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Artificial Intelligence (AI)-Based Occupant-Centric Heating Ventilation and Air Conditioning (HVAC) Control System for Multi-Zone Commercial Buildings

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Abstract: Buildings are responsible for almost half of the world's energy consumption, and approximately 40% of total building energy is consumed by the heating ventilation and air conditioning (HVAC) system. The inability of traditional HVAC controllers to respond to sudden changes in occupancy and environmental conditions makes them energy inefficient. Despite the oversimplified building thermal response models and inexact occupancy sensors of traditional building automation systems, investigations into a more efficient and effective sensor-free control mechanism have remained entirely inadequate. This study aims to develop an artificial intelligence (AI)-based occupant-centric HVAC control mechanism for cooling that continually improves its knowledge to increase energy efficiency in a multi-zone commercial building. The study is carried out using two-year occupancy and environmental conditions data of a shopping mall in Istanbul, Turkey. The research model consists of three steps: prediction of hourly occupancy, development of a new HVAC control mechanism, and comparison of the traditional and AI-based control systems via simulation. After determining the attributions for occupancy in the mall, hourly occupancy prediction is made using real data and an artificial neural network (ANN). A sensor-free HVAC control algorithm is developed with the help of occupancy data obtained from the previous stage, building characteristics, and real-time weather forecast information. Finally, a comparison of traditional and AI-based HVAC control mechanisms is performed using IDA Indoor Climate and Energy (ICE) simulation software. The results show that applying AI for HVAC operation achieves savings of a minimum of 10% energy consumption while providing a better thermal comfort level to occupants. The findings of this study demonstrate that the proposed approach can be a very advantageous tool for sustainable development and also used as a standalone control mechanism as it improves.

Keywords: artificial intelligence (AI); automatic HVAC control; occupant behavior; model predictive control; energy efficiency

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1. Introduction

Due to high demand and the need for an increasing energy supply, energy efficiency becomes crucial. Restricted energy markets have wide effects in areas ranging from household budgets to international relations. Thus, due to high energy consumption, buildings are on the front line of energy efficiency research. Buildings compose approximately 40%

of the total global energy consumption (International Energy Agency, 2019 [1]), and almost 40% of this goes towards heating, ventilation, and air conditioning (HVAC) systems (Yang et al., 2014 [2]). Clearly, the development and implementation of efficient building energy control systems is essential for economic and environmental sustainability. The HVAC system is a commonly used tool to maintain thermal comfort in buildings. It also serves as an essential demand-response source for peak load reduction and system-wide activity stabilization through effective demand-side energy management strategies. Until today, this energy demand in the buildings has been measured with sensors. Since heating and cooling in large masses do not occur rapidly, the inability to respond to sudden changes in occupancy and environmental conditions makes traditional HVAC control systems energy-inefficient, especially in large commercial buildings.

An HVAC is a dynamic mechanism that includes multiple input and output variables and is subject to various fluctuations and uncertainties, including occupant behavior, external air temperature, humidity, air volume, and regulated air temperature (Alcalá et al., 2003 [3]; Mirinejad et al., 2008 [4]). These specific features and characteristics all need to be taken into consideration to operate the HVAC system effectively. Thus, the research question of this paper is "how HVAC systems can be made efficient in meeting the sudden changes in demand responses in large commercial buildings by taking into consideration the occupancy patterns and prediction?" The following section provides a critical review of the literature with related studies in energy management with HVAC control systems to establish the setting for the research.

2. Related Studies

2.1. Traditional and Advanced Control Strategies

HVAC control strategies can be examined in general terms under two headings: traditional control strategies (TCSs) and advanced control strategies (ACSs). This section presents a review of related studies focusing on ACSs. Different control mechanisms are examined, and then a limited number of occupancy-based control approaches are discussed.

TCSs generally include sequencing, on-off, process, and proportional-integral-derivative (PID) controls. Their simple structure, quick response, easy implementation, and low initial costs are the main advantages of TCSs. They also have many disadvantages, such as low accuracy, quality, and performance, and (thus) energy efficiency. Furthermore, they do not interact with the external environment or regulate and adapt to the input variables accurately, in terms of their setpoints, schedules, and working modes, among others (Gholamzadehmir et al., 2020 [5]). Thus, the diversity and complexity of variables make it impossible to create accurate and reliable mathematical HVAC models for TCSs.

ACTs effectively obtain superior results in HVAC applications. These can be divided into four categories: (i) soft-computing, (ii) hard-computing, (iii) hybrid, and (iv) adaptive-predictive control strategies.

2.1.1. Soft Computing Strategies

Reinforcement learning (RL), artificial neural network (ANN)-based deep learning, fuzzy logic (FL), and agent-based controls together comprise the soft-computing control strategies. As a control mechanism, this enables solutions to more complex problems by generating more accurate and statistical responses for unclear and uncertain inputs. The key benefit of fuzzy logic controllers is that no mathematical simulation is needed for controller design (Mizumoto, 1995 [6]; Mirinejad et al., 2008 [4]; Soyguder et al., 2009 [7]). The knowledge-based methodology is the fundamental aspect of a fuzzy controller. This consists of if-then rules, membership functions, and scaling factors constructed based on expert experience or learning and self-organization methods that do not involve the system's mathematical model forms.

Since the human sensation of thermal comfort is subjective, and self-reporting can vary among occupants and over time, linguistic rules, on which fuzzy logic is based, are well suited to characterize HVAC systems and thus ideal for increasing thermal comfort

(Chiou and Lan, 2005 [8]; Mirinejad et al., 2008 [4]). There are two different approaches to the automation of rule-based construction in fuzzy systems, which can be used for optimizing the fuzzy system parameters (Mirinejad et al., 2012 [9]): one involves evolutionary techniques and the other soft-computing methods and technologies, such as ANNs.

Soft-computing methods with ANNs can integrate the learning ability of neural networks with the knowledge representation of fuzzy logic. They are frequently used when the aim is to decrease the error between the fuzzy system output and the target value, as characterized by the general term "neurofuzzy system" (Mirinejad et al., 2012 [9]). ANNs can also be applied to optimize the fuzzy database, including membership functions and scaling factors in a fuzzy system (Egilegor et al., 1997 [10]; Kruse et al., 1997 [11]; Wu et al., 2011 [12]). Some studies have utilized advanced fuzzy methods to optimize the function of existing, traditional PID controllers (Malki et al., 1994 [13]; Ying, 1994 [14]; Wu et al., 1996 [15]; Patel and Mohan, 2002 [16]; Li et al., 2005 [17]), while others have used them more directly in the development of new HVAC control mechanisms (Fanger, 1972 [18]; Alcalá et al., 2003 [3]; Liang and Ru, 2008 [19]; Gacto et al., 2011 [20]; Nowak and Urbaniak, 2011 [21]).

Together with model predictive control (MPC) algorithms, fuzzy control algorithms are implemented in the hierarchical framework for HVAC device control (Nowak and Urbaniak, 2011 [21]). Wei et al. (2017) [22] presented a deep reinforced learning (RL) method to develop an HVAC system that they found to be energy-efficient compared with the traditional rule-based approach. Du et al. (2021) [23] presented a model-free deep RL framework for an optimized control approach for a multi-zone residential building. This proposed RL model was reported to provide substantial energy savings and 98% less comfort violation than a rule-based HVAC control strategy

2.1.2. Hard Computing Strategies

Hard-computing control strategies, which include auto-tuning PID control, gain-scheduling control, self-tuning control, supervisory/optimal control, MPC, and robust control, benefit from a mathematical/analytical model that needs real input variables to respond accurately and rapidly. Some important hard-computing control strategy examples are summarized below, with a focus on MPC applications as these are more important here.

Pasgianos et al. (2003) [24] applied a non-linear feedback approach for climate control in greenhouses, especially for ventilation, cooling, and moisturizing. A non-linear multi-input and multi-output model has been used for an air-handling unit (AHU) control (Moradi et al., 2010 [25]). Robust control was applied to control the temperature in a multi-zone HVAC mechanism (Al-Assadi et al., 2004 [26]) and to supply air temperature (Anderson et al., 2008 [27]). Optimal control strategies were used to manage both single zone heating in buildings (Dong, 2010 [28]) and a multi-zone air conditioning system (Mossolly et al., 2009 [29]). An adaptive optimal control approach was also employed to optimize HVAC system control using a genetic algorithm (Yan et al., 2008 [30]).

MPC is an optimization technique that involves the construction of an objective function and an input sequence considering both specified and forced constraints. Serale et al. (2018) [31] aimed to describe the problem formulation, applications, and advantages of an MPC framework for improving building and HVAC energy efficiency. MPC has four functions in buildings, related to weather, user behavior, grid, and thermal mass. Kusiak et al. (2011) [32] created a predictive model with a data-mining approach to optimize HVAC mechanisms using information gathered from an experiment performed at a research facility. Kusiak et al. (2014) [33] presented an HVAC optimization approach with data-driven models and an interior-point method. The Poisson and uniform distributions modeled the uncertainty of occupant behavior, and the internal heating gain was measured with the stochastic mechanism of the building's occupancy. The results showed that the future performance of HVAC was estimated precisely.

Another data-driven approach for optimizing HVAC energy consumption was proposed by Wei et al. (2015) [34]. For this, a quad-objective optimization problem was built to balance energy usage and occupancy comfort and solve a modified particle swarm optimization algorithm. A substantial amount of energy savings was obtained. Biyik et al. (2015) [35] and Kelman et al. (2013) [36] suggested an MPC solution in a standard commercial building for two traditional HVAC setups to maximize energy efficiency and increase occupant comfort by using weather forecasting data. The effect of occupants on internal load prediction and learning from occupant activity is one of the key features of MPC, which can have a major impact on energy efficiency (Serale et al., 2018 [31]).

2.1.3. Hybrid Strategies

Huang et al. (2015a) [37] carried out a study that proposed a hybrid MPC framework. This integrated a classical MPC with a neural network feedback linearization method to reduce the cost and energy of HVAC in commercial buildings. The results indicated that a significant level of energy-saving could be achieved without compromising thermal comfort. Garnier et al. (2015) [38] implemented predictive control for a multi-zone HVAC mechanism in non-residential buildings using EnergyPLus software for the building model and ANN-based models for the controller's internal models. This took the predicted mean vote index as a measure of thermal comfort. Basic scheduling techniques and the proposed HVAC system using a genetic algorithm for optimization were compared, and the importance of the predictive approach demonstrated. Barzin et al. (2016) [39] carried out an experimental study using weather prediction and a price-based control system for passive solar buildings, with up to 90% energy savings achieved.

Alibabaei et al. (2016) [40] explored a Matlab-TRNSYS co-simulator development for control of the TRNSYS software, which was previously designed and balanced based on a real case-study building and used an advanced predictive controller. This study is important here in terms of the co-simulation application. For various other studies, Afram and Sharifi (2013) [41] supplied a detailed literature review including control techniques that focused on the theory, and implementation of MPC approaches for the HVAC mechanism; Afram et al. (2017) [42] presented another comprehensive MPC review focusing on artificial neural network applications with a case study involving ANN models built and calibrated with the on-site data of a residential house. Trčka and Hensen (2010) [43] and Afroz et al. (2017) [44] presented a critical review of the latest simulation and modeling techniques, used in HVAC, focusing on their benefits, limitations, implementations, and efficiency.

2.1.4. Adaptive-Predictive Control Strategies

The APCS (adaptive-predicted control strategy) method can be adapted to a controlled system with time-dependent variables through online variation of its control gains. Huang et al. (2015b) [45] presented an ANN model-based system identification approach to model multi-zone buildings. This showed the thermal interactions between the zones to be well captured by the ANN model, incorporating the energy input from mechanical cooling, ventilation, changes in the weather, and the convective heat transfer between adjacent zones. Thus, more precise outcomes are obtained than a single-zone model. Javed et al. (2017) [46] introduced a random neural network (RNN)-based controller on an Internet of Things (IoT) platform combined with cloud computing to carry out RNN that estimated the number of occupants inside the area and sent information to the central RNN-based occupancy calculator placed in the sensor node.

Cardoso et al. (2018) [47] introduced a study of HVAC power-demand forecasting based on occupant activity. This influences our study in terms of the use of real data from a research building for estimation. Estimation of HVAC demand plays a vital role in developing a more efficient HVAC system. Yang et al. (2019) [48] proposed an adaptive, robust MPC and compared its performance with predictive model controllers. This study showed that adaptive modeling and robust optimization minimize unsuitable indoor conditions because of uncertainties. Zhou et al. (2019) [49] developed a non-linear MPC by MATLAB using production control systems and weather forecasts and reported a substantial decrease in energy consumption. Finally, Gholamzadehmir et al. (2020) [5]

presented a review of the adaptive-predictive control strategy for HVAC systems in smart buildings focusing on advanced control approaches and their effect on buildings according to energy consumption and cost. This study indicated that although adaptive control strategies eliminate the shortcomings of model predictive approaches, such as uncertainty and unpredictable data, a high degree of inconsistency is observed in the literature.

2.2. Occupancy Related Studies

Since the primary focus of our study is the occupancy pattern and prediction, the following paragraphs look at occupancy-related studies. Erickson et al. (2009) [50] indicate that a 14% reduction in HVAC energy usage can be provided with occupancy prediction and usage patterns. They created a wireless camera sensor network for occupancy data and estimated occupancy with an accuracy of 80%. Erickson and Cerpa (2010) [51] proposed a strategy for HVAC systems using real-time occupancy monitoring and estimation of occupancy with a sensor network of cameras, indicating energy savings of up to 20%. Oldewurtel et al. (2013) [52] developed an MPC framework using occupancy information to investigate the effect of occupancy patterns to achieve a more energy-efficient HVAC mechanism. Furthermore, an RFID-based occupancy detection was presented by Li et al. (2012) [53] to decrease the consumption of the HVAC. The study shows how demand-driven HVAC operation is efficient by integrating an occupancy detection system.

A clustering-based iterative evaluation algorithm for eliminating when and how occupants occupy a building was introduced by Yang et al. (2016) [54], who evaluated energy implications at the building level with building information modeling that provided the building geometries, HVAC system configurations, and spatial information as inputs for the computation of possible energy consequences. Capozzoli et al. (2017) [55] applied an occupancy-related HVAC operation schedule that focused on shifting groups of occupants with similar activity in the same thermal zone. As a result of the new schedule approach, HVAC-related energy use decreased by almost 14%.

Another occupant-centric model, the predictive control approach, was developed by Aftab et al. (2017) [56], who created and applied an occupancy-predictive HVAC mechanism using real-time occupancy recognition, predicting user activity, and building thermal simulation. Aftab et al. (2017) [56] focused on a single-zone mosque area whereas the research in this paper focuses on multi-zone commercial buildings and adopts the use of AI for the prediction of occupancy activity. With these advancements, the research in the paper differs from the one by Aftab et al. (2017) [56].

Shi et al. (2017) [57] used a change-point logistic regression model for precise occupancy estimation to create an occupant-centric model predictive algorithm. Their findings indicated that an HVAC control strategy with real-time occupancy estimation provides energy-saving and increases building occupant comfort. Peng et al. (2018) [58] found that 52% energy saving is possible with occupancy prediction-based cooling control using machine learning in office buildings. A demand-responsive method was developed based on energy-related occupant activity. Nikdel et al. (2018) [59] estimated the benefits of occupancy centric HVAC controls in small office buildings based on programmable thermostats; when compared with no thermostat control, their proposed HVAC control approach reduced electricity and natural gas use by up to 50% and 87%.

Ahmadi-Karvigh et al. (2019) [60] presented an automation system that continually learns occupant behavior to help service system control by determining the set of rules according to the user's preferences and behaviors. Adaptive automation gave better results than inquisitive automation in terms of benefits and occupant satisfaction. Pang et al. (2020) [61] determined the energy efficiency potential of the new HVAC system combined with occupancy sensing methods. Their study involved an energy simulation with three different occupancy scenarios, with occupancy presence sensor and occupant counting sensor providing energy savings in office buildings.

Azuatalam et al. (2020) [62] developed a reinforced learning (RL) framework to optimize and control the HVAC for a whole commercial building. Simulations showed that, compared to a handcrafted baseline controller, an energy saving of up to 22% could be reached. Deng and Chen (2020) [63] developed a smart HVAC control mechanism for multi-occupant offices using the physiological signals of occupants. They applied an ANN model to predict indoor conditions and physiological signals, such as clothing level, (wrist) skin temperature, relative skin humidity, and heart rate. The heating and cooling loads in interior offices were reduced by 90% and 30%, respectively, following coupling with the occupancy-based control through lighting sensors and wristband Bluetooth. This study was vital for our research in terms of its development of occupancy-related HVAC and direct measurement of occupant comfort level. Jung and Jazizadeh (2019) [64] presented a structured literature review examining the user-centric operations and human dynamics of HVAC systems. This study focused on occupancy, comfort, and energy savings aspects. Finally, Jazaeri et al. (2019) [65] analyzed the complex relationships among local climates, building characteristics, and occupancy patterns with the annual and peak HVAC demand of residential buildings. These studies are important for us in terms of occupancy, but as mentioned before there is no study that predicts occupancy without real-time detection tools.

2.3. IDA Indoor Climate and Energy (ICE) Software Background

The IDA Indoor Climate and Energy (ICE) simulation software is one of the four primary building-energy simulation tools used in research (Ryan and Sanquist, 2012 [66]) and one of the twenty main building-energy simulation software packages (Crawley et al., 2008 [67]). As with many other simulation software packages, this uses building geometry as the foundation for accurate measurements of solar radiation distribution in and between spaces. The program dynamically measures energy balances while considering climatic changes and a changing time-step. Heat balance equations are solved by the program using building geometry, design, HVAC conditions, and internal heat loads. The effectiveness and validness of the IDA-ICE software are proved in several studies over recent years (Bring et al., 1999 [68]; Achermann and Zweifel, 2003 [69]; ISO, 2003 [70]; Karlsson et al., 2007 [71]; Loutzenhiser et al., 2009 [72]; Hilliaho et al., 2015 [73]; Salvalai, 2012 [74]; Mazzeo et al., 2015 [75]; Milić et al., 2018 [76]).

3. Aim of the Research

The advanced prediction ability of AI methods can be employed with sensors to determine occupant behavior, which offers an excellent opportunity to minimize the weakness of the traditional HVAC systems. The aim of the paper is to develop an AI-based, occupant-centric HVAC control mechanism that uses actual weather predictions and continually improves its knowledge to increase energy efficiency in a commercial building. Since the cooling problem has gained importance in recent years, the focus will be on the cooling function of the HVAC systems.

The novelty of the work is twofold. Firstly, a new HVAC control algorithm is proposed, based on forecasted weather and occupancy information to establish a sensor-free mechanism. Secondly, an artificial intelligence-based occupancy forecast system is presented, which considers all parameters (weather information, time indicators, social situations) and provides year-round usage with accurate prediction. Although there are limited examples for real-time occupancy detection in multi-zone buildings, any research study involving occupancy prediction without a camera or sensors has not been performed yet. There is also no other study that constructs the relationship between occupancy prediction, real-time weather, and indoor temperature to manage HVAC control via an algorithm. While a sensor-free algorithm allows both low installation cost and high energy efficiency, AI-based occupancy forecasting provides a system that improves itself as these data increase to use control mechanism standalone and obtain better energy savings.

4. Research Methodology

Paper adopts the design science research (DSR) methodology that facilitates the development of innovative solutions for industry and organizations driven by information (Vaishnavi, et al., 2019 [77]). Its characteristics involve iterative design processes leading to development of innovative solutions in the problem domain (Wieringa, 2014 [78]). The DSR methodology integrates both social context and knowledge base technical capability to achieve the aim of the research (Markus et al., 2002 [79]). Wieringa (2014) [78] described that there are two types of DSR: These include "problem-oriented research—evaluation research", and "solution-oriented—technical research". The problem-oriented research looks at what causes/effects a problem has, or how to solve a problem, whereas the solution-oriented research design and validate a system, or a requirement (Peffers et al., 2006) [80].

With DSR, this paper promotes the adoption of AI-based and occupant-centric HVAC control systems in commercial buildings to address the research problem around inefficient energy management of the existing HVAC systems. The DSR features with social context that are relevant to the paper are given in Table 1 and the overall research methodology is illustrated in Figure 1.

Table 1. Design science research (DSR) features.

Design Science Research (DSR) Features	
AI-based occupant-centric HVAC control system in commercial buildings	Design science research
Remove inefficiencies in energy management via HVAC systems Enhance the prediction ability with AI for the determination of occupant behavior for effective energy management in commercial buildings	Design an artifact: Development of AI algorithm for occupant-centric HVAC control system Research instruments-tools: Iterative design and development process for knowledge capture and development
Development of an innovative artifact to achieve and enhance the social context.	Answering the knowledge questions: How does the artifact adopt smart heritage project principles?

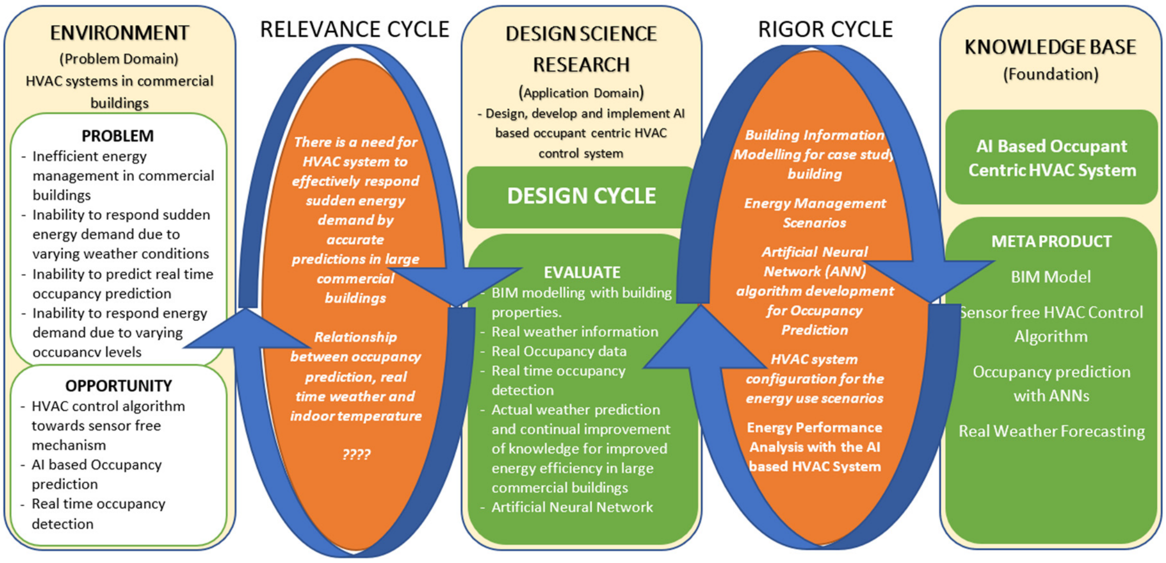

Figure 1. The flowchart of the design science research (DSR) methodology.

The design science research (DSR) methodology enabled developing the HVAC control system for accurate prediction of energy supply in commercial buildings that will serve to meet human needs for energy demand. The system developed via DSR is innovative with the key being the embedment of artificial intelligence that processes the occupancy and these weather data without the use of sensors. This paper with DSR implementation brings not only the novelty but also provides important solution to the practice for energy management in commercial buildings.

In the information systems (IS) science, the DSR methodology is highly preferred to solve identified organizational problems by developing information technologies. The paper is designed in accordance with the DSR methodology. The research problem domain and opportunities are elaborated by means of literature review through the relevance cycle. The design cycle is evaluated in Section 5 regarding the development of the artifact (AI-based occupant-centric HVAC control system) that is extended with the test and demonstration of the proposed artifact in Section 6 through the rigor cycle. This then leads to the accumulation of findings into the new knowledge base, articulated in Sections 6 and 7.

5. Design and Development of the AI-Based Occupant-Centric HVAC Control System

The artifact, which includes novelty about the research problem, is created. This artifact in this paper is the AI-based occupant-centric HVAC control system. Since the purpose of the study is to reveal energy efficiency potential of the proposed HVAC control mechanism, energy analysis according to different scenarios constitute the central part of this section. The research focuses on a specific site to obtain realistic results, using two-year occupancy and environmental conditions data of a shopping mall in Istanbul. Figure 2 shows the architecture of the system, consisting of three steps: predicting hourly occupancy, a new HVAC control mechanism, and comparison of the traditional and AI-based control systems via simulation according to different scenarios.

In the first step, building properties and real occupancy information are collected. In the second step, after determining the attributions for occupancy in the mall, hourly occupancy predictions are made using real data and ANNs, and a sensor-free HVAC control algorithm is developed with the help of occupancy data obtained from the previous stage, building characteristics, and real-time weather forecast information.

ANN is considered one of the traditional and most used artificial intelligence methods, and is still one of the most accurate and effective. This enables traditional and AI-based sensor-free HVAC control mechanism comparison to be performed in the final step, using IDA-ICE 4.8 software developed by EQUA Simulation AB based in Stockholm, Sweden.

5.1. Building Properties, Occupancy, and Environmental Information

According to the Association of Real Estate and Real Investment Companies of Turkey (2019) [81], there are currently 454 shopping malls in Turkey; across Europe, there are more than 9500 malls, with over 1000 in France and more than 1500 in the UK (STATISTA, 2021 [82]). Worldwide, there is a huge number of shopping malls, which makes them a significant target for energy savings and important in the development of sustainable energy policy. These buildings tend not to have good energy efficiency strategies because they are mostly constructed for consumption and entertainment purposes. It is commonplace for them to use varied and excessive lighting to attract people and make them feel good inside the building.

Poor heating and cooling settings disrupt the comfort area for people as well as causing energy inefficiencies. As a complicating factor and unlike office buildings, shopping malls do not have certain daily occupancy distributions, thus accurately gauging correct heating and cooling settings is not easy. It is for these reasons that this study takes a shopping mall as its case study. For more accurate energy analysis, a realistic model of the building is used that incorporates the real properties of the building elements. Furthermore, the solar radiation and weather data for the building location are obtained automatically from IDA-ICE software for energy simulations. Figure 3 shows the model of the building story; Table 2 shows the properties of the building elements.

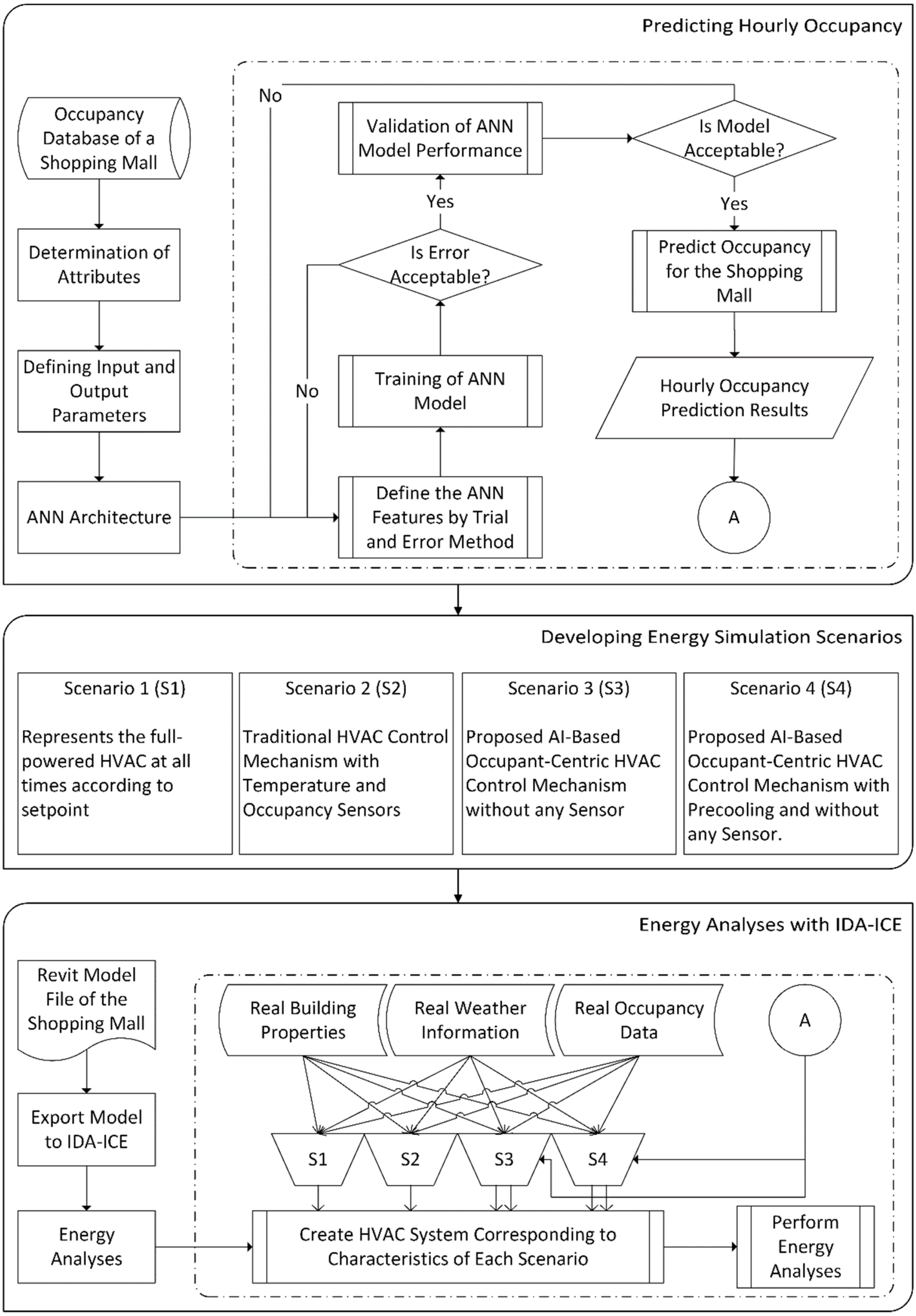

Figure 2. AI-based occupant-centric HVAC control system design.

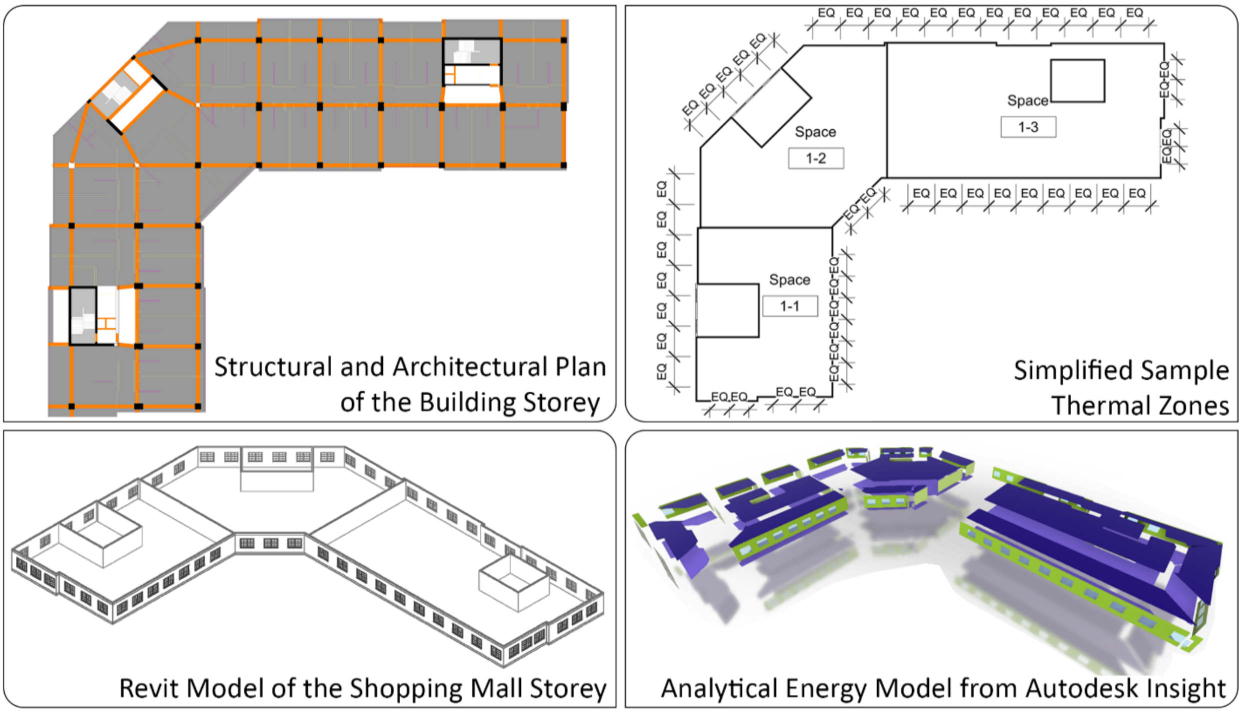

Figure 3. Sample 2D drawings and 3D models of the building story.

Table 2. Building components.

Construction	Material Layers (from Outside to Inside)
External wall	Press brick and supporters—0.088 m | Gypsum board—0.02 m | Light steel wall and XPS Insulation—0.15 m | Gypsum board—0.02 m | Plywood wall panel and supporters—0.07 m
Ground floor	Reinforced concrete—1.5 m | Concrete—0.05 m | XPS Thermal Insulation—0.06 m Concrete—0.03 m | Screed—0.005 m | Floor Covering—0.008 m
Roof	Standing seam roof sheet metal | OSB sheet—0.015 m | Corrugated steel sheet | Steel roof supporters and XPS insulation—0.12 m
Window	Low-e glass double—4 mm + 12 mm argon + 4 mm

5.2. Occupancy Prediction with ANNs

5.2.1. ANN Parameters

Many factors affect the occupancy numbers and distribution of a shopping mall. They can be divided into two categories: social and environmental. When the collected real entrance data are examined, temperature, humidity, and weather conditions along with type and time of a day come to the forefront as significant parameters. Determined as attributes in the ANN calculation, these parameters are thus:

1. Temperature: This is one of the most critical factors affecting the number of people; there are fewer visitors to the shopping mall in winter than in summer days;
2. Humidity: This affects the temperature feel; when the humidity in the air is high, warm moisture stays on people's skin longer and makes them feel hotter;
3. Weather condition: This also affects the occupant number significantly; on rainy or snowy days, shopping malls attract fewer visitors;
4. Time indicators: Days are also significant for shopping mall occupancy; on non-working days, the number of visitors is higher than on working days. In our study, the days are not separated into working and non-working days, as in some studies, but each day of the week is included in the calculation separately; furthermore, month and year information are considered as separate parameters since they are essential variables in the long-term use of the shopping mall;

5. Special days: Public (state) and religious holidays significantly affect occupancy; the number of visitors increases on national holidays and decreases considerably on religious holidays; furthermore, the first day of religious holidays is separately considered because there are far fewer visitors on these days than others;
6. Time of day: This is the most critical factor for sudden changes in the number of people visiting; for example, the occupancy number increases rapidly at the start of the lunch break and decreases rapidly when it finishes.

Table 3 illustrates the detailed categories, variables, and unit/index of attributes used in the ANN model; Table 4 shows a sample of the actual data. Furthermore, the histograms of the temperature, humidity, weather conditions, and occupancy variables are presented in Figure 4 to show the distribution of the collected data.

Table 3. Detailed category, variable, and unit/index information of attributes.

Category	Variables	Unit/Index
Environmental	Temperature	°F
	Humidity	%
	Weather Conditions	1: Fair | 2: Partly cloudy | 3: Mostly cloudy | 4: Light rain 5: Rain | 6: Heavy rain | 7: Fog | 8: Snow | 9: Thunder
Social and Time Indicators	Weekday	1–7 (1: Monday ⋯ 7: Sunday)
	Month	1–12 (1: January ⋯ 12: December)
	Day	1–31
	Year	2017–2018–2019
	Time	10–21 (10: 10:00 a.m. ⋯ 21: 09:00 p.m.)
	Day Type	0: Normal day | 1: Public holiday 2: First day of religious holidays 3: Other days of religious holidays

Table 4. Real data for ANN (sample).

Day of Week	Month	Day	Year	Time	Day Type	Temp. °F	Hum. %	Weather Conditions	Occupancy (Number of People)
Sunday	8	18	2019	10^{00}–11^{00}	Normal	70	83	Partly cloudy	661
Sunday	8	18	2019	11^{00}–12^{00}	Normal	68	88	Light rain	1346
Sunday	8	18	2019	12^{00}–13^{00}	Normal	73	78	Partly cloudy	1448
Sunday	8	18	2019	13^{00}–14^{00}	Normal	72	78	Mostly cloudy	2547
Sunday	8	18	2019	14^{00}–15^{00}	Normal	77	50	Partly cloudy	2921
Sunday	8	18	2019	15^{00}–16^{00}	Normal	79	47	Partly cloudy	3353
Sunday	8	18	2019	16^{00}–17^{00}	Normal	79	47	Partly cloudy	3181
Sunday	8	18	2019	17^{00}–18^{00}	Normal	77	47	Partly cloudy	2455
Sunday	8	18	2019	18^{00}–19^{00}	Normal	77	50	Partly cloudy	2339
Sunday	8	18	2019	19^{00}–20^{00}	Normal	75	50	Partly cloudy	2126
Sunday	8	18	2019	20^{00}–21^{00}	Normal	72	60	Partly cloudy	1644
Sunday	8	18	2019	21^{00}–22^{00}	Normal	70	68	Fair	777
Monday	8	19	2019	10^{00}–11^{00}	Normal	77	54	Mostly cloudy	463
Monday	8	19	2019	11^{00}–12^{00}	Normal	75	57	Mostly cloudy	906
Monday	8	19	2019	12^{00}–13^{00}	Normal	77	54	Mostly cloudy	1418
Monday	8	19	2019	13^{00}–14^{00}	Normal	81	48	Partly cloudy	1690
Monday	8	19	2019	14^{00}–15^{00}	Normal	81	45	Partly cloudy	1643
Monday	8	19	2019	15^{00}–16^{00}	Normal	79	51	Partly cloudy	1379
Monday	8	19	2019	16^{00}–17^{00}	Normal	77	50	Partly cloudy	1547
Monday	8	19	2019	17^{00}–18^{00}	Normal	79	51	Partly cloudy	1494
Monday	8	19	2019	18^{00}–19^{00}	Normal	77	54	Partly cloudy	1907
Monday	8	19	2019	19^{00}–20^{00}	Normal	75	61	Partly cloudy	1806
Monday	8	19	2019	20^{00}–21^{00}	Normal	72	73	Fair	1496
Monday	8	19	2019	21^{00}–22^{00}	Normal	70	78	Fair	727

Table 4. *Cont.*

Day of Week	Month	Day	Year	Time	Day Type	Temp. °F	Hum. %	Weather Conditions	Occupancy (Number of People)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Friday	8	30	2019	10^{00}–11^{00}	Pub. Hol.	77	69	Partly cloudy	1269
Friday	8	30	2019	11^{00}–12^{00}	Pub. Hol.	81	54	Partly cloudy	1406
Friday	8	30	2019	12^{00}–13^{00}	Pub. Hol.	81	48	Partly cloudy	1738
Friday	8	30	2019	13^{00}–14^{00}	Pub. Hol.	82	48	Partly cloudy	2562
Friday	8	30	2019	14^{00}–15^{00}	Pub. Hol.	82	48	Partly cloudy	2601
Friday	8	30	2019	15^{00}–16^{00}	Pub. Hol.	81	54	Partly cloudy	2990
Friday	8	30	2019	16^{00}–17^{00}	Pub. Hol.	81	51	Partly cloudy	2518
Friday	8	30	2019	17^{00}–18^{00}	Pub. Hol.	79	54	Partly cloudy	2428
Friday	8	30	2019	18^{00}–19^{00}	Pub. Hol.	77	54	Partly cloudy	2701
Friday	8	30	2019	19^{00}–20^{00}	Pub. Hol.	75	65	Partly cloudy	2262
Friday	8	30	2019	20^{00}–21^{00}	Pub. Hol.	73	65	Fair	1805
Friday	8	30	2019	21^{00}–22^{00}	Pub. Hol.	72	69	Fair	818

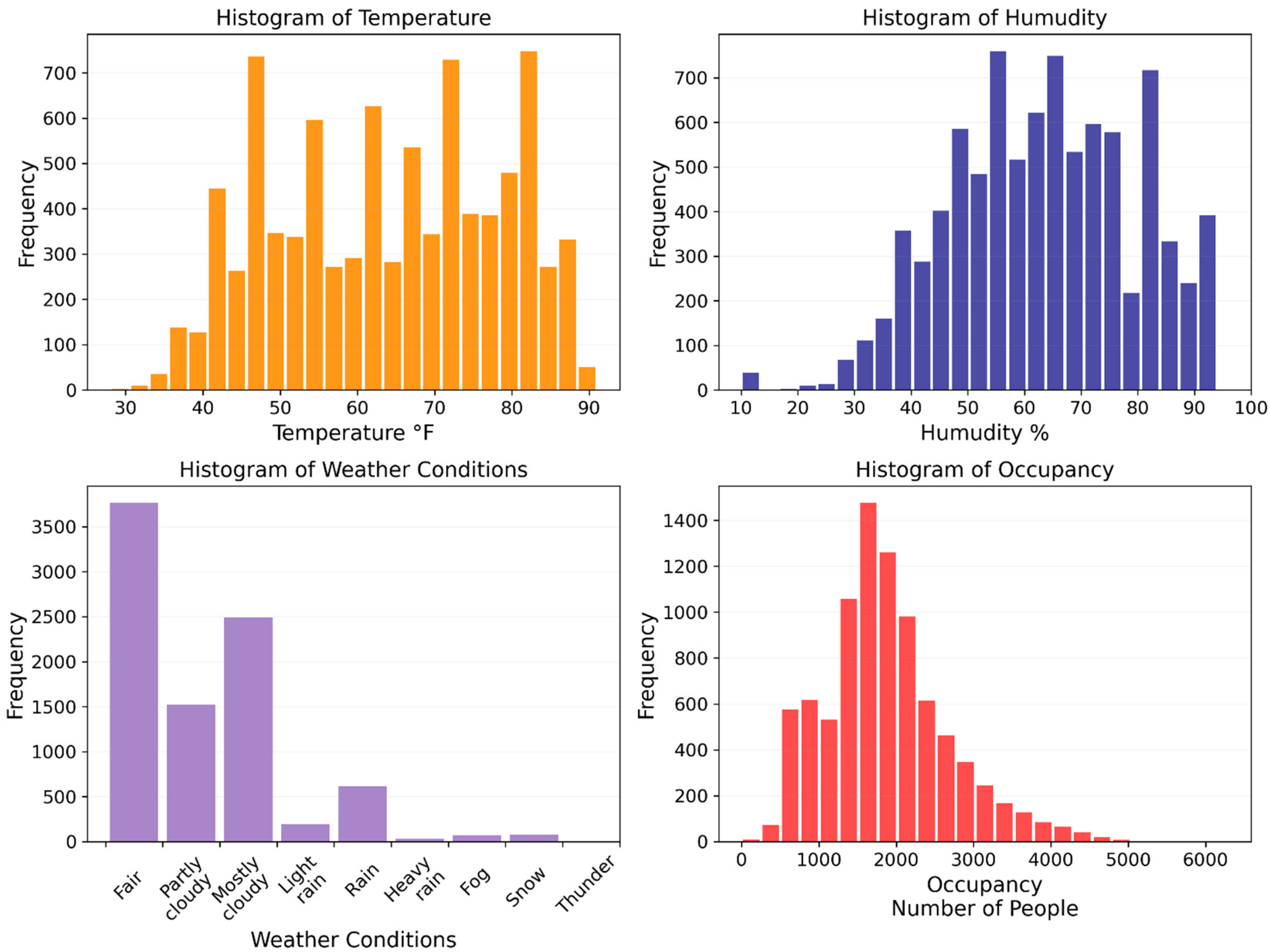

Figure 4. Histograms of the temperature, humidity, weather conditions, and occupancy variables.

5.2.2. ANN Models

Due to their strong logic, error tolerance, versatility, and generalization capabilities, AI methods are used in various applications. The ANN, a mathematical model that imitates the biological nervous system, is one of the most widely used types of AI and has been implemented to solve a variety of practical challenges in many fields of study.

The fundamental biological unit of the nervous system is the neuron, a fundamental processing factor that receives and integrates signals from other neurons through dendrite input paths. The neuron generates an output signal along the axon that links to the dendrites of several other neurons if the combined input signal is sufficiently high. An attempt to model the behavior of biological neural systems was made that led to the development of ANNs, in which artificial neurons model the components of a real neuron. An ANN is thus a set of independently linked processing units that function as parallel-distributed computing networks.

Unlike traditional computers, which are programmed to perform particular tasks, ANNs may learn from examples and eliminate the need for complicated mathematical formulas or costly physical models by acting as (human) brain-like mathematical models. They are fault-tolerant and can work with noisy data, allowing for quick generalization of unknown inputs (Wijayasekara et al., 2011 [83]). They also have specific adaptation abilities that enable them to solve highly non-linear problems in which finding analytical formulations that relate the input data to the output data is especially challenging (Hagan et al., 2014 [84]). Unlike other statistical or parametric approaches, ANNs can extract non-explicit relationships from a massive volume of correlated data using the high computational capabilities of current computers; thus, ANNs have become a prevalent problem-solving strategy in a diverse range of study areas.

The architecture of ANN models is formed by layers with complete or random connections between them. There is a connection between each neuron, and information exchange is performed. The network receives data from the input layer. The nodes in this layer do not have any weights or activation functions, thus it is not a neural computing layer. The hidden layer or intermediate layer includes data processing and computing steps and the final response to a given input, which is called the output layer (see Figure 5). The ANN model is developed using TensorFlow's Keras API and the Adam algorithm is used to train the model. Five-fold cross-validation was applied for splitting the data into two subsets, namely, training and testing. Ninety percent of cases were used for training in each trivial, and the remaining were utilized to test the model accuracy. All equations are adopted from the book *Artificial Neural Networks* by Springer US (2021) [85].

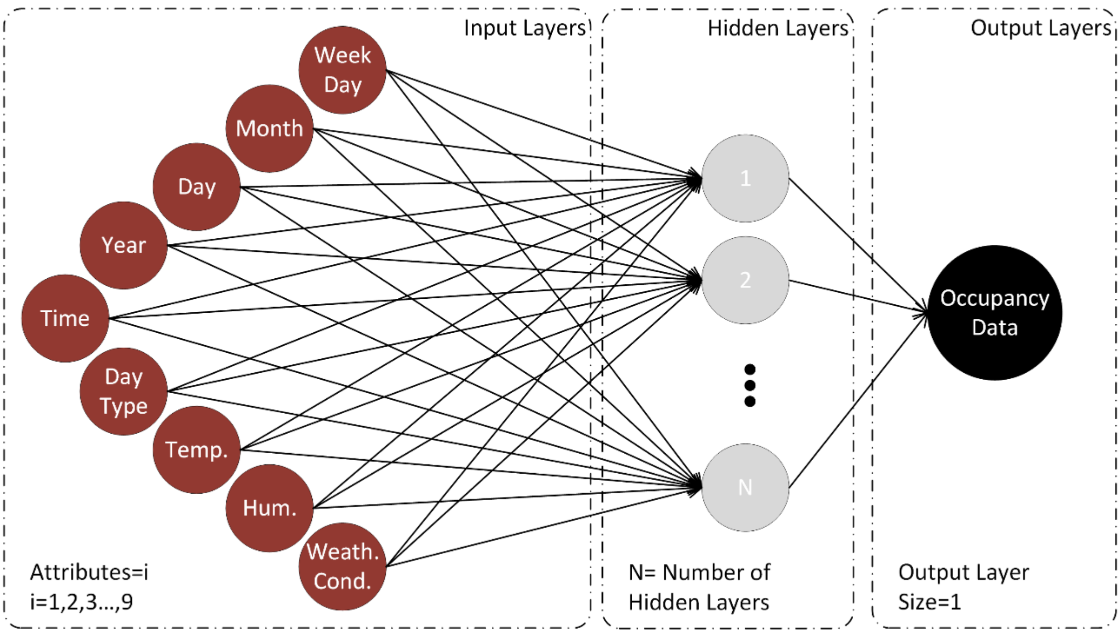

Figure 5. ANN structure for the study.

Generally, the net input of a neuron—activation potential A_i—is equivalent to the product $w_{ij}x_j$, where w_{ij} is the weight of the corresponding connection on the *i*-th post-synaptic neuron and x_j is the input signal (Equation (1)). Connection weights can be considered as storage of the knowledge that underlies the processing. Thus,

$$A_i = \sum_j w_{ij}x_j - a_i \tag{1}$$

where a_i is the threshold activation constant of the neuron. An output can only be obtained by propagating through a specific activation function. After the signal has been thus propagated, an output can be found thus:

$$y_i = \varphi(A_i) = \varphi\left(\sum_j w_{ij}x_j - a_i\right) \tag{2}$$

where y_i is the output of a layer and $\varphi(\bullet)$ is the transfer function.

The sigmoid activation function has been a common activation function for neural networks for a long time. Its input is converted to a value of between 0.0 and 1.0, with inputs that are significantly greater than 1.0 being converted to 1.0, and inputs that are significantly smaller than 0.0 snapped to 0.0. However, due to the vanishing gradient problem, usage of the sigmoid and hyperbolic tangent activation functions in networks with many layers is not true. This problem can be overcome by using the rectified linear activation function, allowing ANN structures to learn faster and increase performance. The formula of the rectifier or rectified linear unit (ReLU) is as follows:

$$f(x) = x^+ = max(x) \tag{3}$$

where x is the input to a neuron. This is also known as a "ramp function" and is analogous to half-wave rectification in electrical engineering. Connection weights are modified by the ANN model using a suitable learning method during the training phase. The network uses a learning mode to obtain the desired output by adjusting the weights. This is executed by introducing input and desired output to the network. The difference between the expected output and the network's output is then used to determine the error value. In the training phase, recalculations are carried out to decrease the error to an acceptable value. Due to zero occupancy on some days, mean absolute error (*MAE*) is used to calculate the error value, thus:

$$MAE = |y_i - \hat{y}_i| \tag{4}$$

where $\hat{y}_i$ is the corresponding desired output value. An error of close to zero shows that the ANN output values match the expected values very well and the network is well-trained. Backpropagation training is accomplished by assigning random weights to all nodes. Equation (5) is used to measure the variation quantity of the connection weights:

$$\Delta w_{ij}(t) = \lambda\delta_i - y_i + \alpha\Delta w_{ij}(t-1) \tag{5}$$

where the training rate is λ, the momentum coefficient is α, and the error of the *i*-th output layer is δ_i, which is calculated thus:

$$\delta_i = y_i(1 - y_i)MAE_i \tag{6}$$

MAE and mean absolute percentage error (*MAPE*) are also calculated as indices to evaluate the performance of the ANN model, thus:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| = \frac{1}{N}\sum_{i=1}^{N}|Relative\ Error_i| \tag{7}$$

where N is the total number of data sequences.

5.2.3. HVAC Control Scenarios for Energy Simulation

The primary goal of establishing HVAC control scenarios in terms of the level of development here is to measure the amount of energy to be saved with the proposed AI-based control approach. Although great progress has been made in air conditioning systems, a large proportion of commercial buildings have the most traditional type of control system, which is one that is operated manually by an attendant (janitor or similar) responsible for turning the system on and off. The most common HVAC control is based on the measurements of environmental conditions via sensors, generally temperature, humidity, and pressure sensors. The most serious deficiency of sensors in terms of energy consumption is the failure to facilitate a quickly responsive control system.

Many shopping malls serve as a lunch-places for people working near the building, which causes short-term occupancy densities during the lunch-break period. The rise in temperature due to sudden increase of people density is a slower process and, by the time this reaches the sensor, the control system responds, and the appropriate ambient temperature is provided, most people will already have left the building to return to work. Moreover, traditional building automation systems depend on quite imperfect occupancy sensors, which retards system responsiveness. Passive infrared and ultrasonic occupancy sensors, for example, are low-functioning devices for this usage since they are unable to accurately assess the occupancy condition, especially when people are stationary for an extended period and have a limited range, which especially affects their effectiveness in large areas.

AI prediction technology offers significantly more accurate occupancy information and improved energy efficiency than traditional building automation systems. Accordingly, our HVAC control mechanism takes predicted occupancy information and the maximum number of people per day and adjusts its power according to occupancy rate over time. Furthermore, new schedule algorithms are developed based on occupancy information, and weather forecasts for the scenarios (S3 and S4) explained below. The on-off status of the HVAC is determined according to these setpoint schedule algorithms. The maximum setpoint value is determined as 24 °C for all scenarios since we focus on the summer period in this study. Finally, four different scenarios—showing a level of development (from traditional to advanced)—are determined, as follows:

1. S1: The S1 scenario represents the full-powered HVAC at all times.
2. S2: The S2 scenario represents the most common traditional HVAC control mechanism based on temperature and occupancy sensors, where the HVAC control system is automatically (de)activated according to the temperature setpoints and temperature measurements from the sensors. In this scenario, occupancy is measured by CO_2 sensors, which record the level of CO_2 in the air. If the number of people in a space exceeds the amount of CO_2 allowed, the sensor triggers the HVAC mechanism to turn on. This type of sensor is more accurate than a standard motion sensor for the measurement of occupancy.
3. S3: The S3 scenario represents the proposed AI-based HVAC control system, which uses predicted occupancy numbers as produced by the ANN model. In this scenario, the HVAC system responds automatically to changes in the occupancy with no lag time, contrary to sensor-based systems. The control algorithm provides an HVAC setpoint schedule to control the system according to real weather conditions (as supplied by weather prediction services) and predicted occupant numbers. The existing sensors can still be used to monitor the real-time indoor temperature, humidity, and amount of CO_2. If the actual thermal comfort parameters exceed the desired values, the control system adjusts itself according to the sensors until thermal comfort is provided. In the energy simulations performed by IDA-ICE, the effect of the real-time sensors is not used to examine the no-sensor control mechanism. For this reason, in the illustrations and graphs for S3 and S4, dashed lines are used to show this potential.

4. S4: The S4 scenario represents the HVAC control system in the S3 scenario with a pre-cooling ability along with a quick response. The control algorithm provides pre-cooling time to control the system according to predicted weather conditions and occupant numbers. All other features are the same as for S3.

Figure 6 provides basic illustrations for the four energy simulation scenarios.

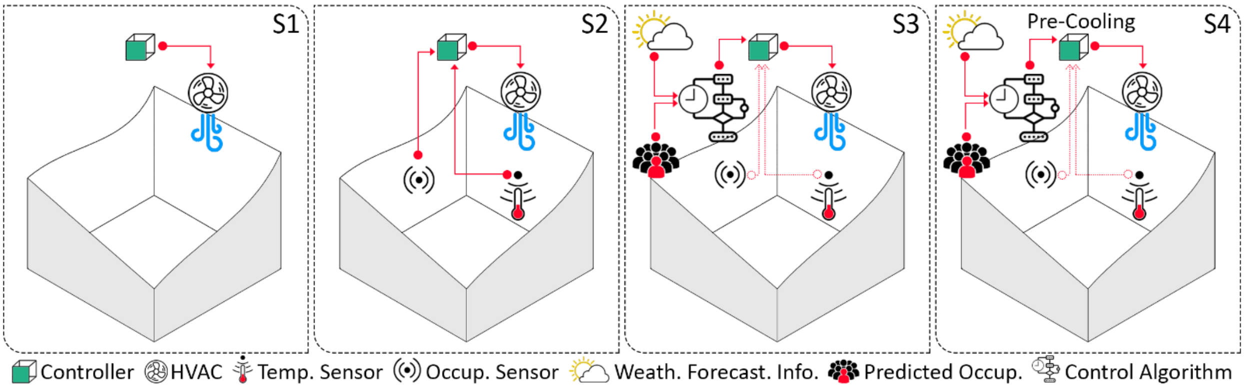

Figure 6. HVAC control scenarios for energy simulations.

Algorithm 1 and Algorithm 2, shown in below, explain the proposed HVAC control schedule algorithms in terms of cooling for S3 and S4. The control algorithm takes occupancy prediction results from the ANN analysis and real weather forecast information from provider websites as inputs (see lines 1–3). In the time intervals when the occupancy volume increases, the HVAC control activates according to the maximum setpoint (lines 4–6); otherwise, the algorithm checks the forecasted temperature and compares it with the maximum setpoint value.

Algorithm 1 HVAC Schedule Algorithm of S3 for Cooling

1 **train** ANN model
2 **make** day-ahead prediction for occupancy
3 **take** day-ahead local weather forecast information
4 **if** $occupancy_t < occupancy_{t+1}$
5     $setpoint_{max}$ ® T_{target}
6   **set** HVAC setpoint to T_{target}
7   **end**
8 **else**
9   **if** weather forecast $temp._t > setpoint_{max}$
10         $setpoint_{max}$ ® T_{target}
11   **set** HVAC setpoint to T_{target}
12   **else**
13   **deactivate** the cooling   • deactivation
14   **end if**
15 **end if**

If the weather forecast temperature for time t is greater than the maximum, the HVAC control uses the maximum setpoint (lines 8–10); if not, while the HVAC deactivates cooling automatically for S3 (lines 12 in Algorithm 1), the algorithm checks the occupancy trend of one hour later for S4. If there is a sudden increase (determined at 250 visitors), it activates the pre-cooling 30 min before the upward trend begins for S4 (line 15 in Algorithm 2).

Due to fluctuations in the occupancy numbers, sudden changes can cause comfort limit values to be exceeded, especially in situations where the number of visitors will increase too much one or two hours later, even if the occupancy trend is downward for the current time. To prevent this, S4 presents a 30-min pre-cooling. If there is no such increase, the HVAC control deactivates cooling (see line 17 in Algorithm 2), just as for the S3 algorithm.

Algorithm 2 HVAC Schedule Algorithm of S4 for Cooling

1 **train** ANN model
2 **make** day-ahead prediction for occupancy
3 **take** day-ahead local weather forecast information
4 **if** occupancy$_t$ < occupancy$_{t+1}$
5   setpoint$_{max}$ ®T$_{target}$
6   **set** HVAC setpoint to T$_{target}$
7   **end**
8 **else**
9   **if** weather forecast temp.$_t$ > setpoint$_{max}$
10   setpoint$_{max}$ ®T$_{target}$
11   **set** HVAC setpoint to T$_{target}$
12   **else**
13   **if** occupancy$_{t+2}$ - occupanc$_{t+1}$ > 250
14   **deactivate** the cooling for first t/2 • deactivation
15   setpoint$_{max}$ ®T$_{target}$
16   **set** HVAC setpoint to T$_{target}$ for last t/2 • start pre-cooling
17   **else**
18   **deactivate** the cooling • deactivation
19   **end if**
20   **end if**
21 **end if**

6. Demonstration and Evaluation of the AI-Based Occupant-Centric HVAC Control System

In this stage, the designed and developed system is tested in relation to the scenarios for energy analysis. According to design science research, research can exploit experimentation, simulation, case study, proof, or other activities to demonstrate the proposed solution to the research problem. Hence, experimentation of the scenarios via simulation using IDA-ICE 4.8 software is performed for the computational energy analysis. The model of the shopping mall was created using Revit software and imported to IDA-ICE in IFC format. Four different energy analyses are carried out according to the four scenarios. For each scenario, the HVAC control system corresponding to the characteristics of the scenario is created in the simulation software using macros. Figure 7 shows the MPC algorithm framework. Simulations are carried out daily, with the results for two days explained in detail in the results section.

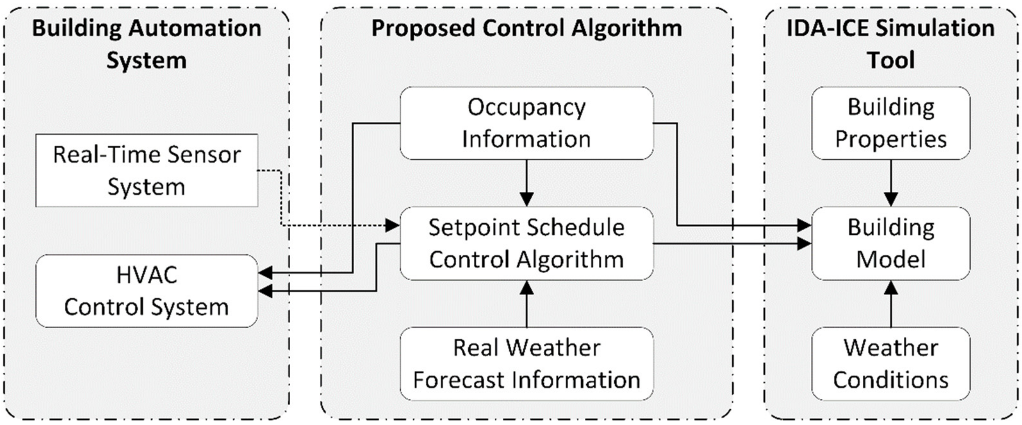

Figure 7. Model predictive control (MPC) algorithm framework.

The weather data of the software are used in the energy analysis. It is seen that the day-ahead predictions give almost the same values as real values. Therefore, the forecasted weather data for the algorithm are not used (to avoid repeating the results and graphics). In scenarios S4 and S5, both the estimated occupancy numbers found as a result of ANN calculation and the real occupancy numbers are used in different simulations to show how the small difference between the real data and ANN prediction affects the energy simulation.

The research artifact, the AI-based occupant-centric HVAC control system, is assessed, and evaluated to conceive how well the developed and demonstrated artifact is considered as a solution to the research problem. At this stage, research can benefit from surveys, feedback, and simulations. If the solution rate, which corresponds to the research problem, or functionality of the solution is not at an acceptable level, the iterative process is performed by turning stage 2 and 3.

6.1. ANN Results

In addition to the initial network settings (attributes, layer design, training algorithm, etc.), ANN parameters (hidden layer size, number of neurons in the hidden layer, batch size, which refers to the number of training examples utilized in one iteration, number of epochs, the number of complete passes through the training dataset, etc.) have a highly significant influence on the network output during the training and prediction phases. While a model with too few neurons has poor predictive performance because it cannot handle a complex model structure, if too many are selected, weak prediction performance follows as overfit too easily results from a minor fluctuation in the data.

Therefore, it is crucial to test the model's output with different design parameters. Different ANN models were trained for this study; as a result of the trials grid search methodology using the number of neurons in each layer and the number of epochs as variables by keeping the number of hidden layers constant at 8. Figure 8 shows the MAPE and R-squared results of the ANN models created using a grid search. Since the computational times are not too long and do not change much between them, they are not considered as parameters. The ANN models with 8 neurons in each hidden layer and with 500 epochs (ANN-1), with 8 neurons in each hidden layer and with 750 epochs (ANN-2), with 16 neurons in each hidden layer and with 250 epochs (ANN-3), and with 16 neurons in each hidden layer and with 500 epochs (ANN-4) give the best results with overall MAPE values of 0.1323, 0.1344, 0.1315, and 0.1335, respectively.

Figure 9 shows the learning curves of the different ANN models. It is clear from the loss curves that training and validation loss values for ANN-1 and ANN-3 (Figures 9a and 10b, respectively) are in the ideal range for model complexity. However, the distance between the training loss line and validation loss line gradually increases after a certain point because of overfitting in the ANN model with 64 neurons in each hidden layer and with 1000 epochs (Figure 9d).

The comparison between actual occupancy numbers and predicted occupancy values as given by ANN-1 and ANN-2 is illustrated in Figure 10. Although the prediction values are naturally far from the real values at some peak points, the prediction trend follows the real numbers in a general fashion. Thus, as the quantity of data increases in the future, more accurate results will be obtained.

Furthermore, to examine the results in more detail, four days (18, 19, 20, and 30 August 2019) were removed from the training data set and used as prediction values. Prediction values for these days were obtained using the ANN-1 features because of the model accuracy and processing time; a comparison with actual occupancy numbers is shown as a list (Table 5) and graphically (Figure 11).

Additionally, 18 August was a Sunday, while 30 August is a national holiday. These days are important in examining the ANN algorithm for weekdays, weekends, and special days. More people are expected to visit the shopping center on weekends and national holidays than on weekdays.

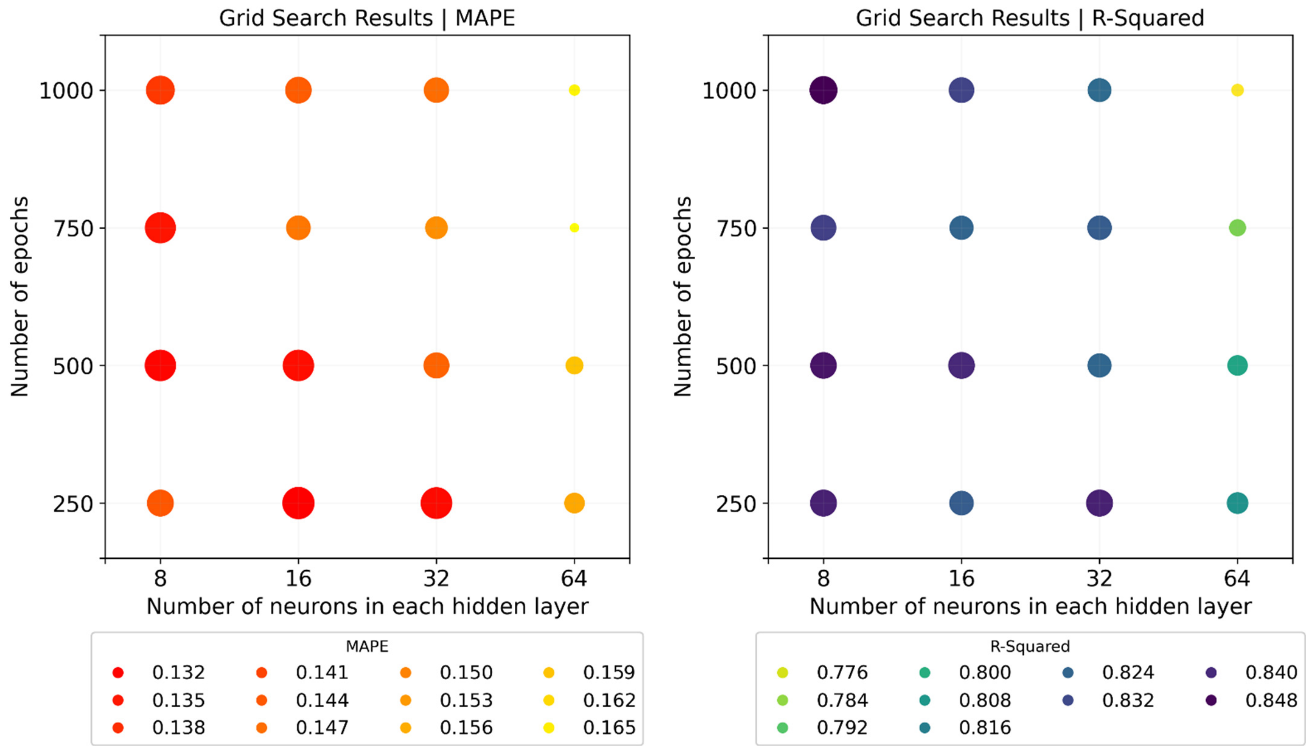

Figure 8. Grid search results of the ANN models according to MAPE and R-squared values.

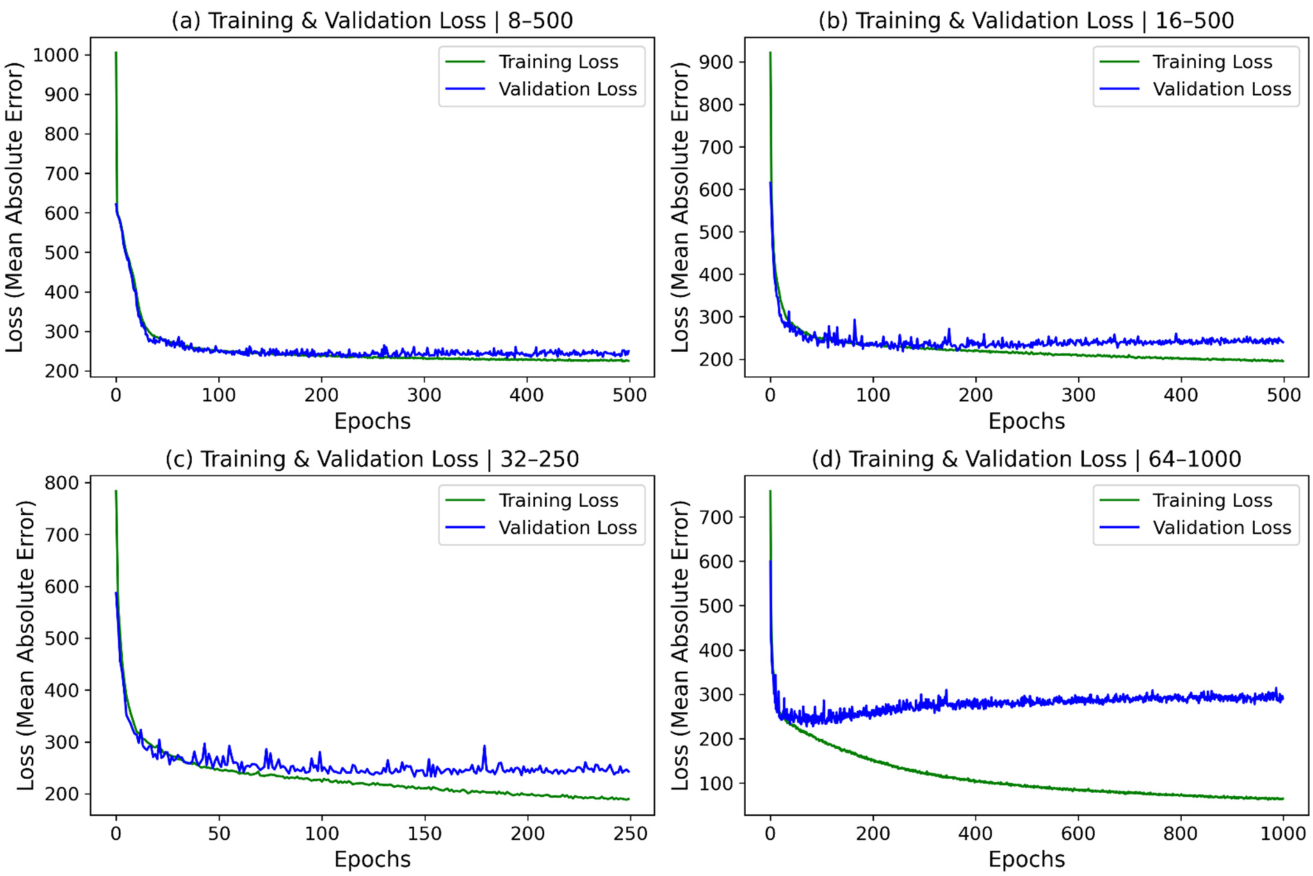

Figure 9. Learning curves of the different ANN models.

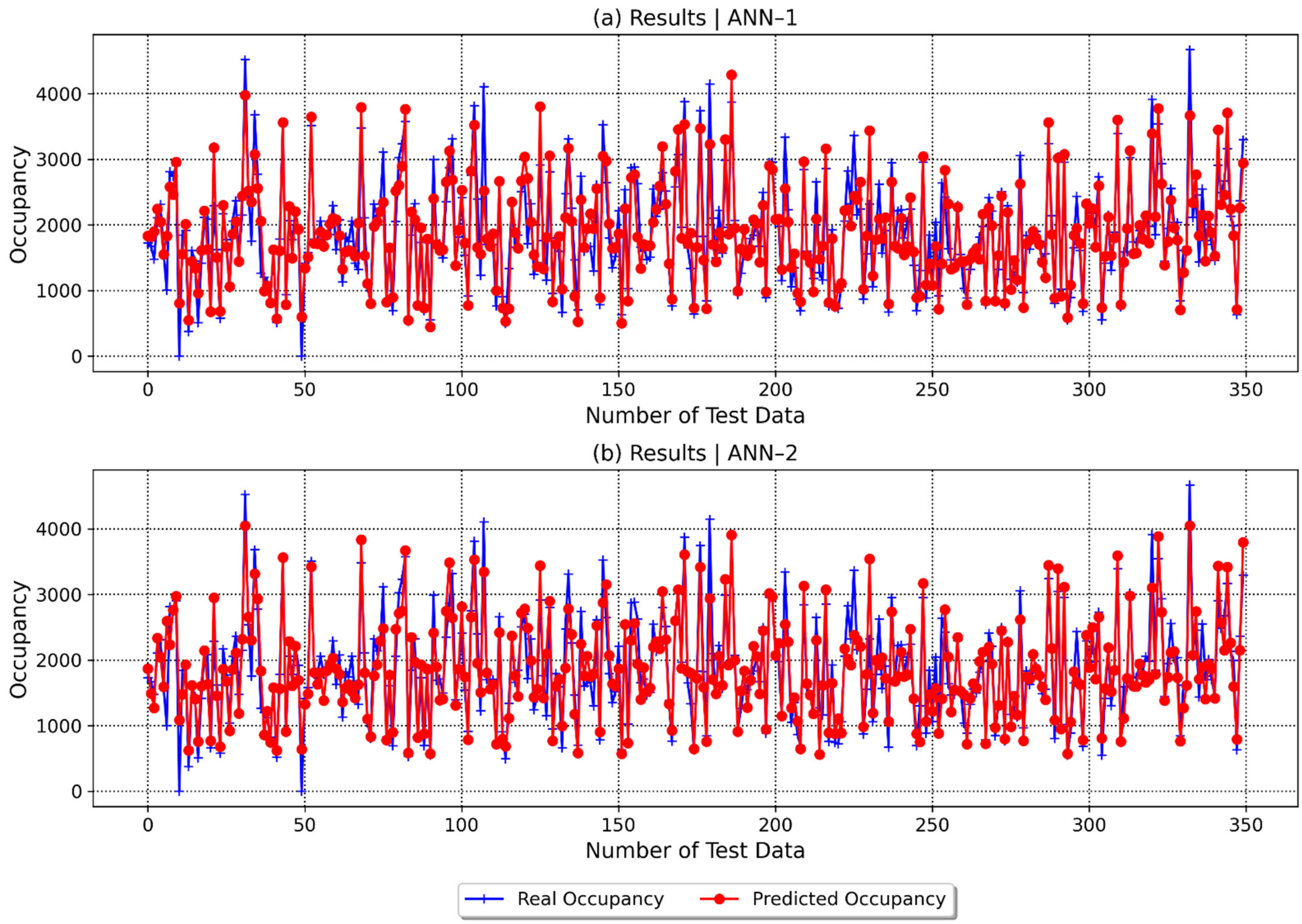

Figure 10. Actual and ANN-predicted occupancy results (ANN-1 and ANN-2).

Table 5. Actual and ANN-predicted occupancy results (hourly).

Time	Sunday, 18 August 2019		Monday, 19 August 2019		Thursday, 29 August 2019		Friday, 30 August 2019	
	Real	Pred.	Real	Pred.	Real	Pred.	Real	Pred.
10:00 a.m.	661	963	463	881	642	697	1269	769
11:00 a.m.	1346	1480	906	1322	1240	1345	1406	1602
12:00 p.m.	1448	1594	1418	2139	2194	2290	1738	1980
01:00 p.m.	2547	2412	1690	1751	1981	1657	2562	2445
02:00 p.m.	2921	3373	1643	1680	1489	1491	2601	3452
03:00 p.m.	3353	3384	1379	1648	1732	1557	2990	2870
04:00 p.m.	3181	3156	1547	1749	1722	1817	2518	2598
05:00 p.m.	2455	2833	1494	1787	1622	1565	2428	2498
06:00 p.m.	2339	2351	1907	2134	2034	1793	2701	2411
07:00 p.m.	2126	1892	1806	1833	2362	1821	2262	1930
08:00 p.m.	1644	1491	1496	1519	2102	1518	1805	1305
09:00 p.m.	777	704	727	635	887	903	818	553

From Table 5 and Figure 11, it is clear that the prediction values show a harmonious performance against time parameters. Moreover, although 30 August was a Friday, this analysis managed to approximate actual values with an accuracy of about 87% as an important measure of the success of predictions.

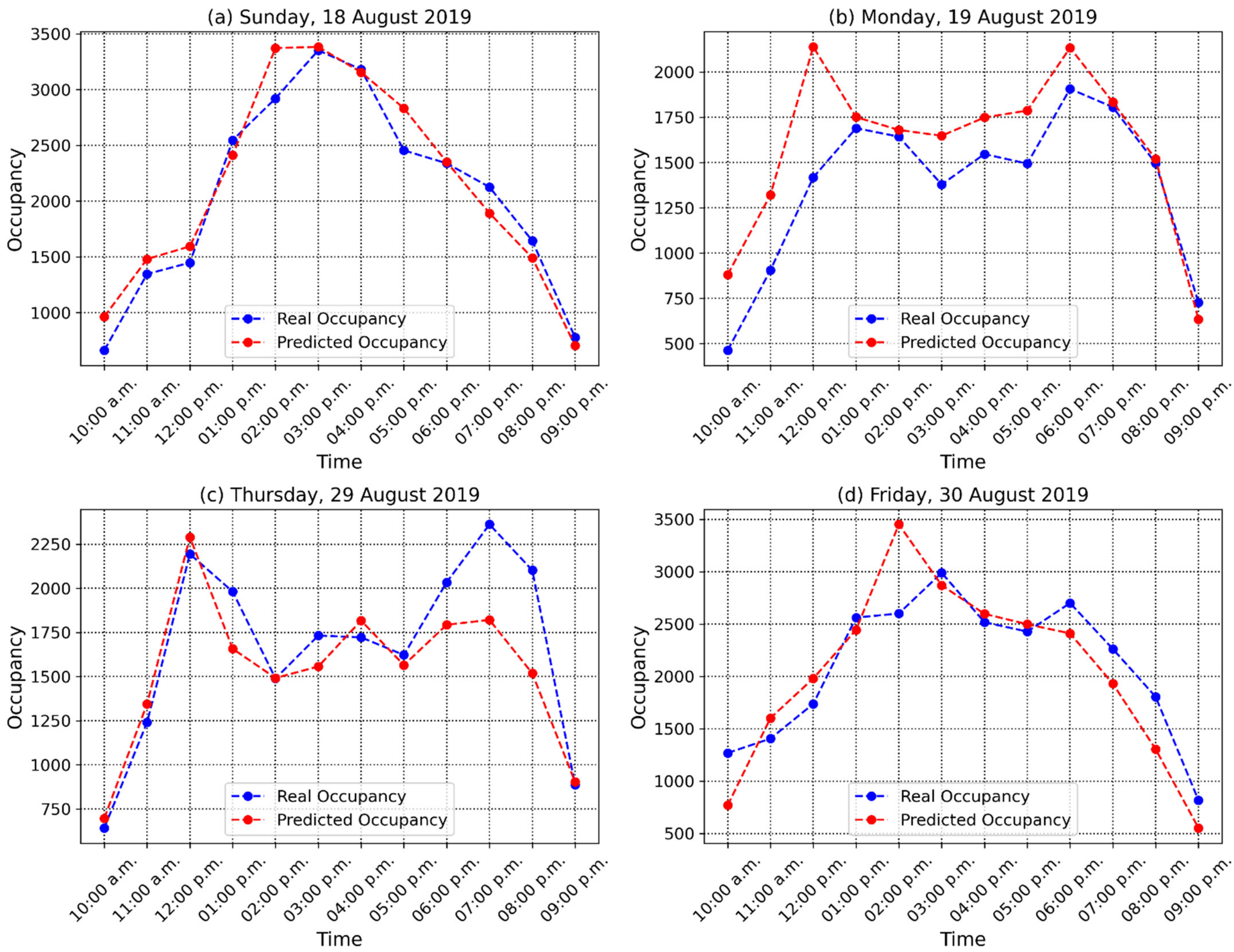

Figure 11. Actual and ANN-predicted occupancy results (hourly).

6.2. Energy Analysis Results

The energy analyses aim to demonstrate the effectiveness of the proposed HVAC control algorithm and compare it with traditional control systems. For this purpose, indoor temperature results and daily energy consumption values for the four scenarios were obtained from the IDA-ICE software. Two days are selected for detailed energy analysis and comparison of indoor temperatures according to energy simulation scenarios, Monday, 29 August 2019, and Saturday, 7 June 2019; these are illustrated in Figures 11 and 12, respectively.

Since the S1 scenario represents the full-powered HVAC at all times, the indoor temperature remains constant with small fluctuations at 24 °C for both 29 August and 7 June (Figures 12a and 13a, respectively), as expected. When the indoor temperature results of the S2 scenario, which represents the sensor-based traditional control approach, are examined for 29 August (Figure 12b), the temperature is found to vary between 23 and 25 °C across wide intervals. This is because basic thermostats allow the temperature to fluctuate a few degrees from the fixed temperature to reduce the frequency with which the cooling device is turned on and off. Consequently, it is seen that the HVAC control mechanism fails to respond to the rapid increase in outdoor temperature and occupancy numbers between 10 and 11 o’clock, and when the maximum occupancy number is reached, the indoor temperature values stay outside the comfort limits. Additionally, although the fluctuations for 7 June (Figure 13b) show a similar pattern, low outdoor temperatures cause the indoor temperatures to return to comfort limit values more quickly.

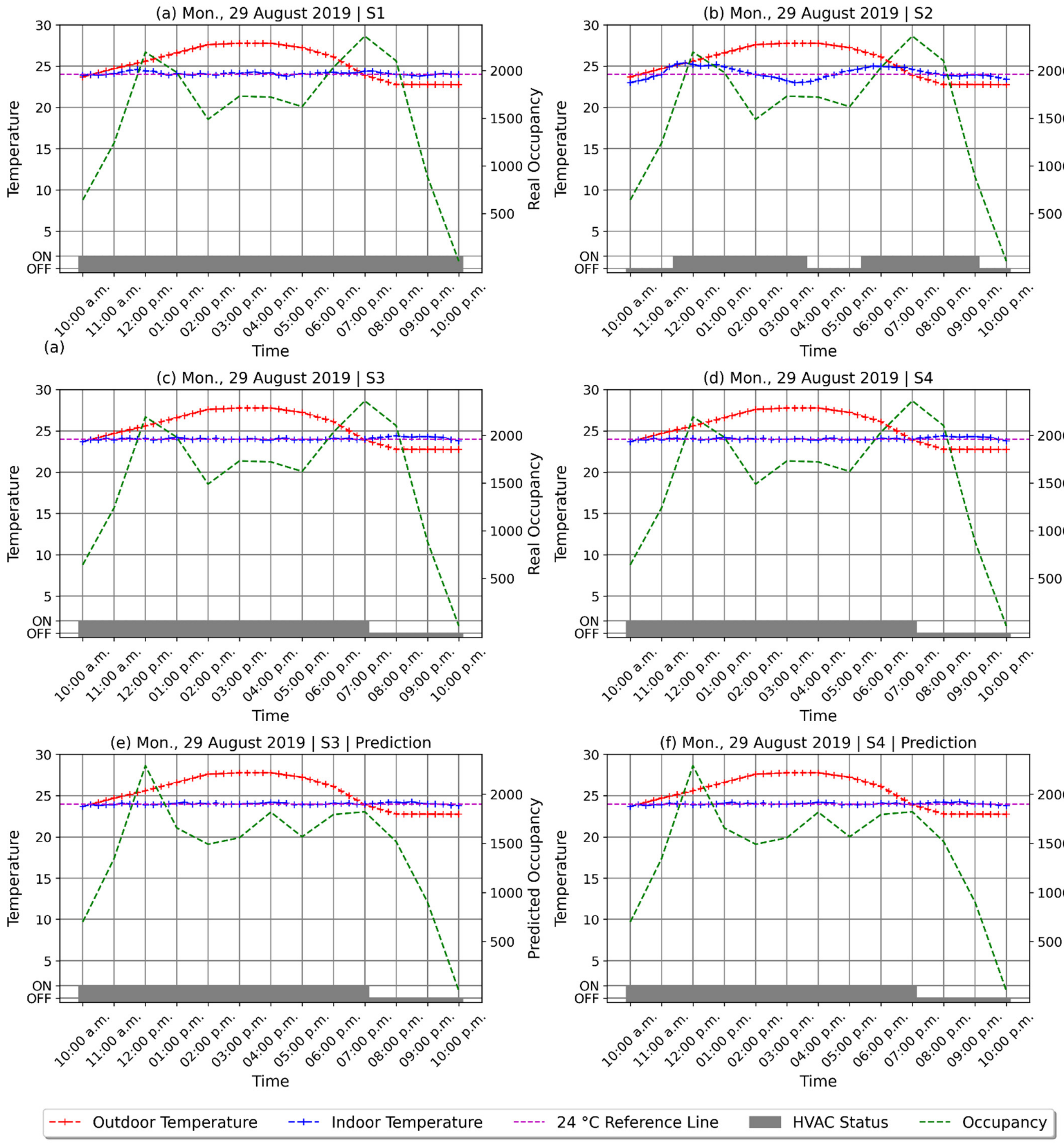

Figure 12. Comparison of indoor temperatures of scenarios for Monday, 29 August 2019.

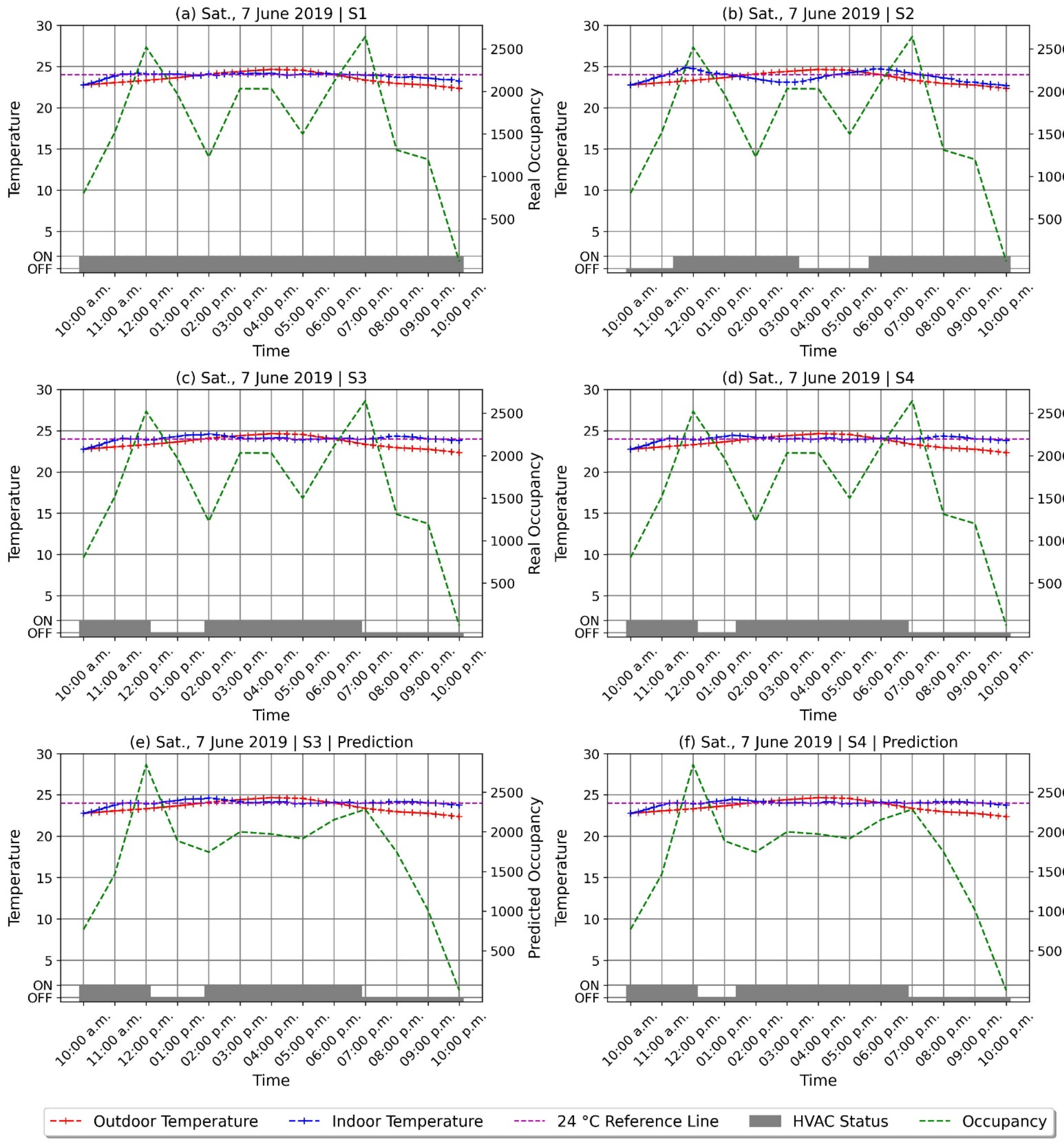

Figure 13. Comparison of indoor temperatures of scenarios for Saturday, 7 June 2019.

The S3 scenario represents the energy simulation according to our new control approach without pre-cooling, which is Algorithm 1, with the HVAC control adjusting according to the occupancy rate. Although there was a decrease in occupancy between 01:00 p.m. and 02:00 p.m. and between 04:00 p.m. and 05:00 p.m. on 29 August, the cooling status remained on as the outdoor temperature was higher than the setpoint (Figure 12c). At 07:00 p.m., as occupancy started to decrease and the air temperature dropped, the cooling went off, and the indoor temperature increased due to the occupancy. As a result of the dramatic decrease in the number of people, this increase ended before exceeding the comfort level. Furthermore, since the HVAC became operational in response to the rise in occupancy, the indoor air temperature remained mostly at the comfort level.

The scenario S4 for 29 August (Figure 12d) produces the same result as does S3 because conditions that would activate the pre-cooling did not arise on this day. Similarly, there is no difference in the application of the algorithm in the simulation with the estimated occupancy values on 29 August (Figure 12e,f) because the increase and decrease trends are captured correctly by ANN. Depending on the difference in occupancy values between real and predicted, small changes are observed in temperature changes and fluctuations. For instance, indoor temperatures do not rise as high for the simulations with predicted values as for the simulation with real values after the cooling is off because the predicted values are smaller than others for those time intervals.

In the S3 scenario for 7 June (Figure 13c), the cooling is switched off between 11:00 a.m. and 01:00 p.m. because the outdoor temperature was below the setpoint with a decrease in the number of people between these hours. An indoor temperature increase is observed to occur naturally in this period, but the low outdoor temperature prevents this increase from reaching significant levels.

Likewise, with the increase in the number of people, the cooling becomes active again from 01:00 p.m. Similar to the scenario for 29 August, cooling is deactivated by the algorithm in the hours close to the shopping mall closing time. While the actual occupancy numbers increase, estimated occupancy values decrease between 03:00 p.m. and 04:00 p.m. However, the S3 scenario simulation with estimated occupancy (Figure 13e) follows the same cooling status as the simulation with actual occupancy (Figure 13c) since air temperature is above the setpoint between these hours. This situation is critical to minimize the failures due to inaccurate estimation by ANN.

The main difference between S3 (Figure 11c,e) and S4 (Figure 11d,f) is that cooling status is active at 12:30 p.m. for S4. The reason for this is that the pre-cooling algorithm is activated under suitable conditions at S4. While there is a decrease in both real and predicted occupancy numbers between 12:00 p.m. and 01:00 p.m., there is an increase of more than 250 people between 01:00 p.m. and 02:00 p.m.. The algorithm starts the cooling 30 min before this increase in occupancy to prevent comfort disturbances caused by the rapid increase. As a result of pre-cooling, the indoor temperature falls to the setpoint level at the beginning of the occupancy increase, contrary to the S3 scenarios. Similar to the simulations performed for 29 August, the actual and predicted occupancy numbers lead to slight differences in the simulations.

When the daily energy consumption results are examined for 29 August (Figure 14), scenario S1 has the greatest consumption with 4090.61 kWh, as expected. Scenario 2 provides an energy saving of approximately 30% compared to S1; with a consumption value of 2279.26 kWh; however, scenarios S3 and S4 consume 22% less energy than S2. When the daily energy consumption results are analyzed for 7 June (Figure 14), the energy consumption trends generally show a similar pattern to that of 29 August. The S2 scenario uses almost 30% less energy than the S1, while S3 and S4 provide an energy saving of approximately 10% over S2. The savings presented by the HVAC control scenario are lower in June than August because delays resulting from the sensor-based approaches at low air temperatures affect the energy efficiency less.

There are also some minor naturally based differences between the simulations performed according to actual and estimated occupancy numbers because the simulation tool adjusts the HVAC power depending on the occupancy. Regarding the ANN values, it is natural to obtain a lower energy consumption because of simulations with predicted values for 29 August, since the average of the predicted occupancy number, 1485.27, is lower than the real occupancy average, 1613.57. Similarly, energy consumption values of simulations with predicted occupancy are greater than simulations with real occupancy because the average of the predicted occupancy, 1755.32, is greater than the real occupancy average, 1679.64.

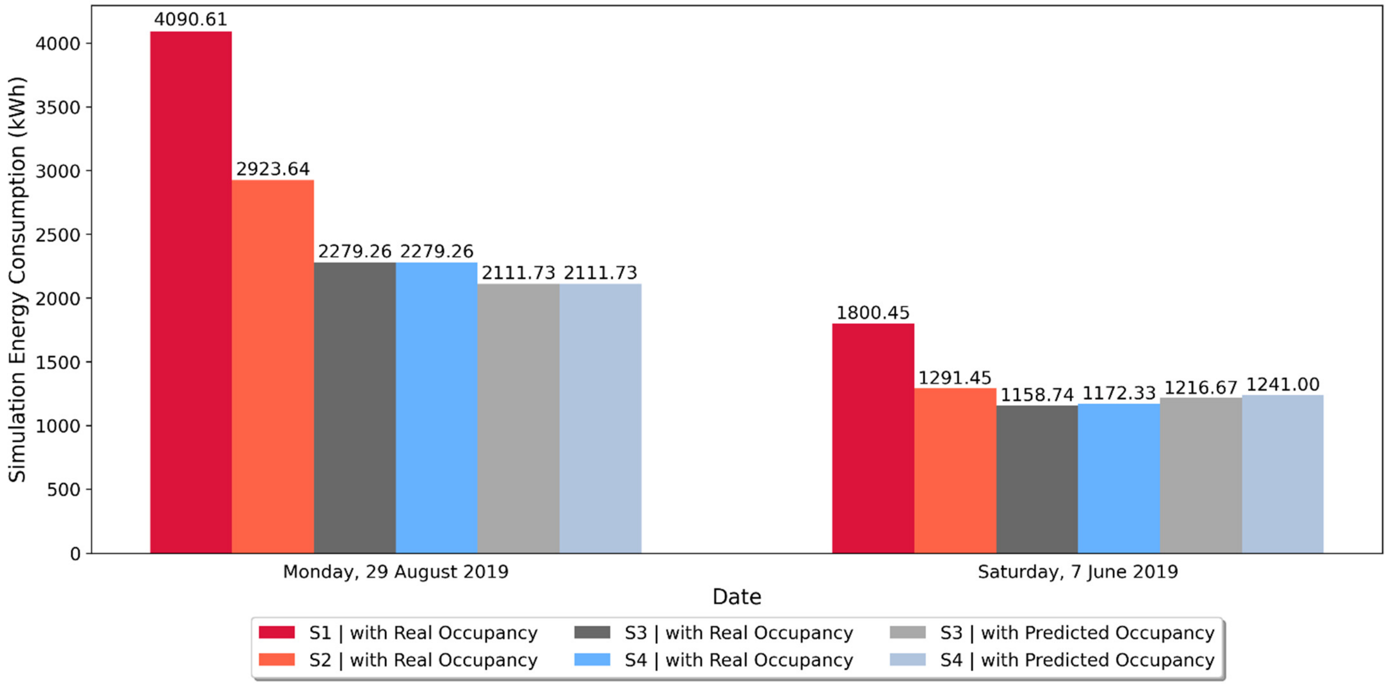

Figure 14. Comparison of energy consumption values of scenarios.

7. Conclusions

This paper presented an analysis of different HVAC control approaches according to their level of development using energy simulations in which ANN features as the focus of the study due to the need for the sensor-free control mechanism. The ANN analysis was performed using real occupancy and weather information collected for each day and hour, with the energy simulations performed for four scenarios using IDA-ICE software.

The ANN results showed that the prediction of occupancy numbers according to time intervals could be calculated with almost 87% accuracy. This accuracy rate was achieved with a limited dataset, and estimation precision should be expected to increase with stronger datasets developed over time. Further, the ANN prediction responded to different parameters, such as special days. This allows the proposed HVAC control algorithm to be used year-round, without exceptions.

According to Wong and Li (2010), "total energy use" is the top selection criterion, followed by "system reliability and stability", "operating and maintenance cost", and "control of indoor humidity and temperature". Since our control strategy is based on data, not real-time detection tools, while it reduces energy consumption, it also very positively affects reliability and operating cost. Different scenarios varying according to level of development were used to measure the effectiveness of our new HVAC control mechanism. A detailed examination of energy simulation results has revealed that the scenarios representing our AI-based occupant-centric control approach (S3 and S4) save a minimum of 10% energy consumption as compared to the traditional sensor-based approach (S2) and a minimum of 35% on those with full-powered HVAC at all times (S1). In the months when the outside temperature is high, these rates reach approximately 20% and 40%, respectively, because traditional approaches allow the indoor temperature to fluctuate excessively, causing an increase in the power consumed for cooling.

Another significant result is that there were only very slight differences in indoor temperature and energy consumption results between simulations performed with predicted and real occupancy numbers. This shows that using estimated values in the HVAC control algorithm does not significantly change the energy consumption or comfort level. Manifestly, the transformation of control approaches proposed has great potential for energy savings.

A few limitations should be noted. First, the proposed control algorithms (Algorithms 1 and 2) were not designed with any complexity; the study design was selected with relatively simple algorithms to show the savings to be made in a simple way. In cases where occupancy tends to decrease slightly for long periods and the outdoor temperature is low, for example, the cooling may remain off for a long time, a situation that was not represented here. In such cases, the occupancy not being very low could cause the interior temperature to rise (i.e., even though the air temperature is low). To avoid such a situation, the algorithm can easily be made more complex with the addition of further parameters, such as occupancy limit and cooling-off time limit.

Second, even though day-ahead weather forecasts mostly make perfect predictions for the following day, some days might fall outside the acceptable margin of error. Such a situation could cause a decrease in the comfort level or inefficiency in the energy consumption, albeit only for very limited periods (or very few days). However, and similarly not considered in this study, existing sensors might be used as an aid tool to measure the real situation and included in the algorithm (as stated) to prevent both these shortcomings.

As a major condition of the experimental design and thus a third limitation, only the cooling function of the HVAC was investigated. Regarding further research, therefore, a control algorithm can also be developed for heating. Then, the method for HVAC control introduced in this study may be applied to the shopping mall by real experimental setup and the results observed in reality. Furthermore (as indicated), more complex control algorithms can be developed according to the specific occupancy pattern of the building studied.

Finally, this study differs from others in considering prediction occupancy numbers with ANN as the main focus in order that significant energy savings can be achieved with a simple control algorithm. For this reason, the study can be a pioneer in terms of a new HVAC system with low installation cost and high energy efficiency. This research can play a major role in guiding the AI-based occupant-centric control tool for sustainable development, which can be used as a standalone control mechanism as it improves.

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References

1. IEA (International Energy Agency). Energy Efficiency: Buildings. 2019. Available online: https://www.iea.org/topics/energyefficiency/buildings/# (accessed on 11 October 2022).
2. Yang, L.; Yan, H.; Lam, J.C. Thermal Comfort and Building Energy Consumption Implications—A Review. *Appl. Energy* **2014**, *115*, 164–173. [CrossRef]
3. Alcalá, R.; Benítez, J.M.; Casillas, J.; Cordón, O.; Pérez, R. Fuzzy Control of HVAC Systems Optimized by Genetic Algorithms. *Appl. Intell.* **2003**, *18*, 155–177. [CrossRef]
4. Mirinejad, H.; Sadati, S.H.; Ghasemian, M.; Torab, H. Control Techniques in Heating, Ventilating and Air Conditioning Systems. *J. Comput. Sci.* **2008**, *4*, 777–783. [CrossRef]
5. Gholamzadehmir, M.; del Pero, C.; Buffa, S.; Fedrizzi, R.; Aste, N. Adaptive-Predictive Control Strategy for HVAC Systems in Smart Buildings—A Review. *Sustain. Cities Soc.* **2020**, *63*, 102480. [CrossRef]
6. Mizumoto, M. Realization of PID Controls by Fuzzy Control Methods. *Fuzzy Sets Syst.* **1995**, *70*, 171–182. [CrossRef]
7. Soyguder, S.; Karakose, M.; Alli, H. Design and Simulation of Self-Tuning PID-Type Fuzzy Adaptive Control for an Expert HVAC System. *Expert Syst. Appl.* **2009**, *36 Pt 1*, 4566–4573. [CrossRef]

8. Chiou, Y.C.; Lan, L.W. Genetic Fuzzy Logic Controller: An Iterative Evolution Algorithm with New Encoding Method. *Fuzzy Sets Syst.* **2005**, *152*, 617–635. [CrossRef]
9. Mirinejad, H.; Welch, K.C.; Spicer, L. A Review of Intelligent Control Techniques in HVAC Systems. In Proceedings of the 2012 IEEE Energytech, Cleveland, OH, USA, 29–31 May 2012. [CrossRef]
10. Egilegor, B.; Uribe, J.P.; Arregi, G.; Pradilla, E.; Susperregi, L. A Fuzzy Control Adapted by a Neural Network to Maintain a Dwelling within Thermal Comfort. *Proc. Build. Simul.* **1997**, *97*, 87–94.
11. Kruse, R.; Klawonn, F.; Nauck, D. Learning from Fuzzy Rules. *Inform. Forsch. Und Entwickl.* **1997**, *12*, 2–6. [CrossRef]
12. Wu, Y.; Zhang, B.; Lu, J.; Du, K.-L. Fuzzy Logic and Neuro-Fuzzy Systems: A Systematic Introduction. *Int. J. Artif. Intell. Expert Syst.* **2011**, *2*, 47–80.
13. Malki, H.A.; Li, H.; Chen, G. New Design and Stability Analysis of Fuzzy Proportional-Derivative Control Systems. *IEEE Trans. Fuzzy Syst.* **1994**, *2*, 245–254. [CrossRef]
14. Ying, H. Practical Design of Non-linear Fuzzy Controllers with Stability Analysis for Regulating Processes with Unknown Mathematical Models. *Automatica* **1994**, *30*, 1185–1195. [CrossRef]
15. Wu, Z.Q.; Mizumoto, M. PID Type Fuzzy Controller and Parameters Adaptive Method. *Fuzzy Sets Syst.* **1996**, *78*, 23–35. [CrossRef]
16. Patel, A.V.; Mohan, B.M. Analytical Structures and Analysis of the Simplest Fuzzy PI Controllers. *Automatica* **2002**, *38*, 981–993. [CrossRef]
17. Li, H.X.; Zhang, L.; Cai, K.Y.; Chen, G. An Improved Robust Fuzzy-PID Controller with Optimal Fuzzy Reasoning. *IEEE Trans. Syst. Man Cybern. Part B: Cybern.* **2005**, *35*, 1283–1294. [CrossRef]
18. Ole Fanger, P. Thermal Comfort: Analysis and Applications in Environmental Engineering. *Appl. Ergon.* **1972**, *3*, 181. [CrossRef]
19. Liang, J.; Du, R. Design of Intelligent Comfort Control System with Human Learning and Minimum Power Control Strategies. *Energy Convers. Manag.* **2008**, *49*, 517–528. [CrossRef]
20. Gacto, M.J.; Alcalá, R.; Herrera, F. Evolutionary Multi-Objective Algorithm to Effectively Improve the Performance of the Classic Tuning of Fuzzy Logic Controllers for a Heating, Ventilating and Air Conditioning System. In Proceedings of the IEEE SSCI 2011: Symposium Series on Computational Intelligence—GEFS 2011: 2011 IEEE 5th International Workshop on Genetic and Evolutionary Fuzzy Systems, Paris, France, 11–15 April 2011; pp. 73–80. [CrossRef]
21. Nowak, M.; Urbaniak, A. Utilization of Intelligent Control Algorithms for Thermal Comfort Optimization and Energy Saving. In Proceedings of the 2011 12th International Carpathian Control Conference, ICCC, Velke Karlovice, Czech Republic, 25–28 May 2011; pp. 270–274. [CrossRef]
22. Wei, T.; Wang, Y.; Zhu, Q. Deep Reinforcement Learning for Building HVAC Control. In Proceedings of the 54th Annual Design Automation Conference, Austin, TX, USA, 18–22 June 2017; Volume 12828. [CrossRef]
23. Du, Y.; Zandi, H.; Kotevska, O.; Kurte, K.; Munk, J.; Amasyali, K.; Mckee, E.; Li, F. Intelligent Multi-Zone Residential HVAC Control Strategy Based on Deep Reinforcement Learning. *Appl. Energy* **2021**, *281*, 116117. [CrossRef]
24. Pasgianos, G.D.; Arvanitis, K.G.; Polycarpou, P.; Sigrimis, N. A Non-linear Feedback Technique for Greenhouse Environmental Control. *Comput. Electron. Agric.* **2003**, *40*, 153–177. [CrossRef]
25. Moradi, H.; Saffar-Avval, M.; Bakhtiari-Nejad, F. Non-linear Multivariable Control and Performance Analysis of an Air-Handling Unit. *Energy Build.* **2011**, *43*, 805–813. [CrossRef]
26. Al-Assadi, S.A.K.; Patel, R.V.; Zaheer-Uddin, M.; Verma, M.S.; Breitinger, J. Robust Decentralized Control of HVAC Systems Using H ∞-Performance Measures. *J. Frankl. Inst.* **2004**, *341*, 543–567. [CrossRef]
27. Anderson, M.; Buehner, M.; Young, P.; Hittle, D.; Anderson, C.; Tu, J.; Hodgson, D. MIMO Robust Control for HVAC Systems. *IEEE Trans. Control Syst. Technol.* **2008**, *16*, 475–483. [CrossRef]
28. Dong, B. Non-Linear Optimal Controller Design for Building HVAC Systems. In Proceedings of the IEEE International Conference on Control Applications, Yokohama, Japan, 8–10 September 2010; pp. 210–215. [CrossRef]
29. Mossolly, M.; Ghali, K.; Ghaddar, N. Optimal Control Strategy for a Multi-Zone Air Conditioning System Using a Genetic Algorithm. *Energy* **2009**, *34*, 58–66. [CrossRef]
30. Yan, Y.; Zhou, J.; Lin, Y.; Yang, W.; Wang, P.; Zhang, G. Adaptive Optimal Control Model for Building Cooling and Heating Sources. *Energy Build.* **2008**, *40*, 1394–1401. [CrossRef]
31. Serale, G.; Fiorentini, M.; Capozzoli, A.; Bernardini, D.; Bemporad, A. Model Predictive Control (MPC) for Enhancing Building and HVAC System Energy Efficiency: Problem Formulation, Applications and Opportunities. *Energies* **2018**, *11*, 631. [CrossRef]
32. Kusiak, A.; Tang, F.; Xu, G. Multi-Objective Optimization of HVAC System with an Evolutionary Computation Algorithm. *Energy* **2011**, *36*, 2440–2449. [CrossRef]
33. Kusiak, A.; Xu, G.; Zhang, Z. Minimization of Energy Consumption in HVAC Systems with Data-Driven Models and an Interior-Point Method. *Energy Convers. Manag.* **2014**, *85*, 146–153. [CrossRef]
34. Wei, X.; Kusiak, A.; Li, M.; Tang, F.; Zeng, Y. Multi-Objective Optimization of the HVAC (Heating, Ventilation, and Air Conditioning) System Performance. *Energy* **2015**, *83*, 294–306. [CrossRef]
35. Biyik, E.; Brooks, J.D.; Sehgal, H.; Shah, J.; Gency, S. Cloud-Based Model Predictive Building Thermostatic Controls of Commercial Buildings: Algorithm and Implementation. In Proceedings of the American Control Conference, Chicago, IL, USA, 1–3 July 2015; pp. 1683–1688. [CrossRef]
36. Kelman, A.; Ma, Y.; Borrelli, F. Analysis of Local Optima in Predictive Control for Energy Efficient Buildings. *J. Build. Perform. Simul.* **2013**, *6*, 236–255. [CrossRef]

37. Huang, H.; Chen, L.; Hu, E. A New Model Predictive Control Scheme for Energy and Cost Savings in Commercial Buildings: An Airport Terminal Building Case Study. *Build. Environ.* **2015**, *89*, 203–216. [CrossRef]
38. Garnier, A.; Eynard, J.; Caussanel, M.; Grieu, S. Predictive Control of Multizone Heating, Ventilation and Air-Conditioning Systems in Non-Residential Buildings. *Appl. Soft Comput. J.* **2015**, *37*, 847–862. [CrossRef]
39. Barzin, R.; Chen, J.J.J.; Young, B.R.; Farid, M.M. Application of Weather Forecast in Conjunction with Price-Based Method for PCM Solar Passive Buildings—An Experimental Study. *Appl. Energy* **2016**, *163*, 9–18. [CrossRef]
40. Alibabaei, N.; Fung, A.S.; Raahemifar, K. Development of Matlab-TRNSYS Co-Simulator for Applying Predictive Strategy Planning Models on Residential House HVAC System. *Energy Build.* **2016**, *128*, 81–98. [CrossRef]
41. Afram, A.; Janabi-Sharifi, F. Theory and Applications of HVAC Control Systems—A Review of Model Predictive Control (MPC). *Build. Environ.* **2014**, *72*, 343–355. [CrossRef]
42. Afram, A.; Janabi-Sharifi, F.; Fung, A.S.; Raahemifar, K. Artificial Neural Network (ANN) Based Model Predictive Control (MPC) and Optimization of HVAC Systems: A State-of-the-Art Review and Case Study of a Residential HVAC System. *Energy Build.* **2017**, *141*, 96–113. [CrossRef]
43. Trčka, M.; Hensen, J.L.M. Overview of HVAC System Simulation. *Autom. Constr.* **2010**, *19*, 93–99. [CrossRef]
44. Afroz, Z.; Shafiullah, G.M.; Urmee, T.; Higgins, G. Modeling Techniques Used in Building HVAC Control Systems: A Review. *Renew. Sustain. Energy Rev.* **2018**, *83*, 64–84. [CrossRef]
45. Huang, H.; Chen, L.; Hu, E. A Neural Network-Based Multi-Zone Modelling Approach for Predictive Control System Design in Commercial Buildings. *Energy Build.* **2015**, *97*, 86–97. [CrossRef]
46. Javed, A.; Larijani, H.; Ahmadinia, A.; Emmanuel, R.; Mannion, M.; Gibson, D. Design and Implementation of a Cloud Enabled Random Neural Network-Based Decentralized Smart Controller with Intelligent Sensor Nodes for HVAC. *IEEE Internet Things J.* **2017**, *4*, 393–403. [CrossRef]
47. Sala-Cardoso, E.; Delgado-Prieto, M.; Kampouropoulos, K.; Romeral, L. Activity-Aware HVAC Power Demand Forecasting. *Energy Build.* **2018**, *170*, 15–24. [CrossRef]
48. Yang, S.; Wan, M.P.; Chen, W.; Ng, B.F.; Zhai, D. An Adaptive Robust Model Predictive Control for Indoor Climate Optimization and Uncertainties Handling in Buildings. *Build. Environ.* **2019**, *163*, 106326. [CrossRef]
49. Zhou, B.; Chikkala, J.; Schmitt, R. A Load-Adaptive and Predictive Control of Energy-Efficient Building Automation in Production Environment. *Procedia CIRP* **2019**, *79*, 245–250. [CrossRef]
50. Erickson, V.L.; Lin, Y.; Kamthe, A.; Brahme, R.; Surana, A.; Cerpa, A.E.; Sohn, M.D.; Narayanan, S. Energy Efficient Building Environment Control Strategies Using Real-Time Occupancy Measurements. In Proceedings of the BUILDSYS 2009—1st ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, Berkeley CA, USA, 3 November 2009; pp. 19–24. [CrossRef]
51. Erickson, V.L.; Cerpa, A.E. Occupancy Based Demand Response HVAC Control Strategy. In Proceedings of the BuildSys'10—2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, Zurich, Switzerland, 2 November 2010; pp. 7–12. [CrossRef]
52. Oldewurtel, F.; Sturzenegger, D.; Morari, M. Importance of Occupancy Information for Building Climate Control. *Appl. Energy* **2013**, *101*, 521–532. [CrossRef]
53. Li, N.; Calis, G.; Becerik-Gerber, B. Measuring and Monitoring Occupancy with an RFID Based System for Demand-Driven HVAC Operations. *Autom. Constr.* **2012**, *24*, 89–99. [CrossRef]
54. Yang, Z.; Ghahramani, A.; Becerik-Gerber, B. Building Occupancy Diversity and HVAC (Heating, Ventilation, and Air Conditioning) System Energy Efficiency. *Energy* **2016**, *109*, 641–649. [CrossRef]
55. Capozzoli, A.; Piscitelli, M.S.; Gorrino, A.; Ballarini, I.; Corrado, V. Data Analytics for Occupancy Pattern Learning to Reduce the Energy Consumption of HVAC Systems in Office Buildings. *Sustain. Cities Soc.* **2017**, *35*, 191–208. [CrossRef]
56. Aftab, M.; Chen, C.; Chau, C.K.; Rahwan, T. Automatic HVAC Control with Real-Time Occupancy Recognition and Simulation-Guided Model Predictive Control in Low-Cost Embedded System. *Energy Build.* **2017**, *154*, 141–156. [CrossRef]
57. Shi, J.; Yu, N.; Yao, W. Energy Efficient Building HVAC Control Algorithm with Real-Time Occupancy Prediction. *Energy Procedia* **2017**, *111*, 267–276. [CrossRef]
58. Peng, Y.; Rysanek, A.; Nagy, Z.; Schlüter, A. Using Machine Learning Techniques for Occupancy-Prediction-Based Cooling Control in Office Buildings. *Appl. Energy* **2018**, *211*, 1343–1358. [CrossRef]
59. Nikdel, L.; Janoyan, K.; Bird, S.D.; Powers, S.E. Multiple Perspectives of the Value of Occupancy-Based HVAC Control Systems. *Build. Environ.* **2018**, *129*, 15–25. [CrossRef]
60. Ahmadi-Karvigh, S.; Becerik-Gerber, B.; Soibelman, L. Intelligent Adaptive Automation: A Framework for an Activity-Driven and User-Centered Building Automation. *Energy Build.* **2019**, *188–189*, 184–199. [CrossRef]
61. Pang, Z.; Chen, Y.; Zhang, J.; O'Neill, Z.; Cheng, H.; Dong, B. Nationwide HVAC Energy-Saving Potential Quantification for Office Buildings with Occupant-Centric Controls in Various Climates. *Appl. Energy* **2020**, *279*, 115727. [CrossRef]
62. Azuatalam, D.; Lee, W.-L.; de Nijs, F.; Liebman, A. Reinforcement Learning for Whole-Building HVAC Control and Demand Response. *Energy AI* **2020**, *2*, 100020. [CrossRef]
63. Deng, Z.; Chen, Q. Development and Validation of a Smart HVAC Control System for Multi-Occupant Offices by Using Occupants' Physiological Signals from Wristband. *Energy Build.* **2020**, *214*, 109872. [CrossRef]

64. Jung, W.; Jazizadeh, F. Human-in-the-Loop HVAC Operations: A Quantitative Review on Occupancy, Comfort, and Energy-Efficiency Dimensions. *Appl. Energy* **2019**, *239*, 1471–1508. [CrossRef]
65. Jazaeri, J.; Gordon, R.L.; Alpcan, T. Influence of Building Envelopes, Climates, and Occupancy Patterns on Residential HVAC Demand. *J. Build. Eng.* **2019**, *22*, 33–47. [CrossRef]
66. Ryan, E.M.; Sanquist, T.F. Validation of Building Energy Modeling Tools under Idealized and Realistic Conditions. *Energy Build.* **2012**, *47*, 375–382. [CrossRef]
67. Crawley, D.B.; Hand, J.W.; Kummert, M.; Griffith, B.T. Contrasting the Capabilities of Building Energy Performance Simulation Programs. *Build. Environ.* **2008**, *43*, 661–673. [CrossRef]
68. Bring, A.; Sahlin, P.; Vuolle, M. Models for Building Indoor Climate and Energy Simulation, A Report of Task 22 Building Energy Analysis Tools. Report of IEA SHC Task. 1999. Available online: https://www.equa.se/dncenter/T22Brep.pdf (accessed on 10 October 2022).
69. Achermann, M.; Zweifel, G. RADTEST—Radiant Heating and Cooling Test Cases. 2003. Available online: http://www.equaonline.com/iceuser/validation/old_stuff/RADTEST_final.pdf (accessed on 10 October 2022).
70. ISO (International Organization for Standardization). ISO 15099:2003. Thermal Performance of Windows, Doors and Shading Devices—Detailed Calculations. 2003. Available online: https://www.iso.org/standard/26425.html (accessed on 10 October 2022).
71. Karlsson, F.; Rohdin, P.; Persson, M.L. Measured and Predicted Energy Demand of a Low Energy Building: Important Aspects When Using Building Energy Simulation. *Build. Serv. Eng. Res. Technol.* **2007**, *28*, 223–235. [CrossRef]
72. Loutzenhiser, P.G.; Manz, H.; Moosberger, S.; Maxwell, G.M. An Empirical Validation of Window Solar Gain Models and the Associated Interactions. *Int. J. Therm. Sci.* **2009**, *48*, 85–95. [CrossRef]
73. Hilliaho, K.; Lahdensivu, J.; Vinha, J. Glazed Space Thermal Simulation with IDA-ICE 4.61 Software—Suitability Analysis with Case Study. *Energy Build.* **2015**, *89*, 132–141. [CrossRef]
74. Salvalai, G. Implementation and Validation of Simplified Heat Pump Model in IDA-ICE Energy Simulation Environment. *Energy Build.* **2012**, *49*, 132–141. [CrossRef]
75. Mazzeo, D.; Matera, N.; Cornaro, C.; Oliveti, G.; Romagnoni, P.; de Santoli, L. EnergyPlus, IDA ICE and TRNSYS Predictive Simulation Accuracy for Building Thermal Behaviour Evaluation by Using an Experimental Campaign in Solar Test Boxes with and without a PCM Module. *Energy Build.* **2020**, *212*, 109812. [CrossRef]
76. Milić, V.; Ekelöw, K.; Moshfegh, B. On the Performance of LCC Optimization Software OPERA-MILP by Comparison with Building Energy Simulation Software IDA ICE. In *Build. Environ.*; 2018; Volume 128, pp. 305–319. [CrossRef]
77. *Design Science Research in Information Systems*; Vaishnavi, V.; Kuechler, W.; Petter, S. (Eds.) Association for Information Systems: Atlanta, GA, USA, 2019.
78. Wieringa, R.J. *Design Science Methodology: For Information Systems and Software Engineering*; Springer: Berlin/Heidelberg, Germany, 2014. [CrossRef]
79. Markus, M.L.; Majchrzak, A.; Gasser, L. A design theory for systems that support emergent knowledge processes. 2002, MIS Quarterly 26, 179–212. *MIS Q.* **2002**, *26*, 179–212.
80. Peffers, K.; Tuunanen, T.; Gengler, C.; Rossi, M.; Hui, W.; Wirtanen, V.; Bragge, J. The design science research process: A model for producing and presenting information systems research. In Proceedings of the First International Conference on Design Science Research in Information Systems and Technology DESRIST, Claremont, CA, USA, 24–25 February 2006.
81. The Association of Real Estate and Real Estate Investment Companies of Turkey (GYODER). 2019. Available online: https://www.gyoder.org.tr/yayinlar/sektorel-yayinlar (accessed on 1 May 2021).
82. STATISTA 2021 (Number of Shopping Centers in Europe 2017, by Country). Available online: https://www.statista.com/statistics/912126/shopping-center-numbers-by-country-europe/ (accessed on 10 October 2022).
83. Wijayasekara, D.; Manic, M.; Sabharwall, P.; Utgikar, V. Optimal Artificial Neural Network Architecture Selection for Performance Prediction of Compact Heat Exchanger with the EBaLM-OTR Technique. *Nucl. Eng. Des.* **2011**, *241*, 2549–2557. [CrossRef]
84. Hagan, M.T.; Demuth, H.B.; Beale, M.H.; de Jesus, O. Neural Network Design. In *Neural Networks in a Softcomputing Framework*, 2nd ed.; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2014.
85. Cartwright, H. (Ed.) *Artificial Neural Networks*; Springer: New York, NY, USA, 2021.