Journal of Engineering and Technology for Industrial Applications

ISSN ONLINE: 2447-0228

ITEGAM-JETIA

Manaus, v.12 n.58, p. 356-366. March/April, 2026.
DOI: https://doi.org/10.5935/jetia. v12i58.3068

RESEARCH ARTICLE OPEN ACCESS

OPTIMIZATION OF ENERGY CONSUMPTION BY HVAC SYSTEM IN BUILDINGS USING DEEP LEARNING BASED CONTROL STRATEGIES

K. Rajalakshmi*[1], R. Thirumalai Selvi [2]

[1]Research Scholar, PG& Research, Department of Computer Science, Government Arts College (Autonomous)Nandanam, Chennai, India.
[2]Associate Professor, PG & Research Department of Computer Science, Government Arts College (Autonomous), Nandanam, Chennai, India.

[1]https://orcid.org/0009-0002-2354-4521, [2]https://orcid.org/0009-0001-7864-1196

Email: *rajalakshmimanimaran2005@gmail.com, sarasselvi@gmail.com

ARTICLE INFO

Article History
Received: December 6, 2025
Reviewed: January 7, 2026
Accepted: January 14, 2026
Published: March 31, 2026

Keywords:
HVAC
Control Strategies
Deep learning
Energy Consumption

ABSTRACT

The building industry, which uses the most electricity, has a significant potential to contribute to energy consumption reduction. Commercial structures use more energy than other types of structures because of their productive and logistic features. In these types of structures, one of the main energy consumers is the HVAC system which comprises of heating, ventilation, and air conditioning, especially in arid conditions. Energy-efficient environment friendly HVAC system conception and execution can significantly lower the use of energy and support ecologically sound growth in business establishments. On the other hand, inadequate implementation of methods for reducing energy use may lead to a decline in the welfare of the environment. Therefore, in order to achieve energy efficiency and maintain the optimum degree of temperature regulation, a comprehensive energy conservation strategy is needed. To accomplish this goal, model predictive control strategy-based methodologies are used in this work. To estimate how much energy will be used in commercial buildings, four deep learning-based methods are utilised: radial basis function networks, multi-layer perceptrons, artificial neural networks, and back propagation neural networks. To further cut down on energy use, four distinct control mechanisms are used. The performance of the suggested solution is examined using performance measures like Mean Absolute Error and Mean Absolute Percentage Error.

I. INTRODUCTION

One of the main sources of energy use, both regionally and worldwide, is buildings. About 32% of the production of greenhouse gases connected to electrical power usage and 35% of worldwide ultimate utilisation of energy in 2019 were attributed to currently existent constructions [1]. One of the most substantial prospective industries for energy conservation is the present-day buildings. Cities with extensive industrial construction materials have significantly higher construction-related utilisation of energy. For instance, buildings in Chinese territories contributed to 69% of the town's greatest consumption of power in 2019; 48% of that amount came from business enterprises exclusively.

As a result, upgrading already-existing buildings has gained widespread support as a useful strategy for combating global warming as well as the associated energy crisis. A commercial office building's ability to house people's workspace is one of its main goals. People labour in their environments for 45 hours a week on aggregate [2]. Furthermore, two important elements that have an impact on worker health and efficiency in the workplace are exposure to environmental pollution and temperature regulation. For instance, it has been discovered that office job efficiency and intellectual capacity are correlated with interior warmth. Proximity to environmental contaminants and airborne particulates, is linked to a number of harmful health consequences.

Decreased warmth or low interior air quality creates an occupational danger and undermines efficiency, resulting in significant financial outlays for healthcare costs and missed work [3]. These days, energy is considered to be one of the highest essential needs and a cornerstone of any kind of financial system. Energy sustainability studies have been sparked by the consequent rise in costs of energy brought on by the world's lack of inexpensive resources for the production of energy. The literature revealed that petroleum and gas account for 83% of global energy production.

The world's consumption of energy has grown by 68% yearly over the past thirty years, while carbon dioxide emissions associated with energy have climbed by 63% as a result. The economic progress and rising standard of life have caused energy consumption to outstrip population growth by a factor of two [4]. Over time, the typical yearly growth in the requirement for energy has been 16%. Maximum demand for electrical power was 896 MW/year in 1979; by 2005, it had increased to 22,674 Megawatt yearly; by 2026, it is predicted to reach 63,000 Megawatt [5]. By the year 2055, the amount of power consumed—which stands at 14 trillion kWh today—could reach 55 trillion kWh [6]. The nation's financial and societal behaviour may be impacted if petroleum and coal reserves run out quickly due to the country's constantly increasing requirement for energy.

For the preceding two decades, building industry has experienced remarkable growth, especially in commercial buildings. According to previous studies, buildings use the majority of the electric energy produced, with the commercial buildings using only 12% of it all [7]. Energy is used in buildings for a number of purposes, such as illumination, warming and air conditioning, and other specialised uses. HVAC systems are regarded as an essential component of buildings in conditions of heat and are vital to the operation of these structures and the maintenance of a suitable indoor environment. Modern buildings need a significant amount of energy, primarily from HVAC (heating, ventilation, and air conditioning) systems. In hot and humid regions, the energy usage of the cooling system could surpass half of the building's overall energy usage.

As a result, upgrading HVAC systems is crucial since it can lower energy consumption [8]. In the meantime, interior ventilation and temperature regulation are significantly influenced by HVAC systems. Varying HVAC system layouts as well as operation principles will result in varying interior conditions and moisture levels, which are crucial markers of temperature regulation. Differences in airborne contaminants intensity can also result from modifications to ventilation and purification, and this can impact how much of these contaminants are exposed interior spaces [9]. The majority of energy used in commercial buildings is attributed to HVAC systems, as can be seen from the usual split of each year's energy consumption in buildings; this suggests chances for improving environmental sustainability while decreasing the expenditure of energy.

Numerous studies have addressed conservation and energy performance as they relate to the construction and functioning of HVAC systems. The findings suggest its possible to enhance in terms of HVAC energy utilisation and temperature regulation if appropriate management as well as administration procedures are implemented. The construction and implementation of energy-efficient HVAC systems have benefited from developments in science and technology, but it has also been discovered that the majority of adopted approaches and practices have led to unfavourable interior conditions. Researchers have created several innovative technologies in the last 20 years to enhance the comfort and energy efficiency of existing buildings [10]. Furthermore, constant certification has been established to guarantee acceptable interior conditions and sustained environmental sustainability in buildings that already exist.

By routinely adjusting temperature levels and achieving reductions in energy consumption, CC has assisted building owners in improving the machinery, especially the controls, to their first commissioning environments, identifying inefficient machinery, swapping out broken parts, and correcting improperly executed sequences. The significance of energy consumption in structures is widely recognised by architects and engineers worldwide, and as such, it has garnered considerable focus. In a similar vein, the significance of the quality of the interior environment is acknowledged and dealt with [11]. HVAC system designers typically prioritise high demand comfort and financial restrictions over energy efficiency and long-term quality of the interior environment.

In order to find chances for energy savings and enhance interior circumstances, it is crucial to evaluate the thermal and energy efficiency of currently operating commercial buildings. However, attempts to design energy-efficient buildings are frequently hampered by an inadequate understanding of how the climate and other environmental and design elements affect structures. The objective of this research is to find out how various HVAC system designs may conserve energy while maintaining a suitable degree of thermal comfort in a business building. A methodical procedure is used to create an energy efficiency model for a typical commercial building in order to accomplish the intended goal.

II. RELATED WORKS

Numerous control strategies have been created or put forth for HVAC systems. Nonetheless, many HVAC systems still use PID control and toggle between on and off switch due to their straightforward nature, which causes these systems to behave differently from one another. The inherent problems with HVAC control can now be addressed by adopting and implementing an appropriate control approach because of advancements in storage of information, analysing, and transmission technologies. This section is devoted to an investigation of HVAC system control methods, with a particular focus on the model predictive control (MPC) approach. The reason for the recent surge in research on MPC development for HVAC systems is its many inherent advantages.

The authors in [12] provided brief summaries of aggressive control and sensitive control strategies, respectively. Amplifier planning, effective regulation, resilient management, asymmetric and reactive management, and comprehensive supervision are some of the aggressive control strategies covered in [13-16]. The sensitive control systems, includes controllers based on evolutionary algorithms, fuzzy reasoning, as well as neural networks. The work in [17] included a study of mixed controllers, which are the outcome of combining aggressive control and sensitive control strategies. A thorough analysis of neural networks as well as evolutionary algorithms for HVAC system energy conservation was done in [18].

The work in [19] provided a description of HVAC techniques addressing the modelling of these systems, regulations, and subsystems. The work in [20] also addressed the efficient use of optimisation methods in monitoring control, including minimal squares, linear search, search including gradient, progressive nonlinear computing and adaptive computing. The survey conducted in [21] is based on sustainable HVAC system techniques, such as recuperation of heat, pressure distribution synthesis, and thermal retention. The work in [22] evaluated numerous autonomous regulators for HVAC systems, including

Parametric management, toggle control, time regulation with predetermined time improved take off and ideal begin and halt. The most widely used techniques for control, including PID management, as well as on or disable control, are included in conventional controllers. An increased and decreased cutoff are used by the toggle controller to govern the procedure within the parameters that have been provided [23]. To accomplish efficient process management, the PID controllers modulate the variable that is being controlled and exploit loss mechanics.

The chilling wrap groups, ambient temperature influence, hinder disparity rate regulation, availability pressure of the air control, availability room temperature control, the outside temperature regulation for component circulation units, evaporator source warmth management, and heating device administration are all dynamically controlled by conventional controlling devices [24]. The majority of research is devoted to developing PID controller auto tweaking and efficient adjusting techniques. The mathematical framework for regulating systems, which includes advance planning management, quadratic management, ideal management, and MPC, is the cornerstone of aggressive controllers. A chaotic system is split into independently normal areas for amplitude planning control.

A different combination of gains is used in the construction of the horizontal PID control scheme for each of the horizontal areas. The literature also suggests using self-tuning PID impulse controllers to adjust the device's outputs according to the system's status. In [25], a radiator-based air conditioning unit has two controllers that are adjusted to match various levels of temperature requirement situations. A parametric controller with outputs dependent on the discrepancy between the observed source atmospheric pressure and the initial setting is used in [26] to regulate the incoming air level. In the realm of control system design, aggressive controller techniques are widely recognised.

Although nonlinear dynamic approaches are efficient, designing a controller necessitates the identification of secure conditions and intricate computational analysis. The design of shifting logic between areas and the identification of proportional areas are essential for gain planning management architecture. It can be laborious to manually adjust several PID controllers in these areas. Because they can reject perturbations and time-dependent variables, effective supervision and precise regulation are potential approaches for HVAC process control. Generally speaking, it is challenging to provide durability in HVAC systems because building conditions can vary. Many of these methods also call for the specification of extra parameters, which makes the integration into HVAC systems potentially challenging and unfeasible [27].

Because it can incorporate perturbation disapproval, restriction administration, stationary adaptive control, and cost-effective strategies into controller layout, Model Predictive Control is one of the most promising aggressive control systems. Digital controllers have made it possible for relatively new sensitive control approaches, like those based on Fuzzy Reasoning (FR) and Artificial Neural Networks (ANN). An ANN is trained using system functioning data, which it then uses to fit a complex computational model. The method itself is a black box simulation approach, meaning that knowledge of the mechanics behind the procedure is not essential. This technique is widely employed in forward feedback management [28]. Combining aggressive and sensitive control strategies results in mixed controllers.

Artificial neural networks, which are sensitive control techniques used at greater tiers of the management structure, and dynamic controllers, which are aggressive control techniques used at lower tiers, make up mixed controllers. FR can be used to calibrate the benefits of controller in PID applications. The complementary nature of aggressive and sensitive control strategies allows for an amalgamation of each of them to tackle problems that may not be conducive to a particular technique working alone. A semi-dynamic fuzzy system for region regulation of temperature employing transmitter-heater energy management and programmable controller for air flow management [29] are two examples of hybrid control.Mixed control acquires the negative aspects of both aggressive and sensitive control techniques, even as it gains from their distinct advantages.

For instance, creating a sensitive control component necessitates user convenience and enormous amounts of information for instruction, but developing and tweaking an aggressive control component may prove problematic given the functional parameters commonly seen in these systems. The MPC has numerous benefits when taking HVAC control system parameters into account. HVAC systems have a lot of tedious, time-constrained operations, and they are affected by dynamic both interior and exterior perturbations. The operating conditions that the system experiences are diverse. There are speed and frequency constraint restrictions on the controllers. Energy has an adaptable cost mechanism in multiple locations. The optimum controller should be able to manage actuator restrictions, fluctuating cost values, varied working conditions, and dynamic perturbations in the face of all these difficulties [30].

II.1 MOTIVATIONS OF CURRENT RESEARCH

It appears that a lot of control systems have a few issues when it comes to HVAC control. For example, conventional controllers perform more impulsively or slowly beyond of the frequency range and need to be adjusted manually. For the controller design, the aggressive controllers necessitate the identification of secure balance locations and an exhaustive statistical analysis. Sensitive control is not practicable for commercial applications since it requires large amounts of knowledge for instruction and take a long time. As an alternative, MPC addresses a number of the previously me]ntioned issues and is employed in the current research.

III. PROPOSED METHODOLOGY

III.1 HVAC SYSTEM MODELS

One of the significant concerns in the research on HVAC systems is how these standard systems would handle the various building demands. These buildings have been connected to the two most popular HVAC systems such as the ventilation coil with a specific exterior air device and an adjustable airflow system as shown in Figure 1. An adjustable air flow system is an entire system that modifies the source air flow speed while maintaining a uniform source ambient temperature to correspond with the decrease in area load during quasi functioning of the system. By doing this, the device preserves an established area parameter—typically the air temperature—while simultaneously conserving motor energy at a decreased flow.

The source humidity level, which is set at 18 ◦C, regulates the primary warming circuit and the secondary cooler coil. Through the air warming containers, necessary prerequisite airflow is transported to the regions, if necessary, it is further heated. The steaming water circuit and suspension in each air reheating box are controlled by an area temperature gauge and have a bidirectional suspension function. This indicates that the unit starts at lowest air circulation and lowest steaming water discharge while in warmth mode. The steaming water flow is raised until it reaches its highest point in response to a rise in the temperature demand. The ventilation valve begins to vibrate if the load is still not reached.

The exterior air blending container, which has a reducer that combines come back and exterior air proportionately to reach the combined air temperature threshold, regulates how much exterior air is supplied. In order to take advantage of free the cooling process, the reducer unit is used to enhance the amount of exterior air wherever feasible. A fluctuating air temperature threshold installed on the source end can enhance the effectiveness of adjustable airflow system. Dynamic temperature regulation can both improve the amount of ventilating capacity and decrease the amount of energy needed for warming. This is accomplished by determining if a particular warming box is operating at an appropriate velocity during chilling periods.

If so, the building administration system raises the ambient temperature of the circulating airflow. In essence, an adjustable temperature and quantity system is an adjustable airflow system with constantly variable source temperature regulation. The ventilation coil with specialised exterior air framework, is a system made up of a moisture distributing component and regions pipe coils that distribute completely air from the outdoors exclusively to satisfy fresh air necessities. Unlike the adjustable airflow system, the cool air delivery range is managed by a temperature-controlled detector that adjusts the temperature between 18 and 23 ◦C to optimise the benefits of unrestricted air conditioning.

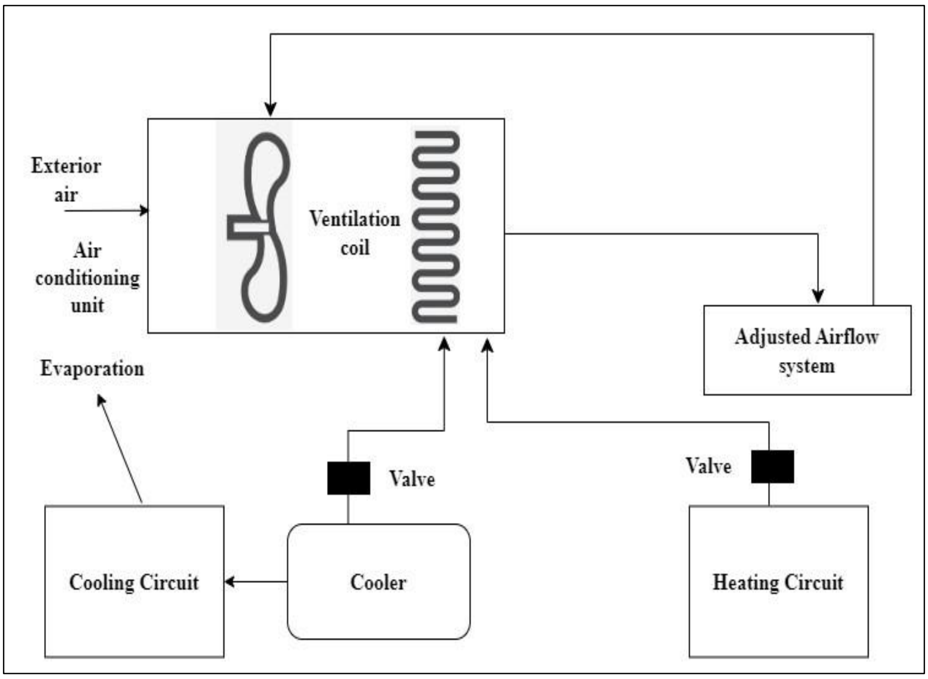

Figure 1: HVAC System model.
Source: Authors, (2026).

However, compared to the adjustable airflow system, the source air capacity is much smaller, which limits the amount of unrestricted air conditioning. A ventilation coil is made up of coils for both cooling and warming as well as a blade for redistributing the air in the space. A regional regulator maintains the environmental conditions inside the space by adjusting the fluid rate that travels through the cooling or warming circuit in response to the requirements in each area. The rotating circuit motor is turned off when neither warming nor chilling is necessary. Implementing an energy recuperation device, which transfers warmth between the source airflow and the expelled air, can prevent the outside environment. Passage valves on the thermal recuperation unit enhance ventilation by reducing the exchanger that conducts heat.

Depending on the type of system, multiple models were used for the characteristics of the source of airflow fan. Adjustable flow blades with a 35% decline frequency are utilised with the adjustable airflow system. Suction blade absorbers manage the system's internal air circulation. The ASHRAE Secondary Toolkit is the underlying basis of the ventilator specifications [20]. Continuous output blowers drive the system's air dispersion. For the ventilation coil system with an energy recuperation device and the adjustable airflow system, the ventilator's inflation rate is adjusted to 850 Pa. Because there is less impedance in the air circulation circuit for the ventilation coil system, the pressure rise is minimised to 500 Pa.

For both systems, both the warm and chill water temperature regimes were identical. The chilled water circuit runs in the 6/13 ◦C regime, while the source warm water temperature is fixed at 84 ◦C with a maximum temperature drop of 10 ◦C. The transport of hot or cold water in main system is maintained by steady-speed motors. When the fluid flow velocity in the radiators is lowered during reduced capacity procedures, excess warm and cold water supply is channelled through diversions.

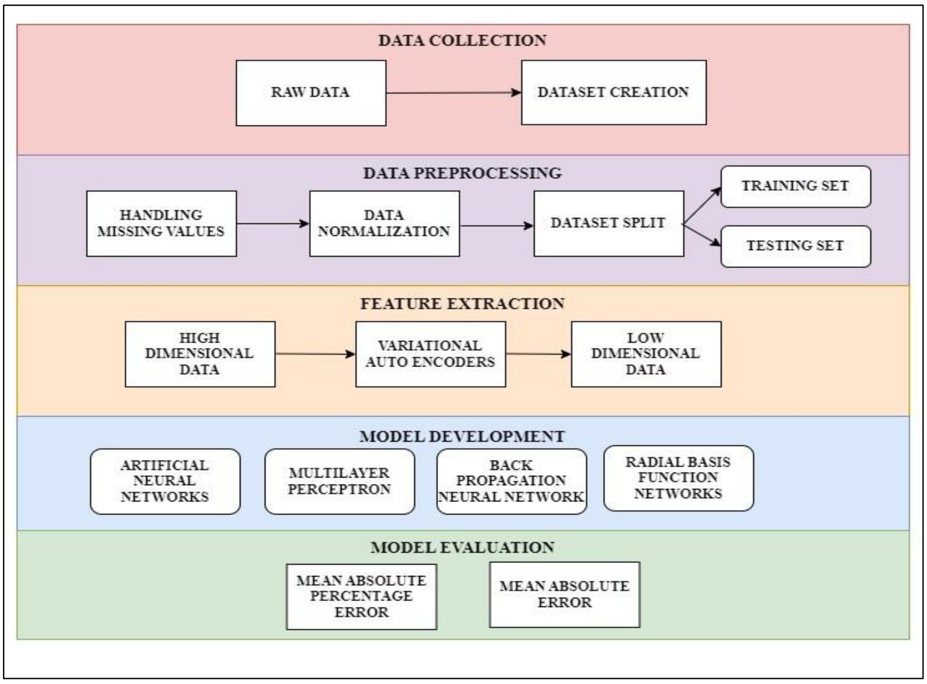

Figure 2: Proposed Framework.
Source: Authors, (2026).

III.2 DATA COLLECTION

A substantial amount of training data that can accurately depict the link between inputs and outputs is required in order to train the prediction model. These data for the study were gathered from the test platform, which simulates a range of working environments. In order to account for a variety of working settings, the simulation runs for five years with the interior temperature setpoint being arbitrarily set between 20 and 28 °C for each hour (such as varied indoor temperature and weather conditions). The building model is configured to operate in the free cooling mode, which allows for an infinite cooling supply. In this mode, the system is programmed to automatically supply a specific amount of cooling that satisfies the need to maintain the interior temperature at its setpoint.

The power consumption under various operating situations can be derived by integrating with the matching steady-state model of the HVAC system. It should be noted that the hot summer and warm winter weather zones are represented in the used meteorological data. Thus, all that is required year-round is cooling. A five-minute simulation interval is chosen. Consequently, twenty sets of data are generated every hour, but only the set in the final point is gathered. The reason for this is that the envelope's and the internal mass's thermal inertia prevent the cooling demand at the start of each hour from accurately reflecting the actual cooling requirement for that hour. As a result, a total of 45,600 sets of data are gathered.

III. 3 DATA PREPROCESSING

Typically, missing or anomalous data is found and fixed (or eliminated) during the data cleaning process. Eliminating data that is useless for the machine learning-based controller's actual use is the primary goal of this investigation. The predictor's prediction accuracy can be greatly improved by this implementation. Two categories of data must be eliminated. First, all datasets outside of working hours are deleted, leaving just those collected between 6 a.m. and 9 p.m. The HVAC system doesn't offer frequency regulation services outside of working hours, thus the machine learning-based controller is only utilised during those times.

Secondly, the datasets with 0% power usage are eliminated. The explanation goes like this. The following scenarios could arise because the indoor temperature setpoint is arbitrarily determined during the data production and collection procedure. While the indoor temperature setpoint is relatively high, the external temperature is relatively low. Since the HVAC system doesn't need to be turned on for cooling, there is no electricity consumption. It is evident that the HVAC system is unable to perform frequency regulation service because it does not even turn on. As a result, the datasets with negligible power consumption are likewise eliminated.

III.4 FEATURE EXTRACTION

An encoder that receives input and creates a reduced version and a decoder that returns the revised version to the source data make up an autoencoder network, also known as a variational autoencoder. The encoder produces two vector formats: a vector to measure the mean value and a vector to denote the variance value. Its infinite hidden space facilitates sample selection and restoration. Because the code being encoded has a significantly lower section frequency than the source data, the challenge is in programming the algorithm to acquire an appropriate and transferable hidden space.

This model gives a likelihood dispersion definition for each hidden property. The m th element of mean and variance, which together make up the components of a sequence of arbitrary parameters of length K, represents these values of the m-th random variable, Am, which was sampled to create the resultant encoded data. Even though these values remain unchanged, the original encoding for the identical source data will vary significantly on every attempt due to randomization. The average of a variable establishes the central point of encoding of source data, whereas the variance value establishes the region or how much a source data may diverge from its average.

The KL divergence allows for continuous restoration and the production of newly formed information by acting as a optimizer in the elimination function. Then, using an assortment of samples drawn from each hidden phase dispersion, the decoding system creates a vector as input for the decoder model in an attempt to replicate the input that was originally provided. Instead of using reverse propagation, which is usually used to determine the connection between every channel variable and the final outcome's loss, expands the values of the parameters. For approaches involving randomly selected examples, reverse propagation is inadequate. As reallocating parameter values optimises the distribution's stochastic variables, the ability to choose samples arbitrarily from the spectrum of values remains intact.

III.5 MODEL DEVELOPMENT

III.5.1 Artificial Neural Networks

Artificial neural networks are mathematically reduced representations of biological neural networks that possess the capacity to learn and offer significant answers for problems including nonlinearity and high levels of complexity. The ANN approach can tackle a wide range of problems and is faster than its conventional procedures. It is also robust in noisy situations. These benefits have led to the widespread adoption of ANNs in real-time applications. In hydrology, three- and four-layered neural networks are most frequently utilised. The first layer receives input, the intermediate layers process the data, and the final layer displays the results.The processing units that are present in every layer of the network are referred to as neurons or nodes.

The first layer to the intermediate layer and the intermediate layer to the final layer are where information flows and is processed in the network. The number of neurons and hidden layers in the network are obtained through test-run based on the specific situation. In order to forecast the input-output relationship, each link is given a synaptic weight that represents the relative connection strength of two nodes at both ends. The sigmoid transfer function is a frequently utilised activation function. The sigmoid function can be used to map a nonlinear process since it is continuous and differentiable everywhere. The main application of the backpropagation technique is in feed-forward neural network training. Every input pattern in the training dataset is processed by the network in this approach, moving from the first layer to the final layer.

III.5.2 Multi-Layer Perceptron

Due to the limitations of the perceptron with one layer to solve exclusive OR usecase, this backpropagation model with multiple layers disperses errors throughout the network using the delta learning rule. It is made up of three parts: input, output, and intermediate (hidden). The node, which contains source data and resultant data is interlinked with every other node in the layer below it and serves as the processing element in each MLP layer. As a consequence, the resultant of one layer happens to be the source of the subsequent layer below it. Data is received by the source layer and sent to the concealed layer. This means that the classification problem determines the count of concealed layer. The output layer generates the outcomes based on the number of components in the final layer after processing data from the preceding layers.

III.5.3 Back propagation Neural Networks

One of the most popular machine learning techniques in the field of research is the feedforward neural network, which is optimised by the back propagation algorithm in a neural network called BPNN [24]. For the majority of forecasting situations, a BPNN can, in theory, be used as a multipurpose estimation to predict the underlying complex nonlinear connection. The source, the intermediate, and the resultant layer are often present in a BPNN. Additionally, the research challenge and goal determine how many input and output neurons the BPNN has. Furthermore, the intricacy of the research problem affects the BPNN method's basic design, which includes the number of concealed layers and nodes in each concealed layer. Weights establish a relationship between each layer and the one below it. An activation function is then obtained by multiplying all of the node terms from the preceding layer by the corresponding weight parameters, which add a bias. The BPNN uses the activation function as the foundation to approximate nonlinear latent functions. Additionally, the backpropagation technique is used to modify the connection weights.

III.5.4 Radial Basis Function Networks

A feed-forward neural network with three layers—an input layer, a hidden layer, and an output layer—is called an RBF neural network. Each buried unit represents a single RBF with a corresponding width and centre position. Kernels or centroids are frequently used to identify these covert units. Each output unit weights and summarises the hidden units. A vast class of functions that may be described as linear combinations of the chosen RBFs can be displayed using a collection of RBFs.

IV. RESULTS AND DISCUSSION

IV.1 DATASET DESCRIPTION

Using Ecotect simulation software, 768 entries from twelve different building types made up Dataset 2. Twelve different building kinds were represented by eighteen 4.5 x 4.5 x 4.5 metre basic cubes. As a result, while the buildings' surface areas and dimensions vary, their volumes do. Each of these structures was designed to resemble an Athens, Greece, residential building. The purpose of this dataset is to look into how dimension affects a building's cooling load (CL). Because of this, the façade system's material attributes, such as the U-values of wall with 1.78 W/m2K, windows with 3.38 W/m2K, floors with 0.86 W/m2K, and ceiling with 0.50 W/m2K, were applied to all fifteen buildings. Latent heat and illumination levels were adjusted to 2 W/m2 and 300 lux, respectively. To model the air conditioning load of the domestic construction, the following characteristics such as position, the amount of surface space, masonry region, ceiling region, total elevation comparative cohesiveness, window region, and window dispersion were employed. The two configurations used in the studies to recreate the building were with and without window options.

Four different types of window region ratios such as 15%, 30%, and 45%—were applied in the proposed system. There are five glazing distributions that are taken into consideration: 40% windows on each face; 60% windows on the west end and 25% windows on the other ends; 60% windows on the south end of the building and 25% windows on the remaining ends; 60% glazing on the north end and 25% windows on the other ends; and 60% windows on the east face and 25% windows on the other ends. Finally, each of the building shapes were turned to point to one of four directions.

IV.2 EXPERIMENTAL EVALUATION

Experiments were conducted using the four models such as Artificial Neural Networks (ANN), Multi-layer Perceptron (MLP), Back propagation Neural Networks (BPNN) and Radial Basis Function Networks (RBFN) and the results are tabulated in Table 1. The metrics such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are computed for each of the techniques to analyse the performance of the models for predicting the consumption of energy resources. It can be seen that the ANN model produces MAE of 63.86 during training and 78.32 during testing. Also, ANN produces MAPE of 7.56 and 8.65 during training and testing respectively.

Table 1: Experimental results.

Techniques		Mean Absolute error	Mean Absolute Percentage error
Artificial Neural Networks	Training	63.86	7.56
	Testing	78.32	8.65
Multi-layer Perceptron	Training	56.34	6.35
	Testing	48.25	7.24
Back propagation Neural Networks	Training	72.36	5.32
	Testing	65.52	4.74
Radial Basis Function Networks	Training	43.25	4.36
	Testing	36.85	4.12

Source: Authors, (2026).

MLP model exhibited MAE and MAPE of 56.34 and 6.35 during training correspondingly. During the testing periods, MLP showed 48.25 MAE and 7.24 MAPE. The MAE and MAPE values produced by BPNN model during training was 72.36 and 5.32 respectively. During testing, it was about MAE value of 65.52 and MAPE value of 4.74. RBFN model exhibited 43.25 MAE and 4.36 MAPE during training phase and 36.85 MAE and 4.12 MAPE during testing phase. Further, the prediction outcomes achieved by each of the model for energy consumption by the buildings is presented in Figures 2 to 5. The results revealed that the models were capable enough to produce prediction outcomes closer to that of the actual values and the RBFN model produced predictions which less deviations from the original results.

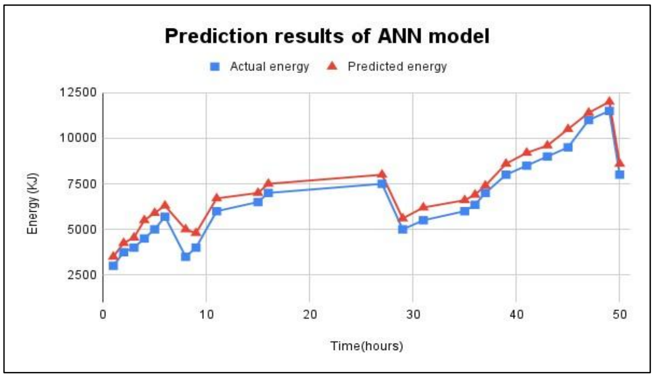

Figure 3: Prediction results of ANN model.
Source: Authors, (2026).

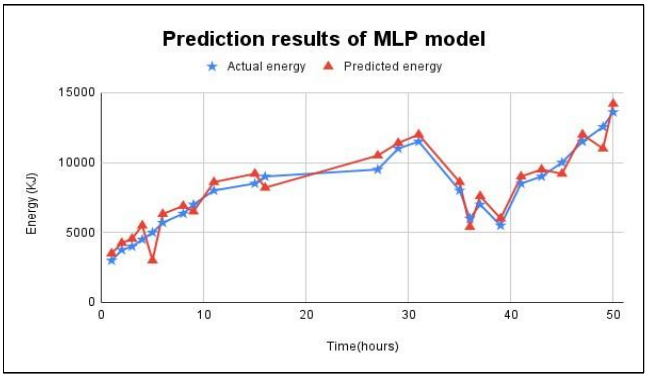

Figure 4: Prediction results of MLP model.
Source: Authors, (2026).

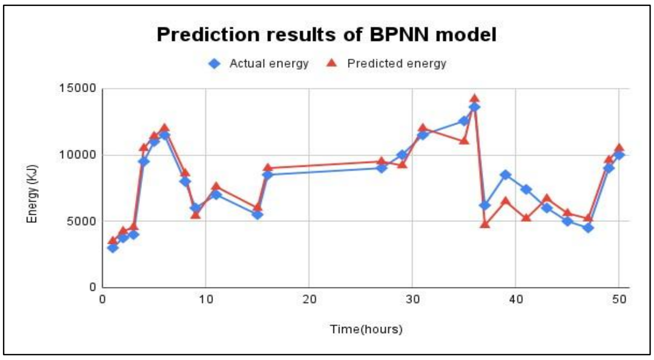

Figure 5: Prediction results of BPNN model.
Source: Authors, (2026).

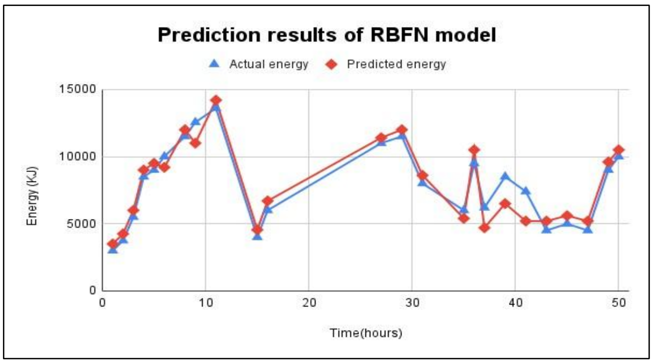

Figure 6: Prediction results of RBFN model.
Source: Authors, (2026).

In addition to this, four control strategies were further suggested in order to minimize the energy consumption by the buildings. This research initially sought to determine how altering the temperature threshold for warming and cooling, affects the total use of energy. One of the thermocouple approaches utilised in HVAC systems is to regulate the temperature threshold, which plays a big part in a building's energy consumption for heated space. Reducing the wintertime warming temperature threshold in a building located in an arctic climate can result in significant energy conservation. The results obtained for temperature threshold approach are presented in Figure.

Lowering the warming temperature threshold results in a notable decrease in the yearly overall energy usage. There is a 25% as well as 5% decrease in the usage of fossil-fuel-powered gas and electric power, respectively. The yearly energy demand dropped to 385.56 kWh/m^2 from 520.76 kWh/m^2. The pace at which energy demand is reduced annually is roughly 21%. Lowering the warming temperature threshold in the building lowers the energy consumption of the ventilation turbines and blades in addition to the energy used for interior heating.

During the months when the air conditioning system is not in use, the building's aggregate energy use remains unchanged when the cooling temperature threshold values are lowered. Whenever a cooling unit is in service during the winter months, overall consumption of electricity falls. For instance, there was an 8% drop in overall usage of energy in September. During the months when the air conditioning fails to function, the total expelled carbon dioxide emissions do not change. Because less energy is used during the months the cooling system is running, fewer greenhouse gases are generated altogether. The building's total displaced greenhouse gases output, which is 95,485 kg, reaches its smallest level in July.

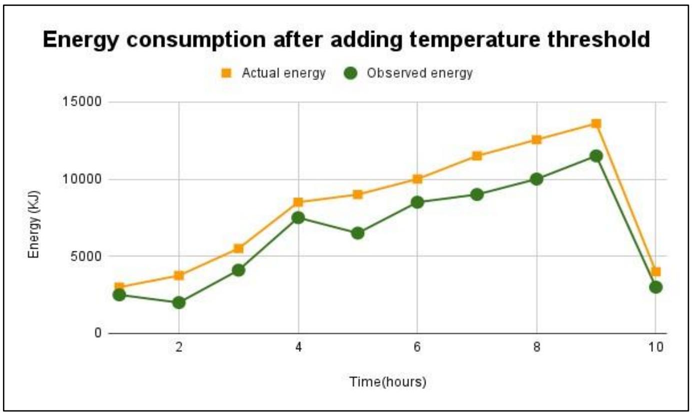

Figure 7: Energy consumption after adding temperature threshold.
Source: Authors, (2026).

An proactive or introspective conditioning technique called night time aeration is used, particularly in large structures, when the facility is situated in an area with an appropriate overnight temperature. Using aeration at twilight is an intriguing approach to lower the amount of energy required for building conditioning without sacrificing heat retention. The basic idea is to use spontaneous or ventilating machinery to use the comparatively cold conditions, surrounding air during the course of the night to regulate the air inside along with structural elements, so acting as a source of heat for the next day's work. All of the building's conditioned spaces aside from the workplaces are occupied and kept cool for the entire period of the day.

Because of this, during the hours that the workplaces are closed, night time aeration can be turned on for workplace buildings. Figure 8 illustrates how the aeration of the workplace areas at night affects the building's energy consumption. The terminal building's energy usage for conditioning is decreased by using night time aeration in workplace spaces. However, in order to ventilate the offices at night, the combustion and circulation blowers installed in the buildings must be turned on. As a result, even if the air condition elements are deactivated in the starting point modelling, the building's overall energy use goes up. Consequently, it was determined that it is not financially feasible to provide night time aeration for the office areas.

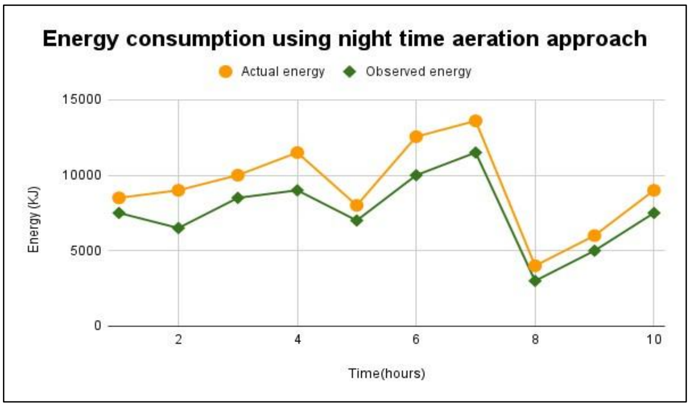

Figure 8: Energy consumption using night time aeration approach.
Source: Authors, (2026).

When the exterior air temperature is adequately cold, air handling units may be employed in HVAC systems as an additional way to save a substantial amount of energy.

Reducers, which give the chilling system unlimited cooling, come in two different forms. This technique reduced the amount of energy used for cooling by suggesting and evaluating the usage of a reducer, which is added in parallel to the chilling unit's reservoir unit. The building's cooling has been provided by chillers with air conditioning. During the winter months, cold water distribution motors move the cold water produced by the cooling units, which is at a temperature of 9 °C. The results obtained by applying this approach is presented in Figure 9.

When the temperature of the exterior air is less than the recirculating temperature, no area of the building needs to be chilled, according to an investigation into the simulation findings. However, because of thermal advancements, the temperature of the interior air in some places may suddenly rise over the cooling initial value. The amount of energy used for cooling rises by a negligibly small amount as a result of this spike in temperature. Therefore, employing this technique hasn't resulted in an improvement in the energy utilisation. As a result, this approach is not advised for usage as it did not lower the building's energy usage and greenhouse gas emissions.

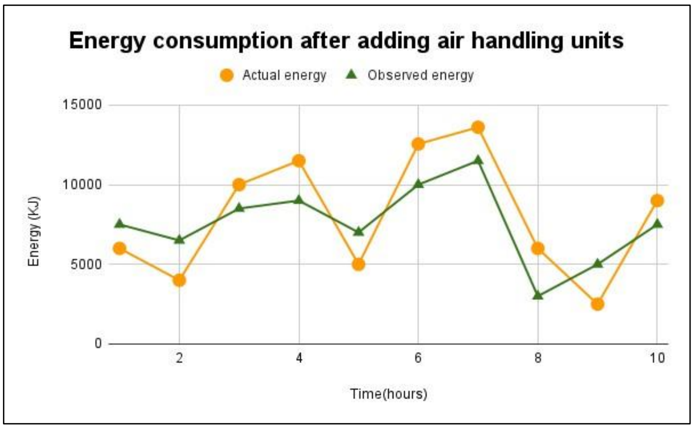

Figure 9: Energy consumption after adding air handling units.
Source: Authors, (2026).

One effective way to lower a building's excessive consumption of energy is through recuperating energy. A radiator is often used in air conditioning units to lower the amount of power required for a structure's thermal or cooling needs. Based on how they operate, the air conditioning units that are currently in the building were employed for this study. These consist of a heat radiator that uses 75% of exterior air to achieve the statutory circulation demand.

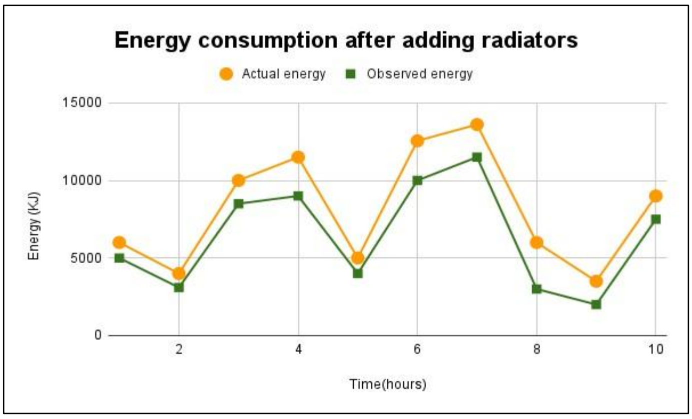

Figure 10: Energy consumption after adding radiators.
Source: Authors, (2026).

Using a radiator is found to lower energy usage throughout the year . Compared to other months, the coldest months see a far greater fall in energy use. For instance, the introduction of a radiator reduces the energy consumption by 52% to 543,632 kWh from the March use of 834,437 kWh. The entire amount of transferred greenhouse gases is lowered as a result of the decrease in energy usage.

V. CONCLUSION

When suitable monitoring and maintenance procedures are implemented, HVAC systems can present significant opportunities for energy conservation. The various energy-saving techniques that can be used with the HVAC system to lower energy usage while decreasing greenhouse gas emissions are discussed in this research. The HVAC system in the commercial buildings uses the most energy when compared to other structures, according to an energy analysis of the building's framework.

In this regard, four different deep learning algorithms were leveraged to forecast the energy usages of the buildings and it was inferred that Radial Basis Function Networks produced predictions with lesser errors and deviations. In addition to this, four control strategies were recommended for further reduction in energy consumption. In terms of energy, expenses, and environmental impact, approaches including modifying the temperature thresholds and installing radiators have been demonstrated to be functional. However, it is discovered that the night time aeration and adding air handling units are not financially a feasible option.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: K. Rajalakshmi, R. Thirumalai Selvi.
Methodology:. K. Rajalakshmi, R. Thirumalai Selvi.
Investigation: K. Rajalakshmi, R. Thirumalai Selvi.
Discussion of results: K. Rajalakshmi, R. Thirumalai Selvi.
Writing – Original Draft: K. Rajalakshmi, R. Thirumalai Selvi.
Writing – Review and Editing: K. Rajalakshmi, R. Thirumalai Selvi.
Resources: K. Rajalakshmi, R. Thirumalai Selvi.
Supervision: K. Rajalakshmi, R. Thirumalai Selvi.
Approval of the final text: K. Rajalakshmi, R. Thirumalai Selvi.

VII. REFERENCES

[1] J. Kim, Y. Zhou, S. Schiavon, P. Raftery, G.S. Brager, Personal comfort models: predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning, Build. Environ. 129 (2017) 96–106.

[2] S. Lu, W. Wang, C. Lin, E.C. Hameen, Data-driven simulation of a thermal comfort-based temperature set-point control with ashrae rp884, Build. Environ. 156 (2019) 137–146.

[3] A. Wj, B. Fj, Comparative assessment of hvac control strategies using personal thermal comfort and sensitivity models, Build. Environ. 158 (2019) 104–119.

[4] W. Jung, F. Jazizadeh, Vision-based thermal comfort quantification for hvac control, Build. Environ. 142 (2018) 513–523.

[5] Z. Wang, T. Hong, M.A. Piette, M. Pritoni, Inferring occupant counts from wi-fi data in buildings through machine learning, Build. Environ. 158 (2019) 281–294.

[6] K.M. Reena, A.T. Mathew, L. Jacob, A flexible control strategy for energy and comfort aware HVAC in large buildings, Build. Environ. 145 (2018) 330–342.

[7] Z. Zou, X. Yu, S. Ergan, Towards optimal control of air handling units using deep reinforcement learning and recurrent neural network, Build. Environ. 168 (2020) 106535.

[8] Y. Peng, Z. Nagy, A. Schluter, Temperature-preference learning with neural networks for occupant-centric building indoor climate controls, Build. Environ. 154 (2019) 296–308.

[9] D. Manjarres, A. Mera, E. Perea, A. Lejarazu, S. Gil-Lopez, An energy-efficient predictive control for hvac systems applied to tertiary buildings based on regression techniques, Energy Build. 152 (2017) 409–417.

[10] A. Ghahramani, S.A. Karvigh, B. Becerik-Gerber, Hvac system energy optimization using an adaptive hybrid metaheuristic, Energy Build. 152 (2017) 149–161.

[11] Z. Zhang, A. Chong, Y. Pan, C. Zhang, K.P. Lam, Whole building energy model for hvac optimal control: a practical framework based on deep reinforcement learning, Energy Build. 199 (2019) 472–490.

[12] P.V. Every, M. Rodriguez, C.B. Jones, A.A. Mammoli, M. Martínez-Ramon, Advanced detection of hvac faults using unsupervised svm novelty detection and Gaussian process models, Energy Build. 149 (2017) 216–224.

[13] S. Lee, P. Karava, A. Tzempelikos, I. Bilionis, A smart and less intrusive feedback request algorithm towards human-centered hvac operation, Build. Environ. 184 (2020) 107190.

[14] N. Gao, W. Shao, M.S. Rahaman, J. Zhai, F.D. Salim, Transfer learning for thermal comfort prediction in multiple cities, Build. Environ. 195 (2021) 107725.

[15] B. Hma, M.A.M. C, D. Lkf, Novel swarm-based approach for predicting the cooling load of residential buildings based on social behavior of elephant herds - sciencedirect, Energy Build. 206 (2020) 109579.

[16] J. Zhang, X. Liu, A hybrid method of dynamic cooling and heating load forecasting for office buildings based on artificial intelligence and regression analysis, Energy Build. 174 (2018) 293–308.

[17] H. Du, Z. Lian, D. Lai, W. Liu, X. Zhang, Method of determining acceptable air temperature thresholds in Chinese hvac buildings based on a data-driven model, Energy Build. 241 (2021) 110920.

[18] S. Yang, M.P. Wan, W. Chen, B.F. Ng, S. Dubey, Model predictive control with adaptive machine-learning-based model for building energy efficiency and comfort optimization, Appl. Energy 271 (2020) 115147.

[19] M. Killian, M. Kozek, Ten questions concerning model predictive control for energy efficient buildings, Build. Environ. 105 (2016) 403–412.

[20] R. Jia, M. Jin, K. Sun, T. Hong, C. Spanos, Advanced building control via deep reinforcement learning, Energy Procedia 158 (2019) 6158–6163.

[21] B. Chen, Z. Cai, M. Bergés, Gnu-RL: A precocial reinforcement learning solution for building HVAC control using a differentiable MPC policy, Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, 2019, pp. 316–325.

[22] A. Jain, F. Smarra, E. Reticcioli, A. D'Innocenzo, M. Morari, NeurOpt: Neural network based optimization for building energy management and climate control, Proc. Mach. Learn. Res. 120 (2020) 1–12.

[23] F. Smarra, A. Jain, T. De Rubeis, D. Ambrosini, A. D'Innocenzo, R. Mangharam, Data-driven model predictive control using random forests for building energy optimization and climate control, Appl. Energy 226 (2018) 1252–1272.

[24] Paone, Antonio, Jean-Philippe Bacher. The impact of building occupant behavior on energy efficiency and methods to influence it: a review of the state of the art. Energies 11, (4) (2018): 953. https://doi.org/10.3390/en11040953.

[25] K. Sun, T. Hong, A simulation approach to estimate energy savings potential of occupant behavior measures, Energy Build. 136 (2017) 43–62, https://doi.org/10.1016/j.enbuild.2016.12.010.

[26] Z. Deng, Q. Chen, Artificial neural network models using thermal sensations and occupants' behavior for predicting thermal comfort, Energy Build. 174 (2018) 587–602, https://doi.org/10.1016/j.enbuild.2018.06.060.

[27] Z. Wang, T. Hong, Reinforcement learning for building controls: the opportunities and challenges, Appl. Energy 269 (2020) 115036, https://doi.org/10.1016/j.apenergy.2020.115036.

[28] M. Jia, R.S. Srinivasan, A.A. Raheem, From occupancy to occupant behavior: an analytical survey of data acquisition technologies, modeling methodologies and simulation coupling mechanisms for building energy efficiency, Renewable Sustainable Energy Rev. 68 (2017) 525–540, https://doi.org/10.1016/j.rser.2016.10.011.

[29] L. Yu, W. Xie, D.i. Xie, Y. Zou, D. Zhang, Z. Sun, L. Zhang, Y. Zhang, T. Jiang, Deep reinforcement learning for smart home energy management, IEEE Internet Things J. 7 (4) (2020) 2751–2762, https://doi.org/10.1109/JIoT.648890710.1109/JIOT.2019.2957289.

[30] Y. Chen, L.K. Norford, H.W. Samuelson, A. Malkawi, Optimal control of HVAC and window systems for natural ventilation through reinforcement learning, Energy Build. 169 (2018) 195–205, https://doi.org/10.1016/j.enbuild.2018.03.051.