research direction might involve developing multiple ad-hoc models, each tailored to specific aspects of the hydronic system (e.g., one model for heat pump operation, another for chiller efficiency, etc.). These models could then cooperate to provide a more accurate prediction and optimisation of environmental parameters and energy consumption in such complex scenarios. However, further research is necessary to fully explore the potential.

Chapter 4

Energy-Efficient Comfort Optimisation

As mentioned in Chapter 1, the Covid-19 pandemic has highlighted the importance of environmental comfort in fostering the well-being and health of people. In modern industrial, commercial, and residential buildings, the required comfort is typically achieved through a combination of passive energy sources, such as solar irradiance and heat exchangers, and HVAC systems. While passive strategies can effectively enhance the livability of indoor spaces at minimal or no energy expense, active strategies based on HVAC machines are often preferred to have direct and immediate control over the indoor environment.

An HVAC system (i.e., VRV) typically consists of one or more air handling units. As depicted in Figure 4.1 and detailed by Ahmad et.al. [57], a standard air handling unit in an HVAC system includes several key components: an outdoor air damper for regulating outside air intake, an exhaust air damper for managing air discharge, a return air damper for recirculation control, a return air fan for extracting indoor air, and heating and cooling coils for adjusting air temperature. Additionally, a supply air fan ensures the flow of conditioned air. Depending on specific requirements, other components (e.g., filters, dehumidifiers, etc.) might also be integrated. Finally, as described by Ghahramani et.al. [58], HVAC systems are typically connected to thermostats and actively operate in response to detected changes in temperature to maintain the desired set point.

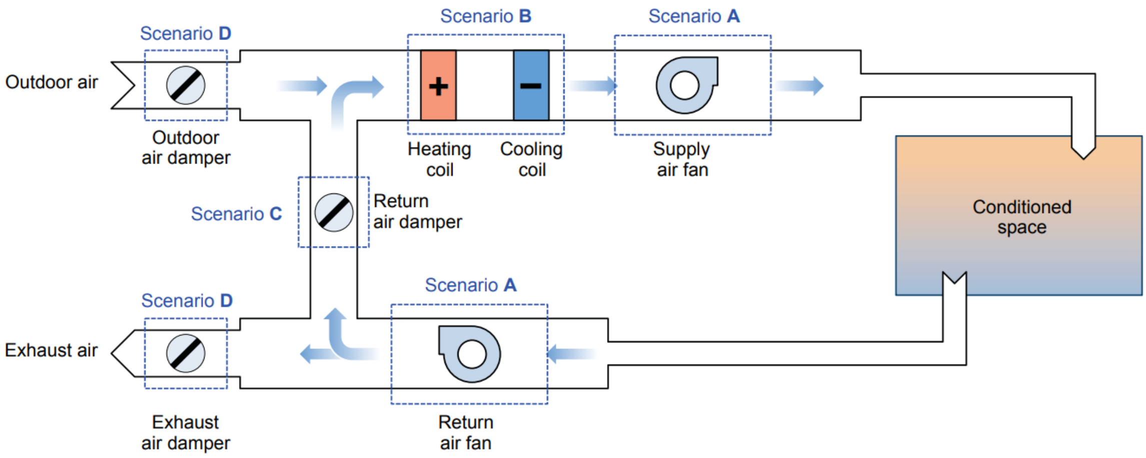


Figure 4.1: The scheme of a typical air handling unit in an HVAC system.

Traditionally, the control of these devices is managed on-site by local personnel, who manually adjust thermostats to regulate thermal comfort, often without adequate attention to energy efficiency. For instance, in commercial buildings, HVAC systems are frequently left active at the end of the day, resulting in unnecessary energy consumption during night periods. In other cases, the operational parameters of these machines are manually set to a fixed set point (i.e., desired target temperature) during working hours or throughout the whole day, regardless of outdoor weather conditions and their impact on indoor environments. These behaviours commonly lead to inefficiencies, impacting both comfort levels and energy consumption.

In response to these challenges, facility managers are increasingly interested in automated systems that can continuously optimise HVAC devices over time. These solutions take a central role in scenarios involving a large amount of geographically distributed and physically heterogeneous sites, each potentially requiring different control strategies. This chapter introduces an intelligent algorithm called EECO to tackle these challenges. EECO efficiently meets comfort requirements throughout the day while reducing the energy footprint in an automated manner. Basically, after an initial configuration of the main parameters (e.g., the desired comfort interval throughout the day, specific parameters of the comfort model), the proposed solution can effectively work shortly after its deployment and it keeps up to date independently over time. This results in an automated and practical solution for HVAC optimisation, ensuring comfort requirements are met during opening hours while balancing both thermal comfort and energy consumption concerns. Indoor comfort is modelled using the Predicted Mean Vote (PMV) index [59, 60], a thermal comfort metric referenced by different indoor comfort standards globally, including the European Standard EN 16798.

This chapter is mainly based on our published paper "Segala, G.; Doriguzzi-Corin, R.; Peroni, C.; Gerola, M.; Siracusa, D. *EECO: An AI-Based Algorithm for Energy-Efficient Comfort Optimisation.* Energies 2023, 16, 7334." [61].

4.1 Motivation

Existing research on the comfort-energy trade-off in indoor environments proposes different approaches. Despite advancements in this field leading to innovative solutions, a major drawback is the limited scalability. This refers to the capability to replicate and automate a specific approach across different environments, regardless of their physical characteristics. Typically, proposed solutions are tailored to the specific environment under study, requiring a comprehensive analysis of each building's layout, materials, location, and installed HVAC systems to define customised physical or mathematical models (e.g., [24–29]). Similarly, other solutions rely on complex building-related information (e.g., [31, 62–64]) and might require customisations within the monitored environment.

Additionally, AI-based solutions (e.g., based on reinforcement learning) often require a significant time-bounded amount of data to train these models. This requirement might impact both short-term deployment and long-term maintenance, making it challenging to quickly implement and continuously update AI models to stay current with environmental changes. In this regard, mechanisms for updating HVAC configurations over time are rarely addressed, except in rare cases [26, 62, 64]. Finally, several works provide theoretical analysis techniques for comfort and energy optimisation but lack real-world validation [65–67].

4.2 Main Contribution

We approach the problem from a different angle, proposing a data-driven AI-based solution called EECO for automated and intelligent regulation of HVAC systems. While designing smart and adaptive solutions using data collected from IoT sensors is essential for optimising HVAC systems [68], our focus is also on ensuring that these solutions are deployable and replicable with minimal human intervention. This aspect is crucial for practical applications, particularly for managers overseeing tens or hundreds of buildings.

The proposed solution does not require any intervention of expert personnel or prior information about the monitored environment (e.g., installed HVAC devices, layout, and materials) to define physical or mathematical models of the environment. It continuously learns from the collected data how the different agents, including passive phenomena, impact the monitored parameters. Basically, after an initial configuration of key parameters (e.g., the comfort interval throughout the day, some parameters of the comfort model), the proposed solution can effectively work immediately after deployment and remains self-updating over time. This adaptive approach allows the system to make short-term decisions based on long-term predictions, continuously selecting the proper HVAC configuration in terms of ON/OFF and set point to optimise thermal comfort and minimise energy consumption.

From an applicability perspective, the proposed solution holds the potential for being applied in any building equipped with a control system capable of gathering environmental and energy consumption data and interfacing with local HVAC devices. The algorithm has been tested during summer and winter periods in a warehouse of a small production plant belonging to a large retail company in northern Italy. Validating AI-control solutions in real environments is crucial to demonstrate their effectiveness in the intelligent control of HVAC systems [7]. Indeed, using simulated data or models might not accurately replicate real-world environments, which can be affected by unexpected events (e.g., windows or doors being opened or rapid increases in occupancy).

4.3 State of the Art

In recent scientific literature, numerous studies address achieving thermal comfort, tackling the trade-off between maximising comfort and minimising energy consumption from different perspectives.

The following sections will offer a detailed overview of state-of-the-art solutions in this field.

4.3.1 Pareto Analysis

Different works [65–67] address the problem using Pareto analysis. This approach provides a set of possible trade-offs between comfort and energy consumption, each of which might be a viable solution for the deployment. Nonetheless, the mentioned research works provide static analysis with a restricted number of software simulations and do not consider any prediction in the future for proactive decision making. Additionally, they model the objective functions through ad-hoc mathematical models tailored to specific environments under study, hence limiting their applicability across multiple sites. Finally, while calculating the Pareto front can be useful, these studies lack an effective strategy to select a single configuration that ensures optimal comfort at minimal cost.

4.3.2 Reinforcement Learning

As mentioned in Section 4.1, most research works address the problem from a different perspective, using simulation software to physically model buildings. This approach provides either simulated environments for analysis or generate a large amount of data to train AI models [26, 28, 29, 31]. For instance, Gao et al. [29] propose a DL solution based on reinforcement learning validated through a simulated building thermal environment and an HVAC system. Their AI models are trained with extensive hourly simulated data. Another solution based on reinforcement learning is presented by Valladares et al. [28]. In their study, a reinforcement learning model is first trained with 10 years of simulated data, following a similar approach to Gao et al. [29], before being deployed in real environments to evaluate the performance. By means of this extensive training data, they achieve a balance among indoor comfort, air quality, and the energy consumption of the air conditioning and ventilation systems.

In contrast to the research works proposed by Valladares et al. [28] and Gao et al. [29], a different solution based on model predictive control (MPC) is proposed by Ascione et al. [26]. However, even this approach relies on simulation-based physical models to optimise the hourly set point temperature for the next 24 hours. Furthermore, Jing et al. [31] propose a simple PMV-based approach to keep the environment within the comfort level and overcome the limitations of typical temperature-based mechanisms. Despite improvements in terms of daily energy savings, the proposed solution only focuses on thermal comfort, with no attention for a trade-off between PMV index and energy consumption in the HVAC control strategy. Additionally, the proposed solution is validated and analysed only through simulation models, with no real-world validation.

4.3.3 Passive strategies

Other works rely on advanced passive strategies. For instance, Liu et al. [24] analyse the applicability and effectiveness of these technologies in residential buildings through physical models, resulting in significant energy savings. Additionally, de Araujo Passos et al. [25], in their study, define a mathematical model to optimise a novel HVAC system by relying on passive energy sources (e.g., solar irradiance and heat exchangers) as much as possible. Their study demonstrates that significant energy-saving results can be achieved, with over half of the energy demand met through passive means.

4.3.4 MPC and other solutions

Alternative approaches that do not rely on physical models of buildings are proposed in the literature. Chen et al. [27] propose an MPC solution by modelling the building through mathematical models. However, complex building-specific information is used (e.g., conduction/convection coefficient, wall thickness, air mass flow rate, etc.). It is worth noting that, in this work, feedback from occupants takes a central role to adapt thermal comfort based on personal perception, leading to improved comfort outcomes. In this regard, other MPC-based studies explore how personal preferences affect the optimisation of energy consumption and the well-being of occupants [69].

To overcome the limitations of physical-based models, as per our goal, Manjarres et al. [63] introduce a framework aimed at minimising energy consumption while ensuring indoor temperatures remain within predefined ranges. The proposed framework outlines an optimal schedule for HVAC ON/OFF and mechanical ventilation (MV) operation for the next 24 hours. However, it requires the deployment of specific sensors (e.g., in the outlet conduct of the air handling unit within the HVAC device). Additionally, it primarily considers indoor temperature rather than thermal comfort (e.g., PMV index) and does not account for updates to the operating schedule throughout the day in response to potential environmental changes. Similarly, Yang et al. [62] propose an MPC approach that integrates AI to overcome the constraints associated with physical models. Additionally, they introduce an update mechanism over time to capture any possible environmental change. However, their solution requires customisations within the environments in terms of advanced sensors (e.g., combined temperature-humidity-pressure-lux (THPL) sensors) to be installed in specific locations as well as detailed information regarding chilled water of HVAC devices. This bounds their approach to the specific environment being evaluated. Martell et al. [64] present another approach that effectively keeps up with with environmental changes but includes complex building-related information. The authors propose a multi-objective control architecture to estimate optimal set points, updating the Pareto front hourly to select optimal temperature settings for each hour of the day. Despite the update mechanism, even in this case, complex parameters closely tied to the evaluated environment are considered. For instance, the authors use heat gains resulting from different natural phenomena (e.g., convection, ventilation, and infiltration) to model the indoor temperature behaviour, which might be different across different sites.

4.4 Background

4.4.1 Predicted Mean Vote

The PMV is a thermal comfort index introduced by Fanger [70] and used by many research works to model the thermal comfort of the occupants. In particular, as observed by Tartarini et al. [71], PMV computes the mean thermal sensation vote of a large number of people according to a sensation scale ranging from –3 to +3, respectively from cold to hot passing through a value equal to 0, which means a neutral condition. In this research work, the open-source Python library *pythermalcomfort* [72] is used to compute PMV index. This library comprises a range of functions for modeling indoor environmental comfort and its associated parameters. In addition, we refer to an online tool [71] to dynamically find the boundaries for the different thermal comfort categories defined by EN 16798 standard. The PMV index is computed as a function of environmental and personal variables [59], in particular:

- Air temperature [°C]. The indoor temperature in the environment.
- Mean radiant temperature [°C], defined as the temperature due to radiant heat exchange between a human body and a given environment [73]. For the sake of simplicity, we assume the mean radian temperature equal to the air temperature.
- Relative humidity [%]. Indoor relative humidity in the environment.
- Metabolic rate [W/m^2]. It is associated with the activity performed by the occupants in the environment. We set it equal to 1.6, which

corresponds to a light activity in the environment coherently with our real test case.

- Relative air velocity [m/s]. It includes the air speed within the considered environment as well as the air speed due to body movement. It is computed by using function *v_relative(v, met)* from library *pythermalcomfort*, with v equal to 0.15 m/s (heating) or 0.25 m/s (cooling) according to standard limits defined by ISO 7730 [74].

- Clothing insulation [clo]. It is the thermal insulation provided by clothing worn by people in the environment. As estimating a single value for each person requires advanced sensors as well as possible customisations within the environment, we modeled such parameter with a unique value. To cope with this task, we used the function *clo_dynamic(clo, met)* from library *pythermalcomfort*, which estimates the dynamic clothing insulation of a moving occupant. Basically, it corrects for the effect of the body movement for met equal or higher than 1, using the same equation of ASHRAE 55 Standard (i.e., clo = clo $\times$ (0.6 + 0.4/met)). The *clo* parameter is computed by means of function *clo_tout(tout, units="SI")*, which computes the daily clothing insulation based on outdoor temperature at 6.00 a.m.. In this way, we provide a dynamic estimate of the clothing insulation throughout the year.

Standard EN 16798 ([75]) defines specific categories for indoor comfort based on the PMV, which are reported in Table 4.1:

Table 4.1: Comfort categories and the related PMV range.

Category	**PMV**
I	-0.2 < PMV < 0.2
II	-0.5 < PMV < 0.5
III	-0.7 < PMV < 0.7
IV	-1 < PMV < 1

It is worth noting that, negative ranges of PMV index are typical for heating mode while positive values are obtained when cooling mode is active.

As underlined by Yau et al. [59], the PMV index serves as an objective measure that can be computed in any indoor environment, regardless installed HVAC systems and conditions of outdoor environment. Therefore, considering its widespread use in the literature and reference in different standards (e.g., ISO 7730, EN 16798), we have chosen to employ such methodology.

4.5 Methodology

4.5.1 Introduction

As previously mentioned, in this chapter we tackle the problem of energy-efficient comfort optimisation in indoor environments. Specifically, we study and develop a methodology for the automated control of HVAC systems, with the aim to ensure the defined comfort requirements within the considered environment during opening hours.

As introduced in Section 4.4.1, the thermal comfort index (PMV) (defined by Fanger [70]) depends on a set of parameters (such as air temperature and humidity of the environment), which, in a real-world environment, can be influenced by the outdoor conditions. In this regard, adapting the HVAC optimisation according to outdoor weather takes a central role from a research perspective [76]. At a first glance, a trivial greedy PMV-Based mechanism that activates the HVAC system when the thermal comfort level is outside the desired range, similar to the approach proposed by Jing et.al [31], might be seen as a viable solution., However, such an approach, which takes decisions only considering the current state, might not work as desired. In particular, let us first define four comfort states (represented in Figure 4.2) based on the comfort interval defined over the course of the day:

- **No Comfort (NC)**: the shop is closed (e.g., at night or on Sundays).

- **No Comfort then Comfort (NC-C)**: usually early morning before the opening.

- **Comfort (C)**: the shop is open (e.g., during a working day).

- **Comfort then No Comfort (C-NC)**: generally late afternoon before closing.

Indeed, a greedy approach might not be able to achieve the target comfort at the beginning of the working time (NC-C state), i.e., when the comfort level is far from the target value because of a long inactivity period (e.g., night closure, holiday, etc.). Similarly, it might activate the HVAC system when the store closure is approaching (C-NC state), leading to inefficient energy utilisation.

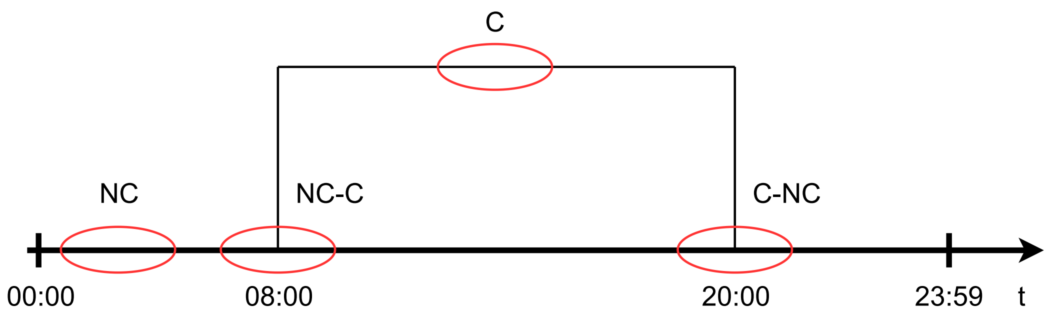


Figure 4.2: Representation of the four control states over the course of a day. In this example, the comfort interval is set between 8 AM and 8 PM.

Based on these premises, we propose an AI-based solution called Energy-Efficient Comfort Optimisation (EECO), in which the 1D CNN described in Section 3.4.2 is employed to predict the future indoor environmental parameters (i.e., temperature, humidity and CO_2) and energy consumption due to HVAC devices, considering both indoor and outdoor conditions. Specifically, given a range of possible HVAC configurations (meaning, ON/OFF and SP), the CNN predicts the effects of each choice on future thermal comfort and energy consumption. At every quarter of an hour, the system generates the predictions for the next m quarters of an hour, building a m-level tree of candidate sequences of HVAC configurations that tracks the environment's evolution in the near future based on past (real or predicted) conditions.

The ultimate goal of EECO is to select the branch of the tree (hence a sequence of future HVAC configurations), which, based on the CNN predictions, minimises an objective function defined as the weighted summation of thermal comfort index PMV and energy consumption.

In the remainder of this Section, we describe the whole process of comfort optimisation, including input/output of the CNN, the structure of the decision tree and the logic behind the choice on the HVAC settings. This process is described in Algorithms 1 e 2 and illustrated in Figure 4.3 and 4.4.

4.5.2 Tree Building

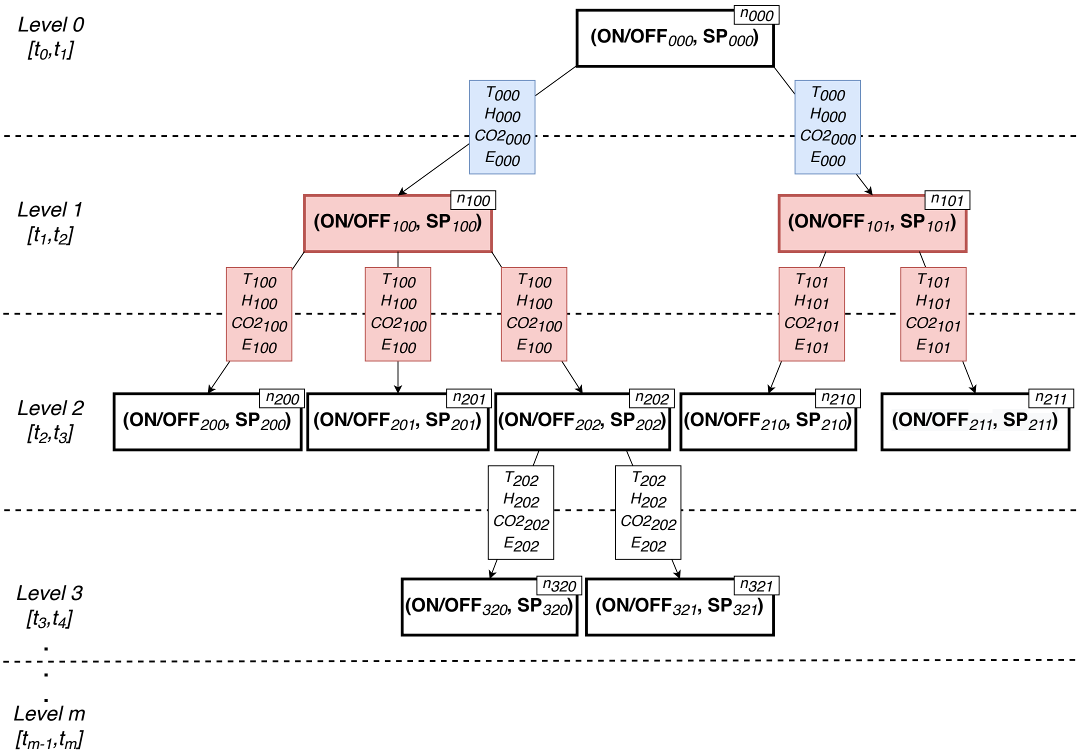


Figure 4.3: The decision tree. Node's attributes are HVAC configurations (ON/OFF$_{ijk}$, SP_{ijk}), which are labelled with 3-digit numbers: the level of the tree (i), the index of the parent node (j) and the index of the node (k). T_{ijk}, H_{ijk}, CO_{2ijk} and E_{ijk} refer to predicted values of temperature, humidity, CO_2 and energy consumption for node n_{ijk} at Level i in the time slot $[t_i, t_{i+1}]$.

The decision tree is built every quarter of an hour (or time slot), using the output from the previous time slot as a root node. The process that builds the tree is formulated in Algorithm 1 BuildTree. BuildTree takes as input the current root node n_{000}, historical data of HVAC settings, weather conditions, energy consumption and the target comfort value $\bar{C}$ (a PMV value) and the operating mode o (either heating or cooling). The root node's attributes include the current HVAC settings, i.e. the operational settings in time slot $[t_0, t_1] = [t_0, t_0 + 15\text{min}]$ In general, a node n_{ijk} of the tree is characterised by a 3-digit label and range of attributes. The first

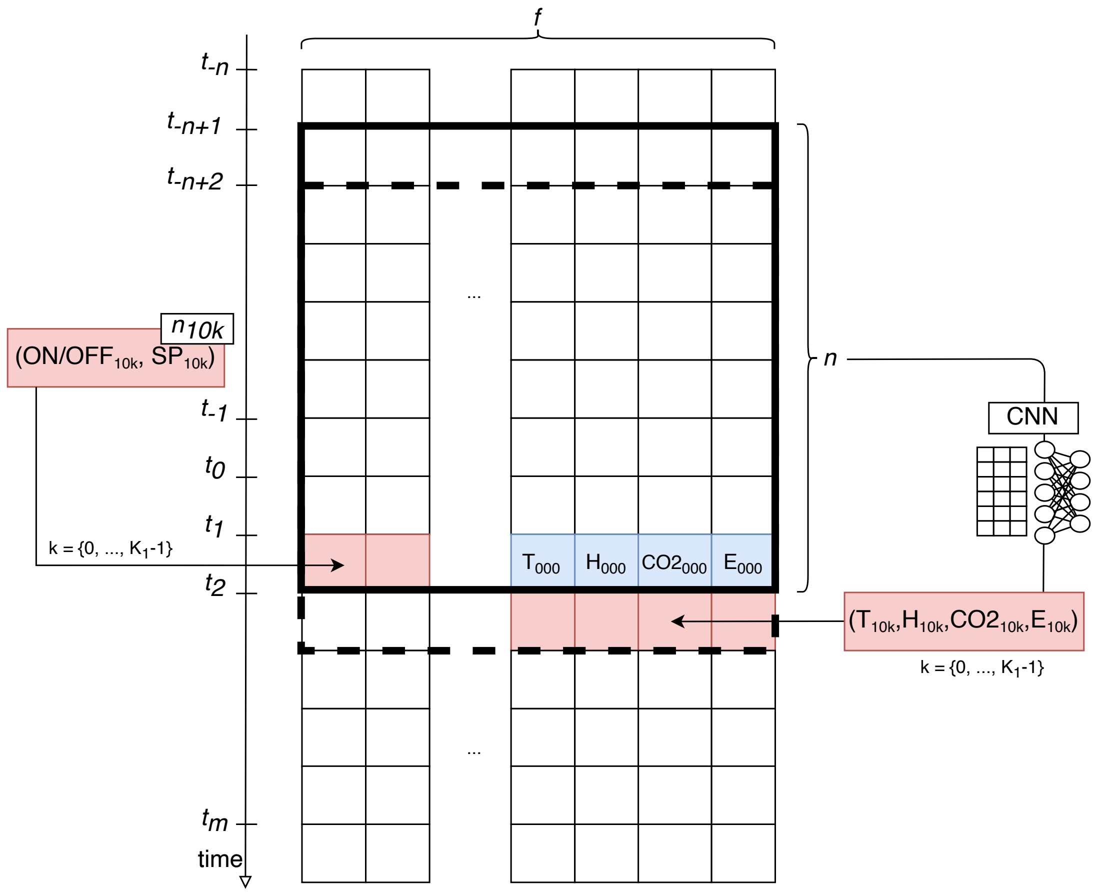


Figure 4.4: The first step of the building decision process at time slot $[t_0, t_1]$, during which a tree of possible HVAC configurations is built iteratively from time slot $[t_1, t_2]$ to time slot $[t_{m-1}, t_m]$. In this example $k = \{0, 1\}$ for the two nodes at Level 1 of the tree (Figure 4.3).

digit of the label indicates the level of the tree to which the node belongs, the second digit is the index of the parent node, while the third digit is the index of the node. The attributes are: the current HVAC settings at time t_i, i.e. the pair of values $(\text{ON/OFF}_{ijk}, SP_{ijk})$, fan speed and operating mode. Node's attributes also include average energy consumption E_{ijk}, indoor temperature T_{ijk}, indoor humidity H_{ijk} and indoor $CO2_{ijk}$.

Figure 4.3 illustrates a portion of the tree built during time slot $[t_0, t_1]$, starting from Level 0, which consists of root node n_{000}. Level 1 of the tree is populated with a set of children nodes n_{10k}, $k = \{0, \cdots, K_1 - 1\}$, each one defined with pair $(\text{ON/OFF}_{10k}, SP_{10k})$, i.e. a set of possible HVAC configurations that could be applied during time slot $[t_1, t_2]$ (Level 1 in Figure 4.3). Like all the other tree levels, Level 1 includes the OFF actuation (line 8 of Algorithm 1), and a set of actuations that are computed with Algorithm 2 (called at line 10 of Algorithm 1) using the indoor temperature of the parent node ($p_{00}(T) = T_{000}$ for Level 1), the indoor humidity of the parent node ($p_{00}(H) = H_{000}$ for Level 1), the target comfort level $\bar{C}$ and the HVAC's operating mode o (either HEATING or COOLING). Algorithm 2 defines the temperature range to be within the desired target comfort $\bar{C}$ and, based on that information and HVAC's operating mode o, selects the strategy to enter the comfort range or move within that through a couple of actuations.

One of the nodes at Level 1 is the output of the process executed during time slot $[t_0, t_1]$, and contains the HVAC configuration for time slot $[t_1, t_2]$. Moreover, such a node will be the root node when the process is executed in time slot $[t_1, t_2]$. Which is the right node? The selection of the most appropriate node is done by populating the tree up to Level m using the predictions of the CNN to simulate the behaviour of the system in different conditions over the time (until time slot $[t_{m-1}, t_m]$). The solution is the node at Level 1 that belongs to the branch of the tree whose sequence of actuations guarantees the best comfort at the minimum energy consumption in the long term. The logic behind this decision is explained in the following steps:

- Given a Level L_i, and a parent node p_{ij}, with $j \in \{0, \cdots, |L_{i-1}|\}$ and $|L_{i-1}|$ the cardinality of Level L_{i-1}, A_{ij} is the list of possible HVAC actuations for time slot $[t_i, t_{i+1}]$ applied to the children nodes of parent p_{ij} (lines 8, 10). In Figure 4.3, $A_{21} = \{(\text{ON/OFF}_{210}, SP_{210}),$ $(\text{ON/OFF}_{211}, SP_{211})\}$.

For each HVAC configuration $A_{ij}[k]$ $k \in \{0, \cdots, K_j - 1\}$, the system predicts the effects of such configuration on comfort and energy consumption starting from the parent's conditions V_{ij} of indoor temperature $p_{ij}(T)$, indoor humidity $p_{ij}(H)$, indoor CO_2 $p_{ij}(CO2)$, and energy consumption $p_{ij}(E)$ (line 14).

Algorithm 1 Tree building.

Input: Root node (n_{000}), Historical data (X), Tree depth (m), Target comfort ($\bar{C}$), Operating mode (o)

Output: Tree (t)

1: **procedure** BuildTree(n_{000},X,m,$\bar{C}$,o)
2: $t \leftarrow L_0(n_{000})$ ▷ Init tree node n_{000} at level 0
3: **for** $i = 1, ..., m$ **do** ▷ Loop over tree levels
4: $L_i \leftarrow \emptyset$ ▷ Init level i
5: $X_i \leftarrow X[-n + i, i - 1]$ ▷ Extract *n-1* rows from X
6: **for** $j = 0, ..., |L_{i-1}| - 1$ **do** ▷ Loop over parents p_{ij}
7: $P_{ij} \leftarrow \emptyset$ ▷ Init list of children of parent node p_{ij}
8: $A_{ij} \leftarrow [(\text{OFF}, p_{ij}(\text{SP}))]$ ▷ Init list of actuations
9: **if** $\bar{C} \neq NC$ **then**
10: $A_{ij} \leftarrow A_{ij} \cup$ GetAct(p_{ij}(T), p_{ij}(H), $\bar{C}$, o)
11: **end if**
12: **for** $k = 0, ..., K_j - 1$ **do** ▷ with $K_j = |A_{ij}|$
13: $(\text{ON/OFF}_{ijk}, SP_{ijk}) = A_{ij}[k]$
14: $V_{ij} = [p_{ij}(T), p_{ij}(H), p_{ij}(CO2), p_{ij}(E))]$
15: $X_{ijk} \leftarrow X_i \cup [\text{ON/OFF}_{ijk}, SP_{ijk}, \cdots, V_{ij}]$
16: $n_{ijk} \leftarrow$ GetNode(X_{ijk})
17: P_{ij}.insert(n_{ijk})
18: **end for**
19: L_i.insert(P_{ij}) ▷ Add nodes of list P_{ij} to level i
20: **end for**
21: t.insert(L_i) ▷ Add level i to the tree
22: **end for**
23: **return** t
24: **end procedure**

Algorithm 2 Get actuations.

Input: Current temperature (T), Current humidity (H), Target comfort ($\bar{C}$), Operating mode (o)

Output: List of actuations (A)

procedure GETACT(T, H, $\bar{C}$, o)
    $A \leftarrow \emptyset$ ▷ Init list of actuations
    $T_{min}, T_{max} \leftarrow$ GETRANGETEMPERATURE(T, H, $\bar{C}$)
    if $T_{min} <= T <= T_{max}$ **then**
        $SP \leftarrow T$
        if o = HEATING **then**
            while $SP <= T_{max}$ **and** $SP <= T + 1$ **do**
                A.insert((ON,SP))
                $SP \leftarrow SP + 1$
            end while
        else if o = COOLING **then**
            while $SP >= T_{min}$ **and** $SP >= T - 1$ **do**
                A.insert((ON,SP))
                $SP \leftarrow SP - 1$
            end while
        end if
    else
        if o = HEATING **then**
            $SP_{min} \leftarrow ceil(T)$
            A.insert$((\mathrm{ON}, \mathrm{SP}_{min}))$
        else if o = COOLING **then**
            $SP_{max} \leftarrow floor(T)$
            A.insert$((\mathrm{ON}, \mathrm{SP}_{max}))$
        end if
    end if
    return A
end procedure

- As sketched in Figure 4.4, the prediction for node k is obtained by feeding the CNN with an array of $n - 1$ rows of historical HVAC settings, environmental values and other features (see Table 3.4) observed from t_{i-1} to t_{-n+i}. While the nth line contains the node's attributes A_{ij} and other features related to $[t_i, t_{i+1}]$. This operation is summarised at line 16 with function GetNode. Node n_{ijk} generated using actuation $A_{ij}[k]$ is added to the list of children nodes P_{ij} of parent p_{ij} (line 17).

- The list of children nodes P_{ij} is added to Level L_i, which is then added to the tree when all the parents of the previous Level L_{i-1} have been processed.

- The above steps are repeated until the maximum tree depth m is reached.

4.5.3 Strategy Selection

The result of the process is a set B of simulated sequences of HVAC configurations from time t_1 to time t_m, which can be also seen as a set of paths across the decision tree (or branches) from the root node to the leaves. The final step consists of choosing the best path, i.e. the path that minimises both PMV and energy values, as formally expressed in Equation 4.1:

$$f_\alpha(C_b, E_b) = \alpha \cdot C_b + (1-\alpha) \cdot \frac{E_b}{E_{max} \cdot m} \qquad \forall b \in B \tag{4.1}$$

The objective function $f_\alpha(C_b, E_b)$ is the weighted sum of predicted comfort and energy for branch b, where C_b is a sum of the predicted values of thermal comfort on each node of the branch, while E_b is the sum of the predicted values of energy consumption. More precisely, C_b and E_b are computed as follows:

$$C_b = \sum_{i=0}^{m} (|C_{b,i}| - |\bar{C}|) \cdot \beta^i \quad E_b = \sum_{i=0}^{m} E_{b,i} \quad \forall b \in B \tag{4.2}$$

where β is a positive number smaller than 1, so that β^i (β at the power of i) decreases as the tree level i increases to give less importance to the nodes far from the root (i.e., far in the future).

The energy is normalised with the estimation of the maximum energy E_{max} consumed by the HVAC system in a quarter of an hour and multiplied by the number of time slots in a branch (m). α controls the relative weight of comfort and energy values. In our analysis we focus on a scenario where comfort holds priority. In this regard, we set $\alpha = 0.9$.

For a given value of α, the solution is represented by the branch $\bar{b} \in B$ such that:

$$\bar{b} = \operatorname*{argmin}_{b \in B} f_\alpha(C_b, E_b) \tag{4.3}$$

Hence, the output of the whole process is the HVAC configuration ($\text{ON/OFF}_{10k_{\bar{b}}}, SP_{10k_{\bar{b}}}$) for the next time slot $[t_1, t_2]$, i.e., the attributes of node $k_{\bar{b}}$ at Level 1 of branch $\bar{b}$. The above process is executed every 15 minutes.

4.6 Experimental Setup

The proposed solution has been tested in a real warehouse of approximately 250 m^2 within an underwear manufacturing plant in northern Italy, owned by an international retail company. The monitored environment is equipped with HVAC devices (i.e., VRV systems) that are interfaced through the Modbus protocol [50] and regulated with same settings in terms of ON/OFF and set point. We provided additional details regarding meters and sensors adopted in Chapter 3, Section 3.4.1. All data collection and control operations within the environment are performed locally on an Intel NUC [77], equipped with an Intel Core i3 CPU and 8 GB of memory, which serves as the master node for all connected devices.

The building under consideration, as mentioned in Section 4.2, is located in northern Italy and generally experiences a Mediterranean climate. During the winter, outdoor temperatures range from approximately 0 °C to 15 °C while in the summer temperatures vary between 18 °C and 35 °C. Both real-world experiments and software simulations have been performed to validate our algorithm, covering both winter and summer days. This provides a performance overview both in heating and cooling mode.

We have compared *EECO*, which dynamically sets the HVAC configuration to achieve a trade-off between thermal comfort and energy consumption, with other two approaches:

- The *Fixed Set Point* approach, which configures the same set point value throughout the whole day.

- The *PMV-based* approach, a greedy strategy that controls the HVAC devices by just analysing the current value of the PMV index. In this regard, the greedy approach aims to achieve the best comfort conditions within the desired range (i.e., the lower bound), switching the HVAC devices off once such objective is addressed.

For all the experiments, we set a comfort time interval of twelve hours between 8 AM and 8 PM in accordance with our partner's requirements. During this interval, a pre-defined comfort level needs to be guaranteed (Table 4.1). Due to lack of activities within the environment on the weekends, experiments were performed exclusively from Monday to Friday. For evaluation purposes, we set the tree depth m equal to 10, starting from the current quarter of hour. This enables us to align the operational schedule of HVAC devices according to EECO with that of the fixed set point strategy (from 6 AM to 8 PM), which is defined by the partner company.

4.7 Experimental Results

In this section, we present the benefits of *EECO* from different perspectives, both through experiments in a real environment and by software simulation.

4.7.1 Indoor Environment Forecast

One of the strengths of EECO is the capability to predict the evolution of the indoor environment and to take proper short-term decisions. To this aim, let us consider a Summer early morning scenario when the HVAC devices need to be activated in advance to reach the desired comfort level at a specific time (e.g., 8 AM). Also, let us select the *category III* (cf. Table 4.1) as the target comfort, i.e., -0.7 < PMV < 0.7 with positive values in cooling mode and $\alpha = 0.9$ in Equation 4.1. With this experiment, we show the ability of our predictive methods in activating the HVAC devices in advance, ensuring the target comfort is achieved before 8 AM.

Figure 4.5 illustrates the actuation strategy in terms of ON/OFF and predicted/actual values of the PMV index and energy consumption over two overlapping time intervals of two hours, one starting at 5:45 AM and the following one starting at 6:00 AM. From the plots in the figure, we can observe that the algorithm turns on the HVAC devices at 6 AM and plans to keep them active over the following two hours to achieve the comfort range on time (i.e., PMV < 0.7 before 8 AM). As reported in Table 4.2, such configuration is expected to achieve a PMV value just below 0.7 at 8 AM. Actually, analysing the dashed line in the PMV plots, which corresponds to the actual comfort values recorded every quarter of an hour, it is possible to notice that the environment meets the comfort requirements from 7 AM, resulting in a PMV value equal to 0.65 at 8 AM. This is achieved thanks to an accurate prediction of the environment's evolution (Table

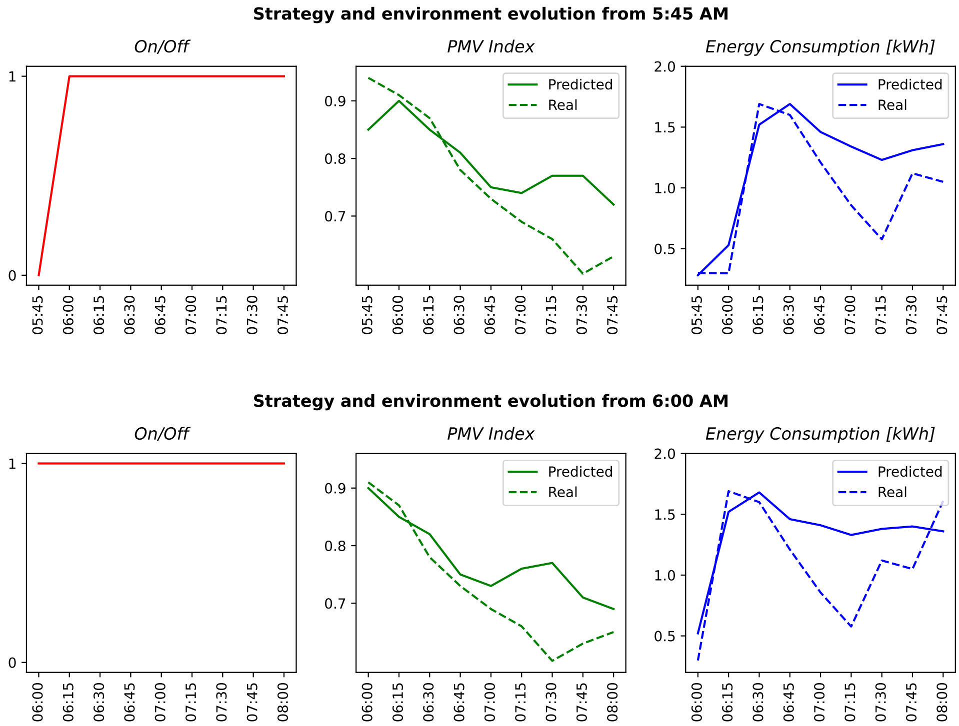


Figure 4.5: Example of actuation strategy in terms of ON/OFF (*left*) and corresponding predicted environment evolution in terms of PMV index (*middle*) and energy consumption (*right*) in the early morning at 5:45 AM (*top*) and 6:00 AM (*bottom*) to achieve the comfort requirements by 8:00 AM.

4.2). Notably, this result would not have been possible with a basic greedy strategy, mentioned in Section 4.5, which would have activated the HVAC devices starting from 8 AM, thereby failing to ensure the required comfort range at the beginning of the working day.

Table 4.2: Accuracy of the predicted environment in terms of energy consumption and PMV as well as difference between the real PMV and the predicted value at 5:45 AM and 6:00 AM, respectively.

Time	**Energy - RMSE**	**PMV - RMSE**	**Real PMV - 8 AM**	**Predicted PMV - 8 AM**
5:45 AM	0.32	0.08	0.65	0.7
6:00 AM	0.37	0.07	0.65	0.68

4.7.2 Indoor Comfort and Energy Consumption Optimisation

In this experiment, our objective is to evaluate the sensitivity of our solution to term α of Equation 4.1, which controls the relative weight between comfort and energy in the HVAC strategy selection. To this aim, let us choose for this test $\alpha = \{0.3, 0.5, 0.7, 0.9\}$, with a target comfort level set to *category I* in cooling mode, i.e., $0 <=$ PMV < 0.2 (cf. Table 4.1). Due to the consistently low outdoor temperatures observed during the period of these experiments, the indoor environment would have exceeded the comfort boundaries of category II or III (which are more appropriate for this specific scenario), regardless of the value of α, while keeping the HVAC devices off (as reported in Section 4.5). This would have affected the performance analysis of our solution on different values of α both in terms of both energy consumption and thermal comfort. As a result, under these conditions, category I (i.e., which is typically defined in environments with vulnerable people) enables us to effectively analyse the behaviour of our solution while varying the α parameter.

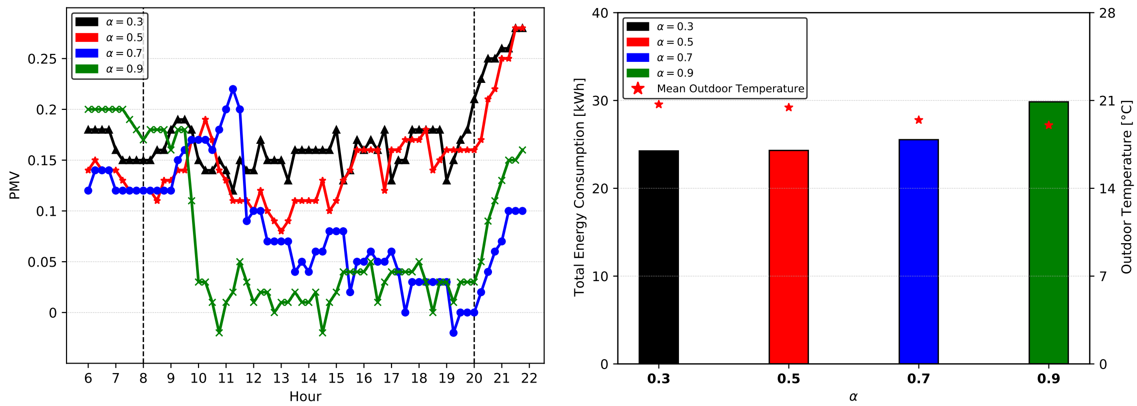


Figure 4.6: The behaviour of (a) hourly PMV index and (b) total energy consumption as the α parameter changes.

Figure 4.6 outlines the behaviour of the PMV index and total energy consumption at different values of α. When $\alpha = 0.9$, the PMV value remains close to zero for most of the day, which corresponds to optimal comfort conditions for the occupants. However, this strategy impacts the building's energy footprint, as HVAC devices are constantly activated to maintain maximum comfort. Reducing the value of α to 0.7 impacts comfort, especially in the morning. Nevertheless, equivalent performance to higher α values is achieved in the late afternoon, due to a decreasing trend in outdoor temperature. Compared to $\alpha = 0.9$, this configuration reduces energy consumption by approximately 5 kWh. Finally, with lower values of α (i.e., $0.3, 0.5$) we penalise the indoor comfort, resulting in higher PMV values ranging between 0.1 and 0.2. We can anyway notice that the reduction in energy consumption is negligible compared to tests with higher values of α. As reported in Table 4.3, lower values of α not only impact daily comfort conditions but also result in higher PMV values the following early morning, leaving the environment in less comfortable conditions at the end of the day. This necessitates increased activity of the HVAC devices to restore the desired comfort level, hence affecting the energy footprint. The table's last column indicates that higher values of α ensure the desired comfort level from the early hours of the next day.

Table 4.3: Average PMV, total energy consumption [kWh] and PMV at 6 AM the next day for different α values.

α	**PMV**	**Total Energy Consumption**	**PMV 6 AM**
0.3	0.15	24 kWh	0.27
0.5	0.13	24 kWh	0.22
0.7	0.08	25 kWh	0.09
0.9	0.04	29 kWh	0.12

4.7.3 Performance Analysis - Real Environment

The previous analysis highlighted that our solution can effectively achieve the comfort objective at different values of α. In this experiment, we focus on guaranteeing a high comfort level with a minimum attention on the energy footprint as well, comparing our algorithm with $\alpha = 0.9$ in Equation 4.1 and a manual approach, where the set point is fixed to the same value throughout the day. We configure our algorithm with *category III* as the target comfort, i.e. -0.7 < PMV < 0.7 with positive values in cooling mod, and we consider both days in heating and cooling mode.

Finally, for the manual approach, HVAC devices are activated at 6 AM to guarantee the same operating interval for both strategies (see the discussion of the experiment in Section 4.7.1).

The evaluation of the two strategies has been performed over 10 days, five days each, in cooling mode. While we have considered 20 days, 10 days each, in heating mode.

Cooling mode

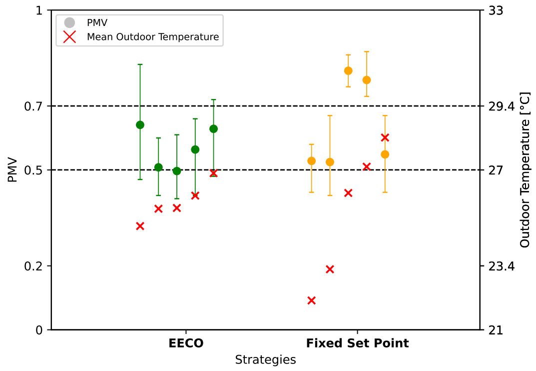
In the manual approach, we set SP=27°C, i.e., the value typically set within the considered environment during cooling periods when the indoor temperature is usually higher. It roughly corresponds to *category III* of the target comfort according to Tartarini et.al. [71] and the configured parameters of PMV index described in Section 4.4.1, which define our evaluated scenario.

Figure 4.7 reports the results in terms of average (a) PMV during opening hours, (b) total energy consumption over the operational interval of HVAC devices against the average daily PMV index, (c) indoor temperature, (d) total daily energy consumption normalised by degree days (i.e., a measure to quantify the deviation of the average daily temperature from a given standard, calculated as the difference between the outdoor temperature and a reference temperature) against the average daily PMV index and (e) variation of PMV during opening hours (i.e., the difference between PMV at 6 AM and PMV at the different quarters of hour).

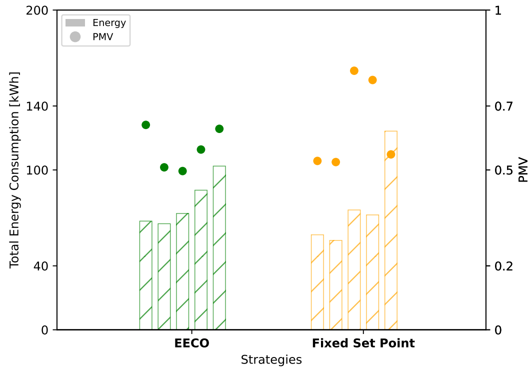
In the case of PMV and indoor temperature, Figure 4.7 reports the confidence interval bounded by the maximum and minimum values. From a comfort perspective, our solution constantly keeps the PMV value close to the lower bound (i.e., 0.5), which corresponds to the best possible indoor comfort conditions within the desired range (Figure 4.7a). The process of comfort optimisation generally requires more activity by HVAC devices (Figure 4.7d), hence affecting the total energy footprint (Figure 4.7b). However, the impact on energy consumption is generally limited, with no relevant peaks on the energy footprint. A slight increase in energy consumption can be observed during the last two days (i.e., day four and five), attributed to slightly higher outdoor temperatures.

On the other hand, the *Fixed Set Point* approach results in unstable thermal comfort (Figure 4.7a). Indeed, with static settings, the HVAC devices are activated only based on the indoor temperature. However, the configured set point value (i.e., 27 °C) might not consistently achieve the target comfort requirements which, in the evaluated scenario, represent a constraint of the problem; as reported in Section 4.4, the PMV index depends on multiple parameters. For instance, clothing insulation, whose value is computed daily using the outdoor temperature at 6 AM, affects the weight of indoor temperature on the computation of thermal comfort. Obviously, this parameter is not considered when using a static set point, potentially leading to discomfort conditions. For instance, on day four of the *EECO* experiment and day three of the *Fixed Set Point* similar clothing insulation values were expected. However, during the former the set point is automatically set to SP=26°C for large part of the day. While, with the *Fixed Set Point*, the set point value is close to the indoor temperature of 27°C, resulting in the HVAC devices operating in an economic mode. HVAC devices typically have a dead band equal to 0.5°C around the control set point, which keeps them active to maintain the target temperature without excessive activity. In terms of energy consumption, if we compare the two days in Figures 4.7b and 4.7d, we can observe that our solution consumed slightly more energy than the *Fixed Set Point* configuration; as underlined previously, the *Fixed Set Point* configuration never reached the required comfort range during that day due to the static set point value that never changes during the day while *EECO* was able to drive the HVAC devices in a way that the comfort requirements were respected throughout the whole day.

In Figure 4.7b we can notice a peak in energy consumption on day five of the *Fixed Set Point* experiment. Compared to days one and two of the same experiment, day five reaches a similar comfort level, but with noticeably higher energy consumption due to higher outdoor temperatures. Despite the extended operation of the HVAC system to maintain the indoor temperature near the set point of SP=27°C, the total energy consumption normalised by degree days, reported in Figure 4.7d, highlights similar energy demands between both approaches. On the other hand, at first glance, days one and two benefit from lower outdoor temperatures, aiding cooling operations and reducing the overall energy footprint. However, a closer analysis of normalised energy consumption in relation to outdoor temperature (i.e., degree days) highlights that *EECO* achieves the same comfort level while optimising energy use. This optimisation is driven by the intelligent control system, which dynamically adjusts to outdoor weather conditions, especially on days when lower outdoor temperature can take a central role in cooling the environment at reduced energy costs.



(a)



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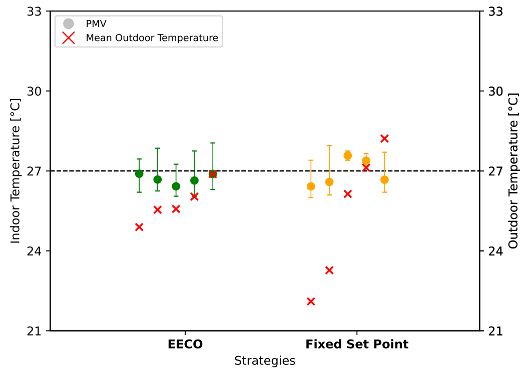

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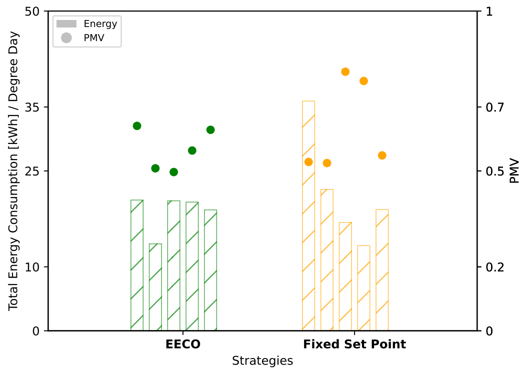

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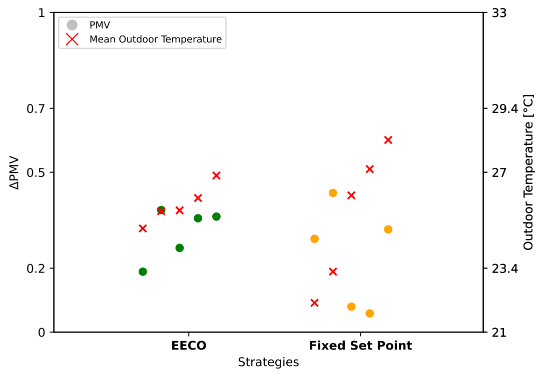


(e)

Figure 4.7: Average daily (a) PMV index, (b) total daily energy consumption against the average daily PMV index, (c) indoor temperature, (d) total daily energy consumption normalised by degree days against the average daily PMV index and (e) variation of PMV index compared to value at 6 AM (PMV_{6AM} - PMV) for both *EECO* and the *Fixed Set Point* approach in cooling mode.

Table 4.4: Overall performance of *EECO* and the *Fixed Set Point* approach in terms of PMV, energy consumption in cooling mode.

	PMV	**Energy Consumption**
EECO	0.56	78 kWh
Fixed Set Point	0.63	77 kWh
Difference	**11%**	**-1%**

In conclusion, as reported in Table 4.4, in cooling mode our solution guarantees better comfort conditions with approximately the same impact on the building's energy footprint compared to the *Fixed Set Point* approach.

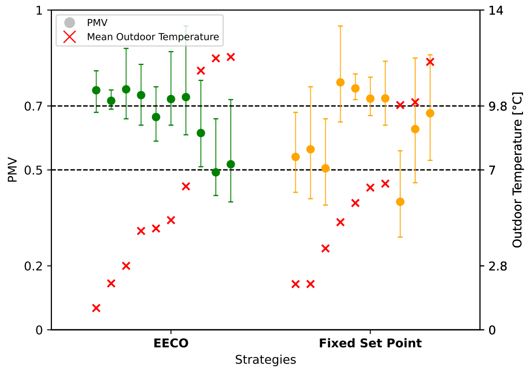
Heating mode

In the manual approach, we set SP=21°C, i.e., the value typically set within the considered environment during heating periods when the indoor temperature is usually lower and roughly corresponding to *category III* of the target comfort. Even in this case, we refer to Tartarini et.al. [71] and the parameters of PMV index described in Section 4.4.1 we set for our scenario.

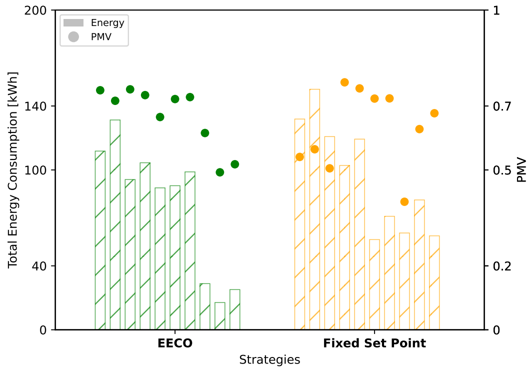
As in the previous subsection, Figure 4.8 reports results in terms of average (a) PMV during opening hours, (b) total energy consumption over the operational interval of HVAC devices against the average daily PMV index, (c) indoor temperature and (d) variation of PMV during opening hours (i.e., the difference between PMV at 6 AM and PMV at the different quarters of hour).

From a comfort perspective, as depicted in Figure 4.8a, our algorithm provides non-optimal results during the coldest days (days one, two and three in both approaches) unlike the *Fixed Set Point* approach. This behaviour is due to some shutdowns of the HVAC devices configured by our approach throughout the day with the aim to effectively achieve a trade-off between the thermal comfort and the energy consumption. However, due to the low outdoor temperature, just a shutdown for a quarter of hour prevents our solution from achieving good PMV values in the long term unlike the *Fixed Set Point*, which constantly keeps the HVAC devices active at 21°C as set point value. Even if the target temperature is not reached, the given comfort category is effectively achieved when the indoor temperature ranges between 20°C and 21°C. Despite such scenario, *EECO* meets the minimum comfort requirements at some point during the day (i.e., in the afternoon), resulting in about 20 kWh on average of saved energy (Figure 4.8b).

When the average outdoor temperature is around 5°C-6°C (from day four to seven in both approaches), EECO generally provides better results in terms of thermal comfort compared to the *Fixed Set Point* approach. Indeed, as depicted in Figure 4.8a, larger improvements of PMV are performed by our approach to enhance the comfort conditions within the desired range. As a result, HVAC devices are forced to have a higher activity, resulting in slightly higher energy consumption (Figures 4.8b and 4.8d) compared to the *Fixed Set Point* approach. In contrast, the latter struggles to maintain comfort in these conditions (e.g., day five falls outside comfort levels). Indeed, the *Fixed Set Point* strategy is driven only by the indoor temperature which is always really close to the set point value (i.e., 21°C) throughout the whole day. This forces the HVAC devices to constantly work in economic mode, as reported previously, limiting their energy consumption but potentially compromising optimal comfort. In such conditions, achieving the desired comfort levels typically requires setting a higher target temperature (e.g., 22°C). In this regard, *EECO* dynamically adjusts the set point value to enhance comfort, resulting in only a marginal increase in energy consumption compared to the *Fixed Set Point* approach.



(a)



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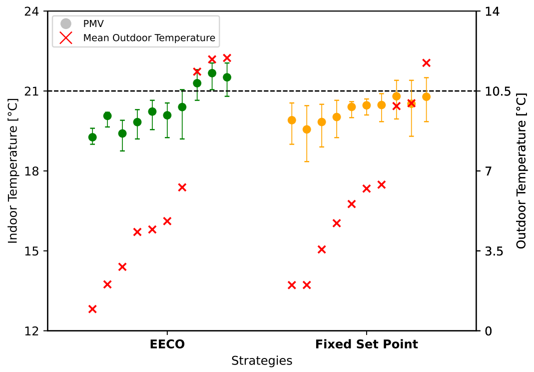

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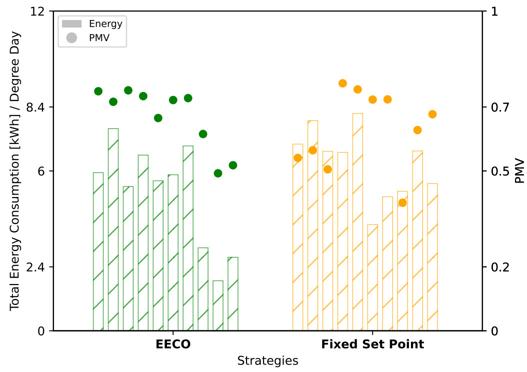

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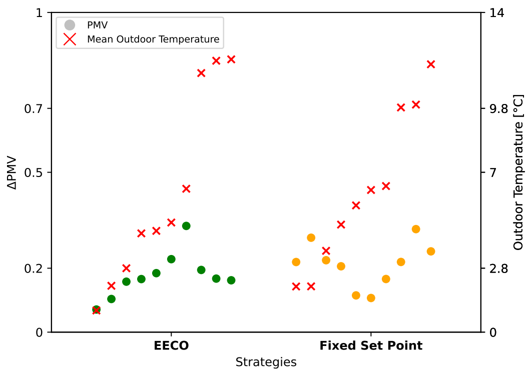

(e)

Figure 4.8: Average daily (a) PMV index, (b) total daily energy consumption against the average daily PMV index, (c) indoor temperature, (d) total daily energy consumption normalised by degree days against the average daily PMV index and (e) variation of PMV index compared to value at 6 AM (PMV_{6AM} - PMV) for both *EECO* and the *Fixed Set Point* approach in heating mode.

During warmer Winter days (from day eight to ten in both approaches), the higher outdoor temperature values help the environment to achieve good comfort conditions with both approaches. In this scenario, our algorithm is capable of reducing the energy footprint by almost 20% compared to the *Fixed Set Point* approach, as also underlined by the total energy consumption normalised by degree days in Figure 4.8d and similarly to what is observed in cooling mode. In this regard, *EECO* not only strategically configures shutdowns of the HVAC devices to take advantage of higher outdoor temperatures for optimising heating operations (as happened in cooling mode in the previous section) but also turns off the HVAC devices once the lower bound of the desired comfort level (i.e., in our case, 0.5) is achieved. In contrast, such behaviour is not included in the *Fixed Set Point* approach. Indeed, the latter is driven solely by the indoor temperature with no attention for thermal comfort. As a result, it always keeps the HVAC devices active, even after achieving the desired thermal comfort level with the configured set point value, as observed on day eight. This leads to a significant amount of wasted energy over the long term, which can be effectively minimised through an intelligent approach like *EECO*, which adapts to real-time environmental conditions.

Table 4.5: Overall performance of *EECO* and the *Fixed Set Point* approach in terms of PMV, energy consumption in heating mode.

	PMV	**Energy Consumption**
EECO	0.67	79 kWh
Fixed Set Point	0.63	95 kWh
Difference	**-6%**	**16%**

To sum up, as presented in Table 4.5, in heating mode *EECO* provides slightly worse overall performance in terms of thermal comfort compared to the *Fixed Set Point* strategy, mainly due to cold days, as discussed previously. While a portion of the energy savings equal to 16% can be attributed to the slightly higher PMV value, it is worth noting that, considering the overall amount of energy saved, a better trade-off between thermal comfort and energy consumption is achieved.

In heating mode, we provide an additional analysis to compare the two approaches on Mondays, which are a particular case in terms of thermal comfort and energy consumption. The initial environmental conditions on Monday mornings are often significantly outside the desired range due to the HVAC inactivity over the weekend. This requires the HVAC devices to operate more intensively throughout the day to ensure the desired comfort level. Although both approaches fail to fully address this task, resulting in out-of-comfort conditions, the *Fixed Set Point* achieves an average PMV value closer to the upper bound of the range than our solution, as reported in Table 4.7. On the other hand, while *EECO* provides slightly less favorable environmental conditions, it significantly reduces the building's energy footprint by more than 40 kWh on average, as underlined in Table 4.6.

Table 4.6: Results of *EECO* during Mondays in heating mode.

Days	**PMV**	**PMV 6 AM**	**Indoor Temperature**	**Outdoor Temperature**	**Energy Consumption**
Day 1	0.81	1.03	19.1 °C	4.3 °C	84 kWh
Day 2	0.89	1.28	19.7 °C	4.8 °C	154 kWh
Day 3	0.82	1.09	19.9 °C	6.6 °C	61 kWh
Day 4	0.72	1.12	20.9 °C	12.5 °C	51 kWh
Average	**0.81**	**1.13**	**19.9 °C**	**7.1 °C**	**87 kWh**

Table 4.7: Results of the *Fixed Set Point* approach during Mondays in heating mode.

Days	**PMV**	**PMV 6 AM**	**Indoor Temperature**	**Outdoor Temperature**	**Energy Consumption**
Day 1	0.75	1.04	19.1 °C	2.8 °C	204 kWh
Day 2	0.77	1.07	19.2 °C	4.5 °C	125 kWh
Day 3	0.74	1.18	19.6 °C	9.1 °C	122 kWh
Day 4	0.77	1.14	20.6 °C	10.3 °C	82 kWh
Average	**0.76**	**1.11**	**19.6 °C**	**6.7 °C**	**133 kWh**

4.7.4 Performance Analysis - Simulated Environment

The validation in real-world scenarios presents challenges that hinder direct comparisons with multiple approaches. Firstly, we are forced to conduct experiments only from Monday to Friday as the building is closed on weekends, thus requiring many weeks to collect a good amount of results for each approach. Secondly, even with a great availability of experimental data, it is difficult to compare more strategies over multiple days due to different outdoor weather conditions.

Considering these limitations, we propose a comparison analysis among our solution, the *Fixed Set Point* approach (in this case, we test it with two different set point values) and the greedy *PMV-Based* approach through software simulations. To simulate the behavior of each strategy throughout selected days and model the environment's response to specific HVAC configurations at each quarter hour, we employ an AI model that we call *Global Model*. This model is based on 1D CNN and trained using all data collected from the warehouse during the evaluated operating mode (from June to October in cooling mode and from November to February in heating mode). The idea is to include as much information as possible, allowing the *Global Model* to learn the environment's response under all the different conditions (e.g., due to outdoor weather), thus maximising simulation accuracy.

In terms of results, we first demonstrate the reliability of the simulated environment by emulating the HVAC settings (i.e., ON/OFF and SP) occurred in the real environment during the day by means of the designed *Global Model*. We then simulate the three different approaches i.e., *EECO*, *PMV-Based*, *Fixed Set Point*. Consistently with the previous analysis in the real environment, we consider *category III* as the target comfort. For a thorough comparison, we examine days in both cooling and heating modes, selecting 8 random days for each month under consideration. Furthermore, we split the results between normal working days and Mondays, as in the subsection 4.7.3. Finally, as observed in the manual approach outlined in Section 4.7.3, both for the *PMV-Based* and *Fixed Set Point* approach we activate the HVAC devices at 6 AM, thus ensuring the same operating interval of our solution.

Simulator Validation

In this subsection, we aim to validate the simulated environment. In this regard, we analyse the accuracy of the *Global Model* mentioned in Section 4.7.4. To cope with this task, we analyse the behaviour of the predicted environment (indoor temperature, humidity, CO_2 and energy consumption) at each quarter of hour upon the actuations (ON/OFF, SP) that occurred in the real environment. Basically, each time, we rely on the previous predictions to forecast the future evolution of the environment for the next quarter of hour. This approach enables us to evaluate the reliability of the simulator by comparing the simulated behaviour of the warehouse throughout each selected day with the real observed data.

Table 4.8: Simulator results during summer months.

	Energy [kWh]		Indoor Temperature [°C]		Indoor Humidity [%]		CO_2 [ppm]	
Months	**RMSE**	**% Error**	**RMSE**	**% Error**	**RMSE**	**% Error**	**RMSE**	**% Error**
July	0.42	10.9	0.43	1.1	2.0	3.1	27.7	3.2
August	0.37	11.9	0.40	1.0	2.0	2.6	24.2	2.6
September	0.36	36	0.34	0.9	1.9	2.7	47.7	4.5
Average	**0.38 kWh**	**19.6 %**	**0.39 °C**	**1.0 %**	**2.0 %**	**2.8 %**	**33.2 ppm**	**3.4 %**

Table 4.9: Simulator results during winter months.

	Energy [kWh]		Indoor Temperature [°C]		Indoor Humidity [%]		CO_2 [ppm]	
Months	**RMSE**	**% Error**	**RMSE**	**% Error**	**RMSE**	**% Error**	**RMSE**	**% Error**
December	0.34	22.1	0.32	1.1	1.4	2.5	35.3	3.6
January	0.33	10.2	0.29	1.1	1.3	2.3	25.0	2.4
February	0.31	11.9	0.49	1.9	1.3	2.8	38.8	3.0
Average	**0.33 kWh**	**14.7%**	**0.37 °C**	**1.3 %**	**1.3 %**	**2.5 %**	**33.0 ppm**	**3.0 %**

Tables 4.8 and 4.9 present the overall monthly results of the simulated environment during the Summer (cooling mode) and the Winter months (heating mode), respectively. To provide a detailed overview of the accuracy of our simulated environment, we report the RMSE between the predicted and actual values for each variable as well as the percentage error (i.e., the percentage difference between the mean of the predicted values and the real ones). Unlike the percentage error used by Mancini et.al. [78] in a similar scenario, the RMSE enables us to highlight possible deviations in the behaviour of each variable.

To the best of our knowledge, few research studies in the literature demonstrate the goodness of their simulated environments in a systematic way. Nevertheless, we try to compare the accuracy of our simulator with results from other works in the same research domain. Unlike the validation results presented by Mancini et.al. [78], our simulated environment achieves better performance in terms of percentage error for all the output variables (except for CO_2, which was not considered by the authors). However, similar to other studies, energy consumption due to HVAC devices results in the most challenging variable to be simulated accurately. In this regard, our results show an average percentage error between 14% and 20%, indicating a slight underestimation or overestimation of the total predicted energy consumption compared to the real behaviour. However, the same amount of error is expected among all evaluated approaches, guaranteeing a fair comparison. Nevertheless, it is worth noting that the RMSE value is limited for all the variables, demonstrating the simulator's ability to accurately model the environment throughout the day.

Cooling mode

In cooling mode, we have done experiments from July to September. As depicted in Figure 4.9, *EECO* provides slightly worse comfort conditions but reduces the energy footprint by at least 6 kWh on average compared to all the other evaluated approaches. In this scenario, the *Fixed Set Point* approach provides better thermal comfort conditions than requested but impacts the buildings' energy footprint more than *EECO* and the *PMV-Based* approach (Table 4.10). This behaviour is particularly clear with a lower set point value (e.g. 26 °C), which forces the HVAC devices to work more, especially during very hot months such as July and August. Conversely, the greedy *PMV-Based* approach achieves PMV values close to the lower bound of the comfort range but consumes slightly more energy than *EECO*. Finally, comparable performance in terms of both thermal comfort and energy consumption is observed on Mondays, as reported in Table 4.11.

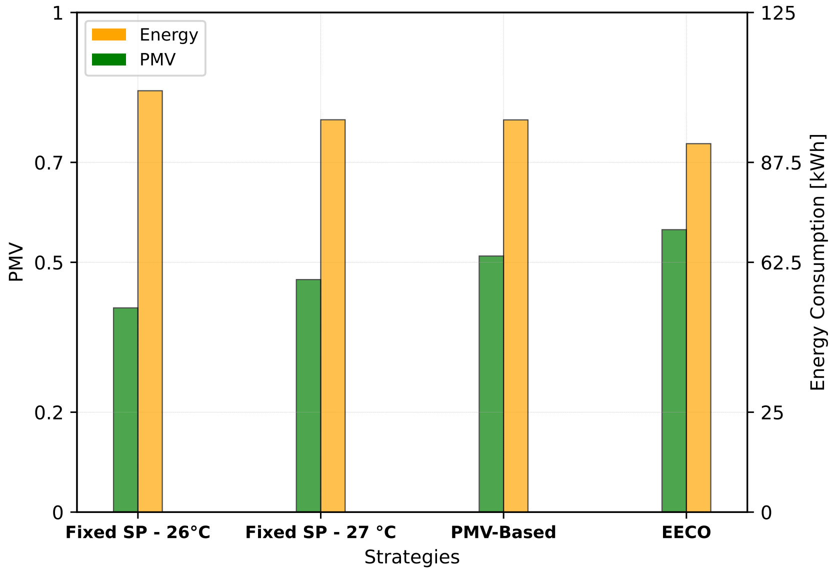

Figure 4.9: Overall average behaviour of PMV index and energy consumption for the evaluated approaches on working days in cooling mode.

Table 4.10: Average monthly behaviour of PMV index and energy consumption for the evaluated approaches on working days in cooling mode.

	Fixed SP - 26 °C		**Fixed SP - 27 °C**		**PMV-Based**		**EECO**	
Months	**Energy**	**PMV**	**Energy**	**PMV**	**Energy**	**PMV**	**Energy**	**PMV**
July	131 kWh	0.51	123 kWh	0.57	126 kWh	0.57	**117 kWh**	**0.65**
August	112 kWh	0.44	113 kWh	0.50	115 kWh	0.54	**105 kWh**	**0.63**
September	67 kWh	0.25	60 kWh	0.33	56 kWh	0.43	**56 kWh**	**0.42**
Average	*104 kWh*	*0.40*	*99 kWh*	*0.47*	*99 kWh*	*0.51*	***93 kWh***	***0.57***

Table 4.11: Average behaviour of PMV index and energy consumption for the evaluated approaches on Mondays in cooling mode.

Fixed SP - 26 °C		**Fixed SP - 27 °C**		**PMV-Based**		**EECO**	
Energy	**PMV**	**Energy**	**PMV**	**Energy**	**PMV**	**Energy**	**PMV**
114 kWh	*0.46*	*108 kWh*	*0.52*	*109 kWh*	*0.53*	***108 kWh***	***0.54***

To summarise the results from simulation data in cooling mode, Table 4.12 shows the improvement of *EECO* compared to the other approaches from both comfort and energy perspectives. In cooling mode, our solution achieves 6% to 13% energy savings while maintaining comfort conditions that are slightly less optimal in terms of proximity to the lower bound of the comfort range.

Table 4.12: Overall performance of *EECO* compared to the *Fixed Set Point* and *PMV-Based* approach in terms of absolute PMV difference from the lower bound of the comfort range and percentage difference of energy saving in cooling mode.

	PMV Distance	**Energy Consumption**
Fixed SP - 26°C	0.03	11%
Fixed SP - 27°C	-0.04	6%
PMV-Based	-0.06	6%

Heating mode

In heating mode, we have compared the different approaches in the period between December and February. In such scenario, as depicted in Figure 4.10, our solution guarantees similar comfort conditions compared to the *Fixed Set Point* and *PMV-Based* approaches while reducing the energy footprint by about 15 kWh on average, resulting in significant energy savings. This efficiency is achieved through strategic shutdowns of the HVAC devices configured by our approach at some quarters of hour during the day: this enables the environment to maintain the desired comfort level while limiting the impact on the energy consumption. In contrast, the *Fixed Set Point* approach lacks this intelligent adjustment, leading to potential energy inefficiencies if the set point value is not optimally set. For instance, increasing the set point value from 21°C to 22°C does not improve the expected thermal comfort but impacts the building's energy footprint in a significant way (Table 4.13). The same behaviour, as reported in Table 4.14, is also observed on Mondays.

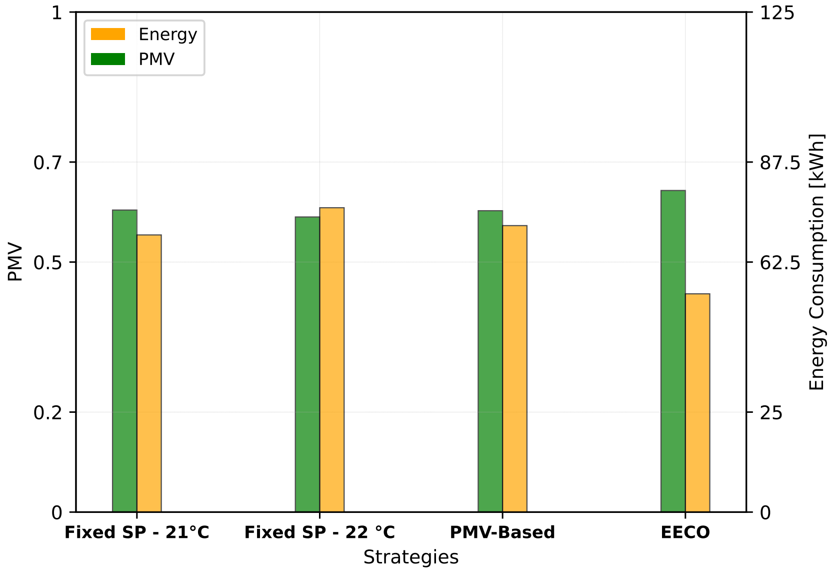

Figure 4.10: Overall average behaviour of PMV index and energy consumption for the evaluated approaches on working days in heating mode.

Table 4.13: Average monthly behaviour of PMV index and energy consumption for the evaluated approaches on working days in heating mode.

	Fixed SP - 21 °C		**Fixed SP - 22 °C**		**PMV-Based**		**EECO**	
Months	**Energy**	**PMV**	**Energy**	**PMV**	**Energy**	**PMV**	**Energy**	**PMV**
December	71 kWh	0.64	79 KWh	0.62	76 kWh	0.62	**56 kWh**	**0.68**
January	65 kWh	0.62	71 kWh	0.61	69 kWh	0.61	**48 kWh**	**0.67**
February	72 kWh	0.54	79 kWh	0.53	69 kWh	0.57	**60 kWh**	**0.58**
Average	*69 kWh*	*0.60*	*76 kWh*	*0.59*	*72 kWh*	*0.60*	***55 kWh***	***0.64***

As highlighted in cooling mode, better results in terms of PMV value are observed during the last evaluated month (i.e., February). This is due to December and January being the coldest Winter months. The PMV values obtained during these experiments underline the difficulties in heating operations to maintain optimal comfort conditions during the harshest winter months.

Table 4.14: Average behaviour of PMV index and energy consumption for the evaluated approaches on Mondays in heating mode.

Fixed SP - 21 °C		**Fixed SP - 22 °C**		**PMV-Based**		**EECO**	
Energy	**PMV**	**Energy**	**PMV**	**Energy**	**PMV**	**Energy**	**PMV**
85 kWh	*0.79*	*92 kWh*	*0.78*	*90 kWh*	*0.78*	***75 kWh***	***0.83***

To summarise, as reported in Table 4.15, in heating mode *EECO* guarantees a comfort level comparable to basic approaches, i.e., *PMV-Based*, *Fixed Set Point*. However, unlike these strategies, our solution achieves energy savings greater than 20%. As discussed previously as well as in Section 4.7.3, this is mainly achieved by selectively shutting down HVAC devices, which minimally affects comfort but significantly improves energy efficiency. Given the building's position, which receives direct sunlight for much of the day, it can take advantage of the outdoor environment for indoor heating. Therefore, as highlighted in the following section, integrating solar irradiation as an input is crucial for further optimising the algorithm. This scenario highlights the limitations of traditional approaches, which have a limited overview of the problem as they follow a single objective function with no attention for the energy footprint. In contrast, an intelligent approach such as *EECO* can guarantee a proper balance between thermal comfort and energy consumption. It is worth noting that these simulated results are consistent with those obtained in the real environment and described in Section 4.7.3.

Table 4.15: Overall performance of *EECO* compared to the *Fixed Set Point* and *PMV-Based* approach in terms of absolute PMV difference from the lower bound of the comfort range and percentage difference of energy saving in heating mode.

	PMV Distance	**Energy Consumption**
Fixed SP - 21°C	-0.04	20%
Fixed SP - 22°C	-0.05	28%
PMV-Based	-0.04	24%

4.7.5 Discussion

Comfort Model

Despite the benefits described in the previous sections, the proposed solution is affected by some limitations. For instance, some parameters of the PMV index (i.e., metabolic rate, clothing insulation, air velocity) have been configured statically. However, some studies suggest the implementation of dynamic configurations for the comfort model parameters (e.g., air velocity [31] and clothing insulation [79]) to align with local environmental conditions. Additionally, other research works [27, 69] underline the importance of personal control by building occupants in satisfying the requirements of a large amount of people and accurately modelling the comfort.

In this study, our primary focus has centered around refining the algorithm responsible for the management of HVAC devices. While we delve into an extensive examination of EECO performance using static PMV parameter values, we acknowledge that the usage of dynamic values and personal control is beyond the current scope and does not impact the designed methodology. Nevertheless, we consider these aspects as opportunities for further investigation and exploration in the future, along with considering other comfort methodologies such as operative temperature, which might better fit the considered scenarios.

Methodology

The proposed algorithm is designed to optimise a single comfort objective as input. However, environments often involve multiple stakeholders (e.g., local personnel, customers), each potentially having conflicting comfort requirements. In this case, a decision-making process is necessary, as this algorithm lacks the capability to simultaneously address multiple comfort objectives. In this regard, this solution particularly fits scenarios where occupants share similar comfort needs or a preference for one stakeholder over the other is exhibited. As a result, the solution's applicability might be better suited to scenarios with a less diverse environment of stakeholder.

Further improvements could also be integrated into the proposed solution e.g., additional input variables might be considered. In this regard, different research studies in the literature include solar irradiation in their solutions [29, 69]. Such information, integrated into the proposed algorithm, might allow for a more accurate selection of the HVAC configuration. This could help fine-tune the use of natural effects (i.e., passive methods), instead of activating HVAC devices at certain times during the day. Considering the complexity of the problem, the promising results and the lack of a reliable source for solar irradiation data in the early stages, we have preferred to not include solar irradiation at this stage while acknowledging it as a promising avenue for future research.

Validation

We underline the possibility to validate the designed solution from other perspectives. Indeed, our partner has provided us with strict constraints to test the proposed solution within a real production environment that includes human presence, preventing us from performing different experiments. In this regard, for instance, specific tests need to be conducted to evaluate the performance on days characterized by alternating comfort and no comfort requirements (i.e., similarly as Yang et.al. in [62]), as opposed to solely focusing on a single comfort interval throughout the day.

4.8 Summary

In this chapter, we have presented a novel algorithm based on AI to regulate HVAC devices in an automated way to optimise thermal comfort while minimising the energy footprint.

Compared to a static approach where the HVAC set point is configured to a fixed temperature, evaluation results show that our solution can slightly improve the indoor comfort with a minimal impact on the building's energy footprint in Summer (i.e., cooling mode). On the other hand, in cold months (i.e., heating mode) it results in significant energy savings (up to 16%) while providing comparable comfort conditions.

Due to clear limitations in comparing multiple approaches in a real environment, we have provided an additional comparison analysis based on software simulations between our solution and other two approaches (i.e., the fixed set point and a greedy PMV-based approach). In this regard, evaluation results show significant improvements in Winter months rather than in Summer, confirming the results obtained in the real-world scenario. Indeed, we have achieved slightly worse performance in terms of comfort requirements but resulting in energy savings greater than 20%.

Despite the promising results obtained in the evaluated scenario, the application of our solution on a very large scale is subject to overcoming of some limitations mentioned in Section 4.7.5. Nevertheless, unlike non-intelligent approaches that just follow a single objective function, the results obtained in the evaluated scenario demonstrate the capability of our solution to guarantee a trade-off between the comfort level and the energy consumption by dynamically selecting the configuration (ON/OFF, set point) of the HVAC devices.

Chapter 5

Business Analysis

My PhD in Industrial Innovation included not only traditional research activities but also a number of business-focused activities. In collaboration with EIT Digital, I participated in the Business Development Experience (BDExp), an activity designed to promote the development of business and innovation skills within the industry. This experience offered me a valuable opportunity to apply the business concepts I had learned during different seminars attended throughout the three years of my Doctorate Program. Specifically, I decided to focus on analysing the impact of my research outcomes on the business operations of my host company, Energenius Srl, with a particular emphasis on the GEM-Retail product. This chapter delves into the different business aspects that emerged from the potential transfer of technological insights gained during my research. It explores how these insights, along with the specific outcomes of my research, can be effectively applied within the business domain of Energenius Srl, enhancing its operational effectiveness and strategic positioning in the market.

This chapter is mainly based on the report developed during the Business Development Experience (BDExp) in collaboration with EIT Digital.

5.1 Introduction and Scenario

Energenius [80] is an Italian innovative small-scale company with high technological know-how, born from the synergy between energy managers, electric engineers, and IT experts in energy measurement and analysis. The company offers tailor-made solutions for monitoring energy consumption and the analysis of collected data using AI. From small retail shops to office buildings and banks, up to extensive production plants, Energenius offers dedicated solutions for energy monitoring through its Genius Energy Manager (GEM) suite.

One of Energenius' latest solutions, GEM-Retail, is specifically tailored to meet the needs of tertiary buildings, with a particular focus on the retail sector (e.g., shops). With escalating energy prices and the effects of climate change, European retailers have to face the dual challenge of improving energy efficiency and maintaining indoor comfort on a large scale, as discussed in Chapter 1. In this scenario, GEM-Retail is an innovative hardware and software solution that leverages cutting-edge technologies such as Edge Computing and AI to reduce energy consumption while ensuring customer satisfaction and well-being in indoor environments.

GEM-Retail is currently undergoing refinements to enhance its competitiveness and better align with market demands. The core technological concept behind GEM-Retail is to move computation to the edge, where a low-power, resource-constrained device is installed. The objective is to increase reliability and scalability, providing fast data analysis and response to potential issues while reducing the monitoring efforts to guarantee sustainability across a large number of sites. Among its implemented functionalities, GEM-Retail enables users (e.g., facility managers, owners) to monitor energy consumption and environmental parameters (e.g., temperature, humidity, CO_2), analyse advanced KPIs to highlight the most critical and challenging shops, compare multiple sites in an automated way, optimise HVAC devices.

5.1.1 Business Impact of Research Outcomes

In the previous section, we introduced GEM-Retail, a product developed by Energenius that aligns perfectly with my research focus. While the research findings might be transferred within the company in different ways, their integration into GEM-Retail appears particularly promising for Energenius. Consequently, this chapter focuses on this potential business direction, highlighting how academic research can positively impact business operations and enhance the existing product.

A significant achievement of my research is the development of powerful AI tools capable of predicting future values of a series of relevant variables, e.g., the Carbon Dioxide (CO_2) level, to prevent it from exceeding recommended thresholds. These models exhibit the capability to achieve comparable predictive accuracy while training on a limited dataset in contrast to other state-of-the-art solutions that require extensive historical data, as described in Chapter 3. This approach offers important advantages from technical and business perspectives:

1. The designed system becomes operational shortly after deployment, making it highly attractive from a business perspective;

2. The lightweight AI models can be continuously updated based on recent local environmental behavior, adapting to changes over time while maintaining high prediction accuracy. This eliminates the need for manual operations and, importantly, there is no requirement to transmit data to costly centralised servers;

3. The AI models can be trained and deployed on cost-effective, resource-constrained devices, with no need for expensive server infrastructure,

thus preventing any escalation in the solution's market price.

In Chapter 4, we demonstrated that these models can be effectively integrated within a novel AI-based algorithm that controls the operation of HVAC devices with the aim to optimise indoor comfort while minimising energy consumption in an automated way, addressing a key concern for managers handling multiple sites. This algorithm yields significant benefits:

1. No need for human intervention or any customisation within the environment;

2. In contrast to many state-of-the-art solutions, no mathematical or physical models of the buildings are necessary, relying only on real collected data;

3. Potential customers (e.g., managers of big retailer companies) can save on operating costs to control the well-being of occupants and lower the energy footprint of their buildings.

This solution ensures replicability and scalability on a broad scale with minimal human effort, enabling managers to enhance the energy efficiency and sustainability of their buildings in an automated and intelligent way.

Considering that the retail sector in the European Union comprises more than 6800 companies, collectively generating an annual turnover exceeding 8000 billion euros, and with escalating energy costs and the growing impact of climate change, European retailers are increasingly interested in improving the energy efficiency and indoor comfort of their sites without negatively affecting the business. In light of the above factors, the obtained outcomes hold the potential to greatly enrich the solution proposed by Energenius from a business perspective, enhancing its competitiveness in comparison to other market-available products or services.

Nonetheless, a comprehensive analysis is fundamental to assess their impact with the aim to not only better penetrate the existing market but also to potentially enter other market segments. In the next sections, we will provide a comprehensive overview of the conducted analysis across different areas (market and competitors' analysis, business opportunities, customer profile and value proposition, business model and business plan), with the aim to emphasize the contribution of my research within the operational business of the industrial company.

5.2 European Market Analysis

Retail market holds a distinctive role in the European economy, contributing 11% to the EU's GDP and engaging one in three companies across the continent. In this regard, factors such as rising energy prices and the effects of climate change force European retailers to face the challenge of constantly improving their energy efficiency. On average, electricity consumption constitutes three-quarters of a store's overall energy requirements, primarily allocated to lighting, air conditioning, heating sales areas, and water heating. At the same time, ensuring optimal comfort conditions is fundamental to make people feeling safe and comfortable within indoor environments, especially after Covid-19 pandemic, as reported in Chapter 1.

As previously mentioned, the retail world has more than 6,800 companies in the EU, with a total turnover exceeding 8,000 billion euros / year. In such scenario, energy management systems (EMS) that allow an organization to collect real-time information on energy consumption through monitoring, evaluation, and visualization, are becoming increasingly popular. Indeed, they help companies gain a competitive advantage, increase productivity, and reduce energy costs, aligning with government policies promoting energy saving and environmental sustainability. While many potential buyers acknowledge the benefits of implementing such systems, a considerable number still rely on conventional technologies and applications. Financial barriers and limited skills emerge as significant challenges for the energy management systems market. Energy monitoring and control hold a significant market share in the energy services segment and is expected to continue to provide profitable business opportunities. The implementation of an information system for energy management proves to be an effective strategy not only to save energy but to continuously optimise and safeguard the health of occupants. Such platform automates tasks that are time-consuming and labour-intensive, allowing management groups to concentrate on more value-added activities. A comprehensive analysis of the current retail market in Europe highlights promising opportunities for solutions like GEM-Retail, particularly in the following sectors:

- The first focus is on the fashion industry since Energenius is already in contact with a major customer in this category. This positions the company advantageously in knowing the specific needs of companies in the sector. Two of the main players in Europe are Inditex [81] and H&M [82]. Through insights from a "per country" analysis, a first strategy to spread GEM-Retail solution include the following countries based on their number of stores:

Table 5.1: Overview of fashion stores per country in Europe.

Country	**Number of H&M Stores**	**Number of Inditex Stores**	**Total**
Spain	146	1225	1371
France	201	268	469
Germany	430	115	545
Poland	188	222	410

Inditex has already collaborated with several international groups to improve energy use and procurement. H&M, one of the largest clothing chains in the world, underline how there is still significant room for improvement, with the primary interest being the adoption of energy efficiency tools for automating systems, including real-time monitoring and indoor temperature adjustments [83]. Additionally, in recent years, H&M has explored outsourcing its efficiency investments through an Energy Service Company (ESCO), which would facilitate communication with energy service managers.

We underline that the availability of other fashion companies potentially interested in GEM-Retail depends on the chosen country. For example, in France, LVMH Moët Hennessy Louis Vuitton SE [84] owns over 500 physical stores.

- Electronic stores offer a similar experience. The electronic store market is more segmented along national borders, despite having a significant size. Here the example of the French retail Fnac Darty, and the German Media Markt:
  - FNAC Darty [85] has around 200 stores in France, and few hundred stores across Europe (e.g., in Spain, Belgium, Netherland, Switzerland)
  - Media Markt [86] is present in Europe through a network of more than 1000 stores in ten countries (e.g., in Spain, Italy, Poland, Germany)
- On the other hand, general stores exhibit great diversity. However, it is important to consider this market sector because of its current size and the potential future growth. Some examples are the following:
  - Aldi [87] dominates the German retail market, managing 5000

stores across the country. They also expanded in Austria, United Kingdom, Switzerland, and Italy.

– Carrefour [88] is France's biggest retailer company with a strong international presence as well. They operate almost 4000 stores in France and more than 6000 shops across the Europe.

– Coop [89], born in Switzerland, is another big player in this sector. Indeed, they handle more than 2000 shops.

Additionally, there are other potential markets that have not been considered in this analysis but are worth mentioning: sports equipment (i.e., Decathlon), pharmacies, and retail space renters. While not fitting the traditional retail model, coworking spaces might also be a viable market, given their focus on enhancing client satisfaction inside their spaces.

5.3 Business Opportunities

During the last years, the business all over the world has been affected by the Covid-19 pandemic. This can be seen as an unforeseen event often known as "Black Swan Event" in the business. In the retail sector, the pandemic has forced everyone to move a lot of activities to online platforms, particularly impacting fashion retail. However, some business activities (e.g., in the food, beverage, and tobacco retail sectors) have remained relatively unaffected, with on-site shopping maintaining an important role in people's lives.

Generally, potential business opportunities for GEM-Retail have emerged because of the Covid-19 pandemic. As highlighted in Chapter 1, until 2020, the primary focus was only on minimising energy consumption. Nowadays, the trend among managers is to prioritise thermal comfort in indoor environments while simultaneously reducing energy consumption. This difference is particularly clear as retail managers now consider ensuring safe and comfortable environments crucial, leading to an increased interest in obtaining relevant IAQ certifications to distinguish themselves from competitors in terms of environmental sustainability as well as to align with the green policies being set in place to fight the global warming crisis.

In this context, the innovative aspects derived from my research outcomes, integrated within GEM-Retail, align perfectly with these emerging opportunities. Additionally, while initially tailored for the retail sector, GEM-Retail now exhibits versatility and applicability across the whole tertiary and commercial sector. This flexibility introduces new avenues for commercial approaches, allowing GEM-Retail to effectively monitor and manage geographically distributed buildings. One potential market segment worth considering is the banking sector. As of the end of 2022, Italian banks and branches of foreign banks in Italy collectively operated 20,986 branches, with 55 percent belonging to larger institutions, and the rest distributed roughly equally among other categories [90]. This expansion into diverse market areas signifies a strategic evolution for the GEM-Retail solution.

Hotels represent another perspective business opportunity for GEM-Retail. Although the tourist demand of the resident population has suffered the impact of the COVID-19 pandemic in 2020, registering an unprecedented contraction, the sector has returned to rapid growth. In this regard, in the latest Horwarth reports (IT and EU Hotel Chains) [91], an evolution of the landscape was outlined thanks to the identification of a cluster of 10 Italian hotel groups based on the total turnover generated in Italy. This cluster includes: Starhotel, Gruppo UNA, Aeroviaggi, ITI Hotels, TH Resorts, Delphina, Blu Hotels, Blu Serena, JSH and Parc Hotels Italia. The cluster represents 31% of the number of Italian chain hotel rooms as well as 20% of all chains (thus including international ones). The segments concerned are for the most part upscale, followed by luxury and midscale.

5.4 Competitors

In the Italian market, different indirect competitors provide generic solutions for monitoring and analysing energy consumption in the retail sector. These competitors include both hardware manufacturers (e.g., Siemens, Electrex, Socomec, Energy Team, IME) and software producers (e.g., Zucchetti, Inspiring, Dexma, Trend). Both categories of competitors focus on selling software solutions exclusively dedicated to the energy monitoring of smart meters, whether owned or third-party. However, they often overlook advanced functionalities and offer generic solutions that are not closely tailored to the target market of GEM-Retail. Specifically, the tertiary buildings, including the retail sector, have different needs compared to the industrial sector, in terms of costs, scalability, and analytics aimed at comparing the performance of individual sites to identify the most critical cases. Additionally, as previously mentioned, managers are committed to fulfilling both energy efficiency and indoor comfort requirements. As a result, we focus on European market, where competitors offer solutions similar to GEM-Retail but are primarily focused on specific energy assessments. Indeed, their aim is to identify energy waste and create alarms that provide maintenance personnel with tools to set up systems efficiently.

In conducting an analysis of the competitive landscape, the main competitors in such market include:

- EnergyCAP [32]. EnergyCAP provides a comprehensive retail energy management solution comprising both hardware and software (EnergyCAP SmartAnalytics). This solution assists proprietors and administrators overseeing an extensive array of buildings in expanding energy efficiency across many sites and stores. It enables prompt responses to real-time fluctuations, such as unusual consumption patterns and unforeseen peaks. The key benefits are:

  - Efficient handling of bulk meter data
  - Continuous monitoring and timely alerts
  - Effective performance and resource management
  - Benchmarking and comparative analysis
  - Accurate measurement and verification

- Phoenixet [33]. Specialized in corporate energy management within the retail sector, Phoenixet's energy management software enables customers to control and handle energy consumption across hundreds or even thousands of buildings. Enterprise Data Xchange (EDX) is an IoT platform that optimises building performance, reduces energy consumption, and enhances customer comfort. Enterprise Data Xchange oversees, manages, and monitors millions of data points from HVAC, lighting, refrigeration, industrial machines, and consumer devices.

- Powerhouse Dynamics [34]. The Powerhouse Dynamics' SiteSage project allows you to monitor, analyse, and control IoT devices. It not only allows to improve consumption but also to focus on monitoring the devices' condition. SiteSage is designed for multisite operators of small commercial facilities; they have a starting point of 20 buildings, but the solution is scalable. Right now, they are specialized in Food Service Facilities.

- DEXMA [35]. Dexma contributes to lowering energy expenses and enhancing customer satisfaction through the Spacewell Energy Platform (Dexma). With DEXMA Detect, you can benchmark performance across various store locations, pinpointing stores with the highest return on investment (ROI) and determining the most effective energy-saving measures for each. After identifying high-consumption sites, DEXMA Analyze provides the capability to scrutinise consumption during specific time intervals, facilitating more precise comparisons. Finally, DEXMA Optimise automates the energy management process with 24/7 powered anomaly detection.

- ENERGIS [36]. They propose Energis.Cloud, an innovative energy management software applied in the tertiary and industrial sectors, particularly for renewable energy producers. It is crafted to assist players in the energy and environmental markets in reaching their energy efficiency objectives. Key advantages include:
  - Multi-site Portfolio: Gather and centralize energy data, enabling the comparison of entire portfolios. Identify underperforming sites and actions that lead to savings.
  - Air Quality and Comfort.
  - Real-time Identification of Inefficiencies.

In conclusion, the common points of the various competitors are related to pricing strategies. Competitors always have a plan that offers a cost of meters equal to 5% of the energetic costs to allow the customers to return the investment in a year. The second point to note is that several competitors offer different flexible plans that scale based on customer's needs. They exhibit great diversification in their offerings, tailoring services based on the specific needs of clients. Noteworthy, there are differences in acquisition, data analysis, direct control of devices, analysis of KPIs, verification, and comparison between multiple shops. Finally, it is worth noting that not all solutions prioritise the trade-off between indoor comfort and energy efficiency or include forecasting features. In Figure 5.1, we compare the competitors' solution based on price and their ability to effectively optimise multiple buildings.

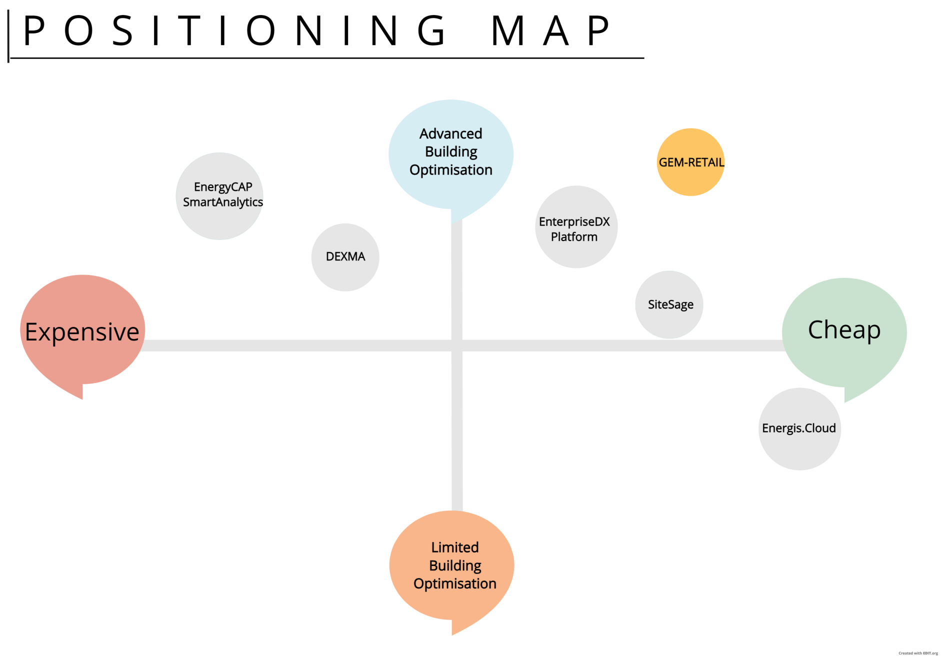

Figure 5.1: Competitor positioning map of GEM-Retail.

5.5 Customer Profile and Value Proposition

In this section, we exploit the customer profile and value proposition, focusing particularly on managers who are tasked with managing multiple sites - a common scenario for large retail companies. To tackle this challenge, the well-known Value Proposition Canvas is used (Figure 5.2). The customer profile is divided into:

- *Customer Job*: Managers need to find new affordable ways to monitor and manage the energy consumption [92] across their sites, detecting possible anomalies and making decisions about the interventions to be carried out to solve them. Additionally, they are responsible for ensuring safe and comfortable environments to enhance customer comfort and potentially boost the sale of goods.

- *Pains*: Managers face challenges to reduce the impact of energy requirements on their balance sheets and ensuring optimal comfort conditions to occupants [93], thereby preventing early customer departures, or discouraging entries. Additionally, they lack sufficient responsiveness to potential issues within their environments. Finally, the introduction of an informative and control system should consider the presence of already existing systems to minimise integration costs and avoid delaying the return on investment from the perspective of managers.

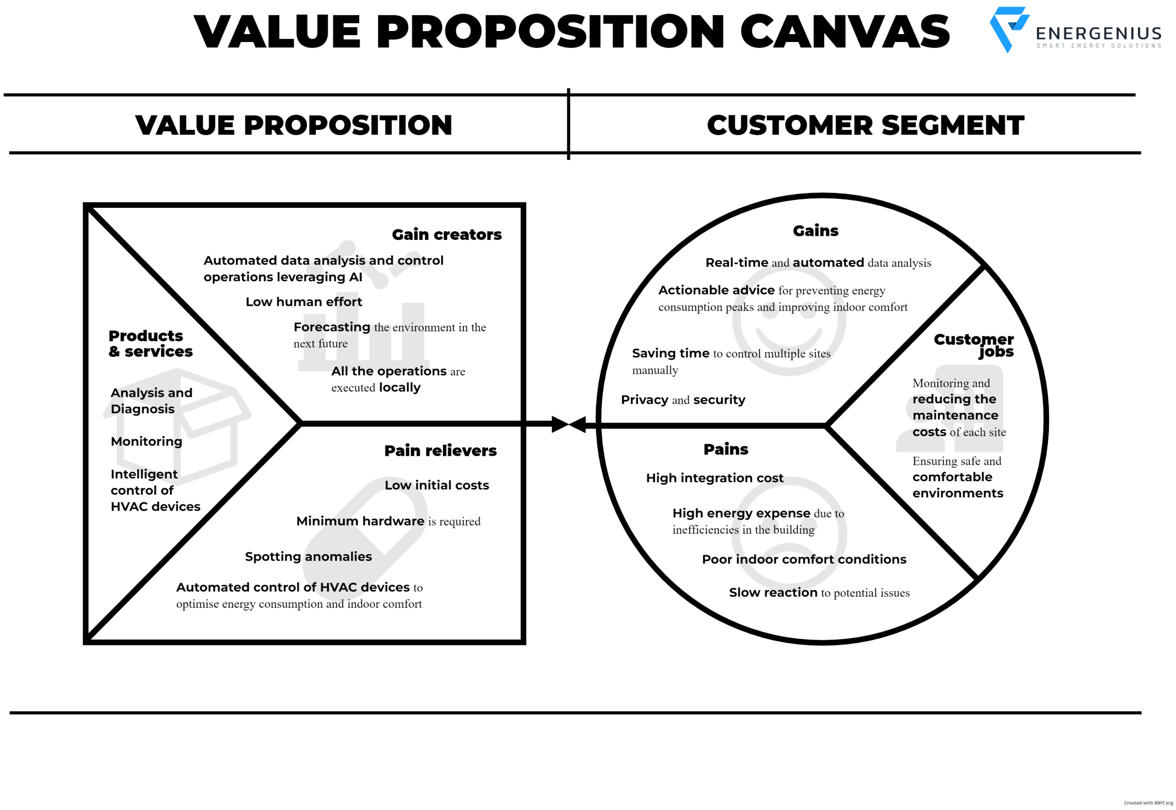

Figure 5.2: Value Proposition and Customer Segment of GEM-Retail.

- *Gains*: Managers need tools that provide real-time analysis and automated monitoring across all their sites. Real-time monitoring and control are crucial, requiring swift and easy-to-read countermeasures to spotted anomalies. This approach overcomes manual operations in managing multiple sites, thereby reducing operating costs. Additionally, considering the potential heterogeneity of sites, privacy and security are paramount.

Given the delineated customer profile, GEM Retail, leveraging the integration of novel functionalities derived from the research outcomes, provides the following value proposition:

- *Product*: GEM Retail consists of three main pillars:

  Monitoring: consistent monitoring of all environments from both energy and environmental perspectives.

  Analysis and Diagnosis: customer assistance while executing automated deep analysis to analyse, forecast and improve the performance of the sites.

  Intelligent control of HVAC devices: Artificial Intelligence engine applied to Big Data to identify the optimal regulations for energy-intensive HVAC devices.

- *Pain Relievers*: GEM Retail leverages Fog Computing to non-invasively install the sensors in the existing plant of shops. Thanks to lightweight AI models resulting from research activities, all the operations (e.g., training of the AI models) are executed on a low-power, resource-constrained device, leading to restrained installation and maintenance costs. This system empowers managers to analyse and reduce energy wastefulness and discomfort conditions in an automated way, thereby lessening the economic impact and enhancing sustainability.

- *Gain Creators*: GEM Retail provides managers with clear and precise details of the energy consumption of all shops, highlighting the most and less performing ones. Thanks to AI, it forecasts the future environment to identify anomalies in terms of energy consumption or environmental parameters (e.g., CO_2) in advance, resulting in a proactive approach to potential issues. Privacy and security concerns are guaranteed: all operations are executed locally with no need for advanced computing in the cloud.

5.6 Business Model

This section proposes a preliminary outline for a prospective business model using the Lean Canvas framework, outlined in Figure 5.3. The draft highlights the different elements of the business behind GEM-Retail, with particular emphasis on the direct contributions arising from my research. These contributions, clearly denoted in bold, exhibit a clear impact on key areas of the envisioned business model (e.g., solution, unique value proposition, key metrics).

While specific details on some Lean Canvas components will not be extensively covered, as they have already been addressed or discussed in previous sections, it is important to highlight a few key areas. Notably, the key metrics take a central role in the business model: the percentage of sites with improved comfort conditions and the percentage of sites with enhanced energy efficiency are crucial indicators for assessing the performance and success of the proposed solution. These metrics are directly linked to the research outcomes. Additionally, the channels for reaching customers include direct sales, B2B events/meetings, online seminars and partnerhips with ESCOs. The cost structure includes expenses related to hardware, wages for the sales and marketing team, and software upgrades.

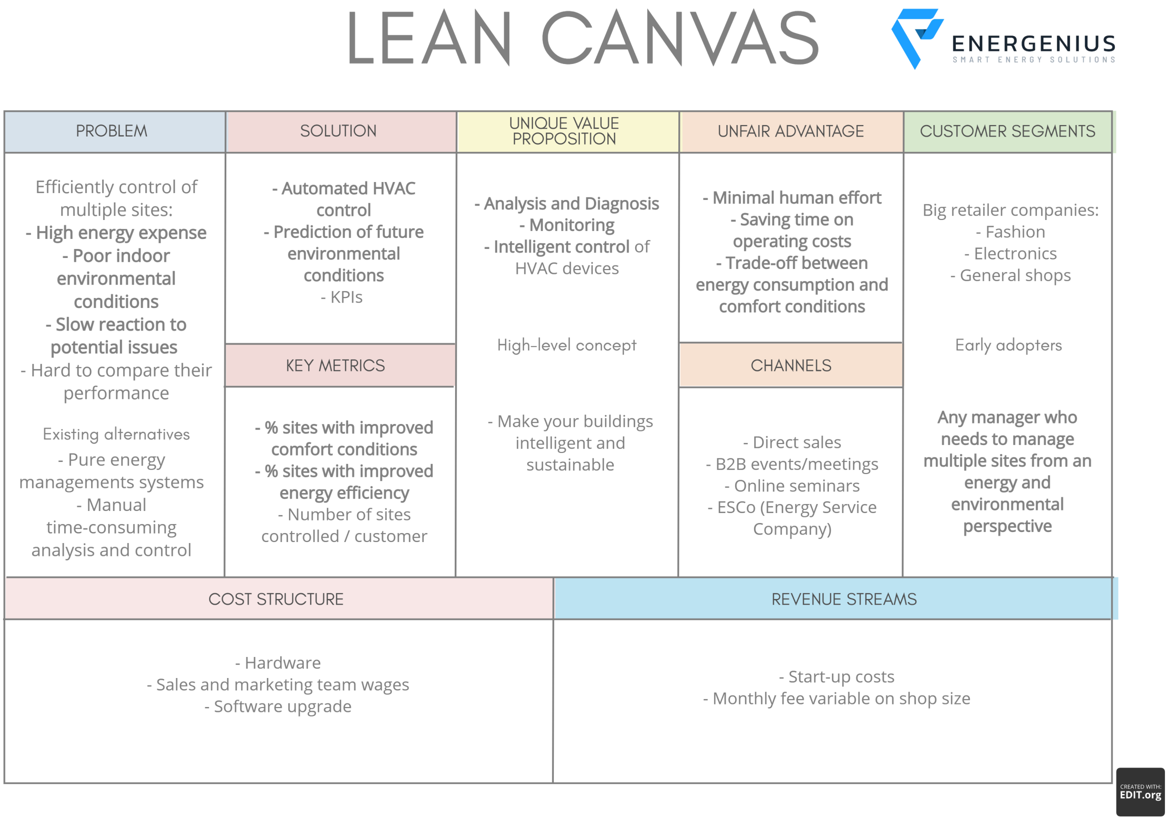

Figure 5.3: Prospective Business Model using Lean Canvas of GEM-Retail.

5.7 Business Plan

In alignment with the proposed business model, this section presents a prospective business plan collaboratively developed with Energenius to integrate the HVAC optimisation algorithm derived from the research outcomes and described in Chapter 4. The plan is based on the current business scenario of GEM-Retail, which, as of 2023, involves the management of 25 shops. These shops are categorized into 7 small shops, 10 medium shops, and 8 large shops. The selected pricing strategy, as outlined in the revenue stream section of the Lean Canvas (Figure 5.3), includes an initial startup cost and an annual maintenance fee for the service. The pricing is differentiated based on the size of the shop or building, resulting in varied costs for GEM-Retail, similar to strategies offered by competitors.

Basically, our value proposition proposes two distinct solutions:

1. Data monitoring and analysis only (*M&A*)

2. Intelligent HVAC control in addition to data monitoring and analysis (*CONTROL*)

Tables 5.2 and 5.3 provide an overview of the setup costs, selling prices, and annual fees for the *M&A* and *CONTROL* solutions, respectively. The setup cost covers hardware and engineering expenses, which are higher for the *CONTROL* solution due to the need for additional hardware to interface with HVAC devices. Unlike the *M&A* solution, which only requires a limited-power, resource-constrained device and energy meters/ambient probes to collect environmental and energy data, the *CONTROL* solution typically necessitates one or more electronic interfaces compatible with the specific brand of HVAC units (e.g., Daikin, LG) to enable communication between the edge node and the installed equipment (e.g., through Modbus protocol), hence providing control operations. While modern buildings might already have the necessary infrastructure, eliminating the need for extra hardware, GEM-Retail is usually deployed in older stores with outdated systems. As such, the setup costs account for this extra hardware, with the assumption that these costs are similar across different HVAC systems and increase in relation to store size. Given the added value of the *CONTROL* solution, we have adjusted the margin between the selling price and setup cost accordingly.

Table 5.2: GEM-Retail pricing strategy for monitoring and analysis solution.

Size	Setup Cost	Selling Price	Annual Fee
Small shops (up to 500 m^2)	€1,200.00	€1,900.00	€120.00
Medium shops (500 m^2 < area < 1000 m^2)	€2,200.00	€3,500.00	€265.00
Large shops (over 1000 m^2)	€2,800.00	€4,400.00	€335.00

Table 5.3: GEM-Retail pricing strategy for the intelligent HVAC control solution.

Size	Setup Cost	Selling Price	Annual Fee
Small shops (up to 500 m^2)	€1,800.00	€2,600.00	€400.00
Medium shops (500 m^2 < area < 1000 m^2)	€3,300.00	€4,800.00	€700.00
Large shops (over 1000 m^2)	€4,200.00	€6,000.00	€1100.00

The annual maintenance fee for the intelligent HVAC control includes the monitoring and analysis fee as well as an additional fee based on the potential energy savings estimated in Table 5.4, derived from the research outcomes presented in Sections 4.7.3 and 4.7.4. On average, our research indicates an energy saving of approximately 15 kWh daily for an indoor environment of 250m^2. We extrapolate this savings rate for environments up to 500m^2. Larger sites are expected to achieve higher energy savings, estimated at 25 kWh for medium sites and 40 kWh for large sites. By considering the average yearly PUN value (i.e., the reference price for electricity in Italy) over the past years [94], we can estimate the potential annual energy savings for each site based on its size, as summarised in Table 5.4:

Table 5.4: GEM-Retail potential energy saving in 2022 and 2023 through intelligent HVAC control for each type of site.

Size	**Year**	**Average PUN**	**Potential Savings**
Small shops	2022	€0.303	~ €1,658.00
	2023	€0.127	~ €695.00
Medium shops	2022	€0.303	~ €2,764.00
	2023	€0.127	~ €1,158.00
Large shops	2022	€0.303	~ €4,423.00
	2023	€0.127	~ €1,854.00

The annual fee for the intelligent HVAC control is determined based on these potential energy savings. Considering that the average PUN of 2022 was exceptionally high due to unprecedented energy price increases, we base our estimates on more typical PUN values, hence considering the potential savings for 2023 outlined in Table 5.4. The estimated savings range from €695.00 to €1,854.00, depending on the size of the monitored site. The basic annual fee for the *M&A* solution is tied to the number of measurements points (i.e., the number of smart energy meters and ambient probes), which increases with the store's size. As defined by Energenius, annually each energy meter costs €25.00 while each ambient probe costs €20.00, with the total determining the basic annual fee. For the *CONTROL* solution, an additional fee is applied based on potential energy savings. This extra fee is approximately 40% of the projected savings reported in Table 5.4, resulting in total annual fees from €400.00 to €1,110.00, depending on the size of the controlled site.

Further details about the pricing strategy based on the size of the shop are as follows:

- Small shop/site (up to 500 m^2):
  - For the *M&A* solution, the setup cost is estimated at €1,200.00, with a selling price of €1,900.00, resulting in a revenue margin of 58%.
  - For the *CONTROL* solution, the setup cost is €1,800.00, and the selling price is €2,600.00, resulting in a revenue margin of 44%.
- Medium shop/site (500 m^2 $<$ area $<$ 1000 m^2):
  - For the *M&A* solution, the setup cost is estimated at €2,200.00, with a selling price of €3,500.00, resulting in a revenue margin of 59%. The annual fee is €265.00.
  - For the *CONTROL* solution, the setup cost is €3,300.00, and the selling price is €4,800.00, resulting in a revenue margin of 45%.
- Large shop/site (over 1000 m^2):
  - For the *M&A* solution, the setup cost is estimated at €2,800.00, with a selling price of €4,400.00, resulting in a revenue margin of 57%. The annual fee is €335.00.
  - For the *CONTROL* solution, the setup cost is €4,200.00, and the selling price is €6,000.00, resulting in a revenue margin of approximately 43%.

Based on a preliminary cost analysis, we observe that, in a fair view, Energenius expects to manage 160 shops in 2026, divided into: 40 small, 70 medium and 50 large stores, as reported in Table 5.5. In our opinion, it is reasonable to expect that customers will prioritise monitoring and optimising medium and large sites, where the potential for significant sustainability improvements is greater. Indeed, medium and large stores typically consume more energy due to their larger footprints and more

HVAC devices. As such, the application of advanced optimisation techniques in these environments can lead to substantial reductions in energy consumption and operational costs.

Table 5.5: Number of retail stores adopting GEM-Retail in the upcoming years.

Size	**2023**	**2024**	**2025**	**2026**
Small shops	7	14	26	40
Medium shops	10	22	40	70
Large shops	8	14	24	50
Total	**25**	**50**	**90**	**160**

In Table 5.6, we present the projected costs and revenues for the *M&A* solution. Our forecasts indicate that the margin for 2023 is €30,700.00, which is expected to increase significantly to €239,130.00 by 2026. The margin for Energenius offering the intelligent HVAC control solution is even higher, starting from €35,000.00 in 2023 and potentially reaching €334,640.00 by 2026, as reported in Table 5.7. Specifically, if we consider 2026 to highlights the benefits:

1. Small shops: The setup cost for the intelligent HVAC control amounts to €72,000.00 compared to €48,000.00 for the *M&A* solution. However, the expected revenue in the first case is €120,000.00, whereas it is only €81,640.00 for the *M&A* solution.

2. Medium shops: By 2026, the setup cost for the intelligent HVAC control is €231,000.00 compared to €154,000.00 for the *M&A* solution. The corresponding revenue is €382,190.00 for the intelligent HVAC control, significantly higher than €264,080.00 for the *M&A* solution.

3. Large shops: In 2026, the setup cost for the intelligent HVAC control is €210,000.00 compared to €140,000.00 for the *M&A* solution, while the

revenue is €344,650.00 for the intelligent HVAC control, as opposed to €235,410.00 for the *M&A* solution.

Table 5.6: Prospects for costs and revenues for GEM-Retail in the upcoming years for the *M&A* solution.

Size		**2023**	**2024**	**2025**	**2026**
Small shops	Cost	8,400.00 €	16,800.00 €	31,200.00 €	48,000.00 €
	Revenue	13,300.00 €	27,440.00 €	51,920.00 €	81,640.00 €
Medium shops	Cost	22,000.00 €	48,400.00 €	88,000.00 €	154,000.00 €
	Revenue	35,000.00 €	79,650.00 €	148,480.00 €	264,080.00 €
Large shops	Cost	22,400.00 €	39,200.00 €	67,200.00 €	140,000.00 €
	Revenue	35,200.00 €	64,280.00 €	112,970.00 €	235,410.00 €
Internal Costs		**52,800.00 €**	**104,400.00 €**	**186,400.00 €**	**342,000.00 €**
Internal Revenues		**83,500.00 €**	**171,370.00 €**	**313,370.00 €**	**581,130.00 €**
Profit Margin		**30,700.00 €**	**66,970.00 €**	**126,970.00 €**	**239,130.00 €**

Table 5.7: Prospects for costs and revenues for GEM-Retail in the upcoming years for the *CONTROL* solution.

Size		**2023**	**2024**	**2025**	**2026**
Small shops	Cost	12,600.00 €	25,200.00 €	46,800.00 €	72,000.00 €
	Revenue	18,200.00 €	39,340.00 €	76,420.00 €	120,800.00 €
Medium shops	Cost	33,000.00 €	72,600.00 €	132,000.00 €	231,000.00 €
	Revenue	48,000.00 €	113.050.00 €	215,840.00 €	382,190.00 €
Large shops	Cost	33,600.00 €	58,800.00 €	100,800.00 €	210,000.00 €
	Revenue	48,000.00 €	93,400.00 €	169,850.00 €	344,650.00 €
Internal Costs		**79,200.00 €**	**156,600.00 €**	**279,600.00 €**	**513,000.00 €**
Internal Revenues		**114,200.00 €**	**245,790.00 €**	**462,110.00 €**	**847,640.00 €**
Profit Margin		**35,000.00 €**	**89,190.00 €**	**182,510.00 €**	**334,640.00 €**
Customer Savings		**∼ 17,669.00 €**	**∼ 65,958.00 €**	**∼ 154,252.00 €**	**∼ 315,456.00 €**
Customer Real Costs		**∼ 96,530.00 €**	**∼ 179,831.00 €**	**∼ 307,857.00 €**	**∼ 532,183.00 €**

The intelligent HVAC control solution, while initially more expensive in terms of setup costs, yields significantly higher revenues over time. The key factor driving this revenue growth is the significant energy savings that the automated optimisation of HVAC devices provides to customers. Based on the estimations outlined in Table 5.4 for a single site, the customer could see significant energy savings over the years, starting from approximately €17,669.00 in 2023 and increasing to €315,456.00 by 2026. Importantly, the revenues figures for each year account for both the new stores added in that year and the recurring fees from stores installed in previous years. These savings translate into lower effective costs for the customers after just a couple of years, as the total amount paid basically equals the total revenues for Energenius minus the savings from the intelligent energy management of HVAC devices. For instance, in 2025, the *M&A* solution would cost the customer €313,370.00, while the *CONTROL* solution would cost about €307,857.00. The cost difference becomes even more pronounced in 2026: the real cost for customers with the intelligent HVAC control solution is approximately €532,000.00, compared to about €581,130.00 for the *M&A* solution. This creates a margin of over €50,000.00 in favor of the *CONTROL* solution by the fourth year, demonstrating a clear financial benefit for customers who choose the intelligent HVAC control.

Customer savings, when compared to internal revenues (i.e., the cost of the solution to the customer), indicate that the estimated payback period for the *CONTROL* solution is approximately 4 to 5 years. This relatively short payback period results from its intelligent, direct control over HVAC devices, which leads to significant energy savings and efficiency improvements. In contrast, estimating the savings for the *M&A* solution is more complex. Unlike the *CONTROL* solution, the *M&A* solution lacks automated control of HVAC devices, requiring manual intervention. This effort increases with the number of environments managed, leading to potential inaccuracies, higher operational costs and reduced energy savings. Consequently, the payback period for the *M&A* solution is expected to be longer, approximately around 10 years.

The prospects for the upcoming years highlight the significant business potential of the intelligent and automated HVAC control derived from our research. This innovative solution creates a win-win scenario for both Energenius and its potential customers. Energenius can anticipate substantial revenue growth over the years, driven by the increasing adoption of this advanced technology. Meanwhile, customers will spend progressively less money compared to a basic monitoring and analysis solution. In addition to cost savings, they will achieve substantial benefits in terms of energy efficiency, reduced operational costs, and enhanced sustainability, as underlined in the previous chapters. This dual advantage not only enhances Energenius's market position but also supports customers in meeting their energy management and sustainability goals more effectively.

5.8 Summary

In this chapter, we have conducted a business analysis to evaluate the impact of our research outcomes on Energenius' business strategies, specifically focusing on the GEM-Retail product.

Our analysis demonstrates that the research findings offer significant advantages for the company from a business perspective. Specifically, the EECO algorithm, detailed in Chapter 4, has the potential to generate substantial revenue in the coming years if integrated into the GEM-Retail product. By implementing this algorithm, Energenius can provide customers with significant energy savings, leading to lower system costs and enhanced customer satisfaction in managing their sites from a sustainability perspective. This not only positions Energenius in a privilege position in energy-efficient solutions for smart buildings but also creates a competitive advantage in the market.

Chapter 6

Conclusions

In this thesis, we have addressed the challenge of optimising indoor environments from energy and environmental perspectives, aligning with current research directions.

In Chapter 3, we have introduced an adaptive and practical approach for predicting indoor environmental and energy parameters. This approach leverages a dynamic mobile window, facilitating rapid system deployment and ensuring AI models remain current with environmental changes. Our findings demonstrate that this kind of approach does not compromise prediction accuracy. Even with a limited input dataset, our solution achieves prediction accuracy comparable to existing methods, providing clear benefits during the initial start-up phase and throughout regular system operation. Additionally, evaluation results further indicate that the proposed system can efficiently run on resource-constrained devices. Consequently, each device installed within a certain environment or building operates independently using only its collected data, eliminating the need for expensive cloud infrastructure, as discussed in Chapter 5. This capability reduces costs, enhances system reliability, and improves scalability, making it a viable solution for widespread adoption in different business contexts. The result is a potential zero-touch approach for predicting key parameters within indoor environments.

Nonetheless, there are still research gaps to be explored to enhance the proposed solution for forecasting, especially in terms of robustness. For instance, future work could focus on improving the solution's resilience to missing data. Currently, the proposed approach relies on a robust data collection system, which means that if there are gaps in the data (because of, e.g., communication issues, sensor failures), the system is unable to predict future values and could miss relevant samples in the training data. To address this issue, a mechanism could be developed to identify the largest continuous time window with complete data (i.e., no holes) for making predictions. The challenge lies in balancing the size and age of the old data window: a sufficiently large window is necessary for accurate predictions, but it is important to avoid using outdated data that might misrepresent current indoor environmental conditions. Additionally, another area for improvement is the capability to identify and handle abnormal readings or measurement errors from IoT sensors. Inaccurate or corrupted data can lead to faulty predictions, degrading overall accuracy. Introducing logic to detect and filter out anomalous data points can enhance the robustness of the predictive solution.

In Chapter 4, we have demonstrated the effective application of our predictive approach to regulate HVAC systems. We have introduced an automated solution called EECO, which continuously adjusts HVAC devices to optimise thermal comfort while minimising energy consumption. Unlike traditional methods, this solution operates without requiring preliminary information about the local environment or any physical or mathematical modeling. By leveraging the collected data and the designed AI model for forecasting, EECO implicitly evaluates the impact of various factors, including building features (e.g., wall thickness, orientation, window presence), outdoor environment (e.g., outdoor temperature, humidity) and passive phenomena (e.g., passive heating), on the monitored parameters, thereby adapting to the observed environment. In contrast to existing research, we have addressed the challenge of scalability, facilitating the applicability of our solution in real-world scenarios while minimising the manual effort required for deployment and long-term maintenance.

Beyond the aspects covered in this thesis, there is a range of open issues related to the optimisation of environmental and energy parameters in indoor environments. Extensive testing across diverse environments and integration with other building management systems should be explored to obtain a broader understanding of performance, as discussed in Section 4.7.5. Due to clear limitations, we were unable to test the proposed solution across a large number of sites. Additionally, it is crucial that input datasets be representative and balanced. In HVAC control algorithms leveraging AI models, configuration strategies not reflected in the data might be evaluated in EECO's tree-building process (discussed in Section 4.5.2), potentially leading to poor HVAC control, especially during the initial deployment phase. To address this challenge, further research is necessary. In parallel, additional input variables (e.g., solar irradiance) might be introduced to account for outdoor environmental factors and lead to more accurate HVAC control, as outlined in Section 4.7.5. In terms of occupant behaviour, while CO_2 levels provide valuable information regarding indoor occupancy (i.e., they typically increase and decrease with the number of people present), integrating data from other sources, such as motion sensors, might offer a more comprehensive model of the indoor environment. Finally, another key aspect is the integration of electricity prices into HVAC optimisation to increase energy efficiency, which is often overlooked in the literature, as noted by Ala'raj et.al. [76]. The authors highlight the importance of analysing the impact of energy prices on HVAC modelling, control and optimisation and, in our opinion, in the trade-off between thermal comfort and energy savings. In recent years, fluctuations in energy prices have become increasingly important in controlling energy-intensive devices in terms of ON/OFF and operating point, in both the industrial and tertiary sectors. Therefore, this represents a promising research direction not explored in this thesis.

Finally, in Chapter 5 we have presented a detailed analysis to understand the impact of the obtained research outcomes on the business of Energenius. This analysis offers valuable insights into increasing the revenues and attractiveness of the GEM-Retail solution. Aligned with the objectives of the Doctorate Program in Industrial Innovation, this analysis provides a practical example of how research can directly enhance business operations, potentially increasing the competitiveness of companies in the market while increasing revenues.

Overall, the contributions of this thesis offer important insights into addressing some of the limitations present in the current literature on building sustainability and beyond. In this regard, the designed methodology might find application in other sectors for different objectives, such optimising production processes in industry, where maximising outputs while minimising production costs under changing conditions is often crucial. While further research is fundamental to comprehensively explore sustainability from different perspectives, the obtained outcomes can draw the interest of managers seeking to manage indoor environments more effectively by reducing operating costs, improving thermal comfort, and lowering energy consumption in an automated and intelligent way. During my research at Energenius, I integrated the developed AI algorithms and predictive models into the GEM-Retail product, discussed in Chapter 5. Specifically, the designed approaches were included in the existing software solutions, which can then be downloaded and configured onto devices (e.g., Raspberry Pi) installed in buildings for optimising indoor environments. The predictive engine and intelligent HVAC control operate alongside other software modules (i.e., data collection and actuation modules) to provide these advanced functionalities. In this regard, my doctoral experience at Energenius demonstrates how collaborative efforts between academia and industry can facilitate the technology transfer, ensuring the practical viability and effectiveness of innovative solutions in different real-world scenarios. By bridging the gap between theoretical research and practical application, this collaboration highlights the potential for academic research to directly enhance business operations and contribute to broader environmental and economic benefits.

Activity Report

Research/Study Activities

The activities conducted during the Doctorate Program are the following:

- **Industrial Research Projects at Energenius S.r.l.**: I actively participated in different industrial research projects directly related to my research area:
  - GEM-Retail - "Programma operativo FESR 2014–2020" of Provincia autonoma di Trento
  - DIHC4CPS: Fostering DIHs for Embedding Interoperability in Cyber-Physical Systems of European SMEs - European Union's Horizon 2020 Research and Innovation Programme under grant agreement no. 872548
  - EUHubs4Data: European Federation Of Data Driven Innovation Hubs - European Union's Horizon 2020 Research and Innovation Programme under grant agreement no. 951771
  - i-NERGY - European Union's Horizon 2020 Research and Innovation programme under grant agreement no. 101016508
- **Geo-Mobility Period with EIT Digital**: As part of the EIT Digital Doctoral Program, I spent four months (01/05/2022 - 31/08/2022) at the Institute for Automation of Complex Power Systems (ACS)

hosted at E.ON Energy Research Center (RWTH) in Aachen and directed by prof. Antonello Monti.

- **Business Development Experience (BDExp)**: Within the EIT Digital Doctoral Program, I participated in the Business Development Experience (15/05/2023 - 03/09/2023). As reported by EIT Digital, this activity expects to provide a report on a business topic selected by the student, with the goal of fostering the development of business and innovation skills within the industry.

- **Business Seminars by EIT Digital**: Within the EIT Digital Doctoral Program, I participated in the following business seminars:

  – I year: Research To Value

  – II year: Business Change, Business Modelling

  – III year: Business Development, Business Growth

- **Courses at the University of Trento**: I completed the following courses offered by the University of Trento:

  – Research Methodology

  – Academic Writing for the Sciences and Engineering

- **Online Courses**: I attended the following online courses (on Coursera):

  – Neural Networks and Deep Learning

  – Improving Deep Neural Networks: Hyperparameter Tuning, Regularization and Optimization

List of publications

The International Journal Papers published during the Doctorate Program are the following:

- Segala, G.; Doriguzzi-Corin, R.; Peroni, C.; Gazzini, T.; Siracusa, D. *A Practical and Adaptive Approach to Predicting Indoor CO2.* Appl. Sci. 2021, 11, 10771. [37]
- Segala, G.; Doriguzzi-Corin, R.; Peroni, C.; Gerola, M.; Siracusa, D. *EECO: An AI-Based Algorithm for Energy-Efficient Comfort Optimisation.* Energies 2023, 16, 7334. [61]

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