IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 6 March 2023, accepted 19 March 2023, date of publication 29 March 2023, date of current version 5 April 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3262934

RESEARCH ARTICLE

Design of an EnergyPlus Model-Based Smart Controller for Maintaining Thermal Comfortable Environment in Non-Domestic Building

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This work was supported in part by the Gulf University for Science and Technology, and in part by the Centre for Applied Mathematics and Bioinformatics (CAMB) under Project ISG-278736.

ABSTRACT Heating, Ventilation, and Air Conditioning (HVAC) systems account for 59% of energy consumption in domestic buildings and 36% in non-domestic buildings. According to a study, around 39% of occupants are dissatisfied with indoor temperature in non-domestic buildings. To maintain thermal comfort and indoor air quality, HVAC systems are widely used in non-domestic buildings. This research aims to develop energy-efficient control techniques for HVAC systems while ensuring indoor thermal comfort. Three control strategies, namely EnergyPlus model-based Model Predictive Control (MPC), Sliding Mode Control (SMC), and simple ON/OFF control, are employed and compared at the Department of Electrical and Computer Engineering, COMSATS University Islamabad, Lahore Campus. Furthermore, a machine learning-based Predicted Mean Vote (PMV)-based temperature setpoint estimator is designed to ensure occupant thermal comfort. The control techniques estimate the temperature setpoints and supply air temperature of the Variable Air Volume (VAV) system to control indoor room temperature. The energy consumption and indoor thermal comfort of the building are compared under different control techniques. The results show that MPC with PMV-based setpoints consumes 17.20% less energy during winters and 14.67% less energy during summers than a simple ON/OFF controller.

INDEX TERMS EnergyPlus, building energy management, thermal comfort, artificial neural network (ANN), model predictive control (MPC), sliding mode control (SMC).

I. INTRODUCTION

Buildings consume more than 30% of the total energy consumption worldwide, and carbon dioxide (CO2) emissions from buildings account for 28% of global CO2 emissions. The electricity consumption of buildings accounts for 55% of global electricity consumption [1]. Heating, ventilation, and air conditioning (HVAC) consume 59% of total energy consumption in domestic buildings and 36% of the total energy consumption in non-domestic buildings [2]. According to a study [3], 36% of occupants in offices are not satisfied with the indoor temperature, and 36% of occupants believe that the indoor air temperature reduces their productivity. The energy consumption of HVAC systems can be reduced in various ways, such as by increasing airtightness, increasing appliance efficiency, better insulation, inactive ventilation schemes, advanced control, and so on. To adjust HVAC control parameters and ensure optimal performance, HVAC systems should be constantly supervised by technicians [4]. A well-designed automatic control would perform better than manual control

The associate editor coordinating the review of this manuscript and approving it for publication was Mohammad Ayoub Khan.

for such tasks, especially when highly complex objectives are considered.

In buildings, the energy consumption of HVAC systems depends on several factors including the number of occupants, occupants' behavior (preferred heating and cooling setpoints), building type, building area, and building load profile [5]. The primary objective of HVAC facilities is to control temperatures in various segments of the building while ensuring better air quality. In Pakistan, buildings consume 55% of the total energy consumption, and due to the prolonged summer season, the cooling load demand is very high [6]. In [6], the authors found that the preferred heating setpoint in Pakistan is 20°C, and the preferred cooling setpoint is 24°C. Humans spend more than 90% of their time in buildings; therefore, maintaining a thermally comfortable indoor environment in a building is crucial. Thermal comfort is described as the state of mind that expresses satisfaction with the thermal environment. In [7], two methods named Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) are used to compute thermal comfort. The PMV is utilized to determine the mean thermal sensation vote on a standard scale for occupants. The standard seven thermal sensation scales for the PMV index are [+3 hot, +2 warm, +1 slightly warm, 0 neutral, −1 slightly cool, −2 cool, and −3 cold]. Fanger's comfort equation calculates the PMV index based on cloth insulation, activity level, air velocity, air humidity, air temperature, and mean radiant temperature [7].

Standardizing simulation models is crucial for achieving precision and ease of use in energy simulation. EnergyPlus software is one of the energy simulation tools that use the heat balance method for heat transfer calculations in buildings. The EnergyPlus tool is based on a forward modeling approach (physics-based models), but some advanced modules are generated through a data-driven approach. EnergyPlus is used as a front-end stage to assist consumers in obtaining various modules of the system in the back end [8]. The MLE+ is a MATLAB toolbox that interfaces EnergyPlus with MATLAB/Simulink to execute different control techniques for energy-efficient building operations [9].

In this paper as a test setup,

- The Electrical and Computer Engineering (ECE) Department building, located at COMSATS University Islamabad (CUI), Lahore Campus, Pakistan, is modeled using EnergyPlus and DesignBuilder. For the analysis of building performance, a single duct variable air volume (VAV) system with reheat boxes is used.
- The PMV-based heating and cooling setpoints are computed using Artificial Neural Network (ANN).
- Three different control techniques, i.e., simple ON/OFF controller, Model Predictive Controller (MPC), and Sliding Mode Controller (SMC), are utilized to reduce the energy consumption of the ECE department while maintaining thermal comfort based on heating and cooling setpoints.
- The designed building model is simulated in EnergyPlus and Simulink with the co-simulation of MLE+ software, and the performance of the controllers is compared in terms of HVAC energy consumption, Mean Absolute Error (MAE), Mean Square Error (MSE), and average PPD%.

The main contributions of this paper are:

- This paper proposes a novel machine learning-based estimator for heating and cooling temperature setpoints for a single-duct VAV with reheat box HVAC system to maintain thermal comfort during both winter and summer seasons.
- We developed novel SMC and MPC techniques to reduce the energy consumption of HVAC while maintaining a comfortable indoor environment in the ECE department building at CUI, Lahore Campus. The SMC/MPC-based smart controller maintains a comfortable indoor environment by regulating PMV-based temperature setpoints for heating and cooling and controlling the supply air temperature of the HVAC.
- A detailed comparative analysis of the MPC, SMC, and the Simple ON/OFF controller for building energy management is conducted in both winter and summer seasons. To the best of our knowledge, this comparison has not been done before for building energy management systems. The controllers are compared in terms of HVAC energy consumption, MAE, PMV, and PPD.

The rest of the paper is organized as follows: Section II presents the literature review on different control techniques and topologies employed for HVAC system modeling and optimization. In Section III, detailed information about the building structure is provided. The proposed control methodologies are explained in Section IV. Section V discusses the results along with a comparative analysis. The paper is concluded in Section VI along with future research directions

II. RELATED WORK

In [10], different HVAC system control strategies were discussed, including Classical control (PID controller, ON/OFF controller), Soft Control (ANN, Fuzzy Logic), Hard control (MPC, Robust Controller), and Hybrid control, which includes the fusion of two controllers, i.e., Neuro-Fuzzy controller and Adaptive Fuzzy. Due to better constraints handling, multiple operating points, and energy conservation strategies, [10] mainly focused on MPC. The authors in [11] developed a PMV-based HVAC control strategy by predicting the mean radiant temperature using machine learning techniques. The simulation results showed that the proposed technique reduced energy consumption by 10%. Similarly in [12], the authors compared PMV-based control and conventional temperature-based control techniques for HVAC control in a typical glazed office room. Simulation results showed that the PMV-based control technique achieved better thermal comfort and reduced energy consumption by 1.6%.

In [13], the floor plan created in Autodesk Revit was exported to DesignBuilder for accurate modeling of the building's geometry. EnergyPlus was interfaced with MATLAB using the Building Controls Virtual Test Bed (BCVTB) to simulate the building and generate data for training the ANN model. Two optimization scenarios were introduced to achieve a reduction in energy consumption: Standard Tariff and Time Of Use (TOU) tariff. For better performance, the optimization was run in two modes: first with Genetic Algorithm (GA), and second with MPC. With a Standard Tariff, a 25% reduction in energy consumption was achieved, while a TOU tariff minimized energy cost by 27% as compared to a simple baseline technique. The authors in [14], used ANN for the prediction of building air temperature. The ANN based model predictive control (NNMPC) reduced cooling energy consumption by 27.34% and heating energy consumption by 39.04%. In [15], an EnergyPlus-based Model Predictive Control was proposed to reduce HVAC system energy consumption and improve comfort levels. Data exchange between EnergyPlus and MATLAB/Simulink was facilitated by the MLE+ MATLAB toolbox, while parameter identification was performed in MATLAB/Simulink using the System Identification Toolbox. The proposed system reduced HVAC system energy consumption by 28.9% for the heating season and 2.7% for cooling mode as compared to a simple baseline strategy. In [16], a Multilayer Perceptron (MLP) neural network with the best network After Multiple Iterations (BNMI) algorithm is used to model the system. Moving average and median smoothing filters are applied to eliminate random and spike noise in the data. The operating cost of the MPC is compared with a fixed set point, and the results show that the MPC reduces the operating cost between 6% and 73%, depending on the season. The authors in [17] developed an MPC for an institutional building, utilizing AI techniques to model the building. The MPC is used to reduce the consumption of natural gas by optimizing the conversion between daytime indoor setpoints and night setback values as a function of the predicted weather. Building heating demand is decreased by 4.3%, and natural gas consumption and greenhouse gas emissions are reduced by 22%. In [18], the authors proposed a new technique in which the HVAC system learns the occupants' preferences and sets the temperature according to requirements. Occupants were tracked through RFID, and user interaction was done through a webpage/mobile app. The Application Core (APPC) confirms room temperature and saves the user's voting in a database, then determines new set points based on user voting and sends them to the HVAC system in EnergyPlus. APPC and EnergyPlus were interfaced with Ptolemy II software. The K-Means learning algorithm was also simulated to adjust room temperature. Due to this, users could express their comfort and by voting, change the temperature by 10 °C from its present value. The proposed technique achieved better thermal comfort and reduced energy consumption by 26.79% compared to a simple baseline. An EnergyPlus-based energy management system (EMS) ON/OFF controller is developed in [19]. The authors compared the results with and without the use of an ON/OFF controller in EnergyPlus, and the results showed that the ON/OFF controller improved the HVAC energy use by 19%. Researchers in [20] described the implementation of data-driven algorithms, i.e., rule-based control, reinforcement learning, MPC, and learning MPC techniques in a complex building. Data-driven schemes were used to predict internal and external disturbances acting on the system and also create building models. Learning MPC is described as having high potential based on four different characteristics. An occupancy-based control model based on a nonlinear optimization scheme for reducing energy cost with a better comfort level is proposed in [21]. The Monte-Carlo simulation method is used to determine the probabilistic occupancy schedule. This method reduced the energy consumption of Doha and Phoenix cities by 14.71% and 15.19%, respectively, compared to other strategies like an always-on thermostat, a schedule-based model, and a rule-based occupancy-driven model. In [22] and [23], the authors compared the conventional rule-based control with model predictive control and proposed a strategy in which latent heat and humidity are considered in MPC. The proposed strategy performed better than the other two schemes in terms of thermal comfort, energy consumption, and humidity control. In [24], a deep reinforcement learning approach is implemented to control the HVAC system with demand response purposes so that thermal comfort and less energy consumption are achieved with better demand response. Energy consumption is reduced by 22% using reinforcement learning with normal HVAC operation compared to the baseline controller. In the case of reinforcement learning with demand response, energy consumption is increased and decreased by up to 50%, keeping thermal comfort within suitable limits.

The SMC scheme is used to demonstrate robustness against uncertainties for temperature and humidity set points in the Air Handling Unit (AHU) [25]. Optimal values for temperature and humidity are achieved by regulating the airflow and water flow rate in the AHU. SMC outperformed PID in terms of energy consumption due to its shorter settling time and lower overshoot for air and water flow rates in AHU. In [26], the SMC technique is used to optimize the energy consumption of the building for a nonlinear minimum phase VAV system. For the regulation of temperature in the zone, the airflow rate in the VAV system is optimized. In the presence of disturbances, SMC ensures robustness by effectively tracking set points for temperature, resulting in less overshoot and negligible settling time compared to conventional PID. An integral terminal sliding mode controller (ITSMC) is used to regulate/control the superheat temperature of the evaporator and enhance energy efficiency [27]. This research suggested ITSMC is more effective than SMC in controlling the HVAC system.

In this work, the ECE department has been modeled in EnergyPlus, and thermal comfort-based temperature setpoints are maintained in the building using PID, MPC, and SMC controllers. Machine learning techniques are used to estimate the thermal comfort-based temperature setpoints for heating and cooling. Multiple training algorithms are compared to model PMV-based temperature setpoint estimation. Furthermore, a unique comparison of ON/OFF, MPC, and SMC has been made for their control accuracy and the indoor thermal comfort maintained by these controllers. To the best

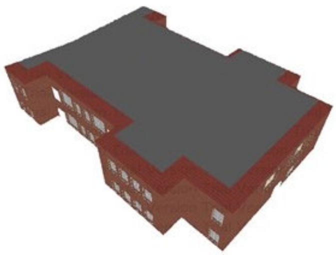

FIGURE 1. Building model used for simulation in EnergyPlus.

of our knowledge, such a comparison has not been made before.

III. SYSTEM MODEL

In this work, the ECE Department at CUI, Lahore Campus (31.55 °N, 74.33 °E), is modeled for testing of our proposed controllers. The building is a two-story structure consisting of offices, laboratories, lecture halls, and bathrooms with a floor area of 26264.69 ft^2. The construction materials used for the floor and walls are concrete tiles and bricks, respectively. The heating and cooling system is a single duct VAV system with reheat boxes serving the two-story building. The building is modeled in DesignBuilder and then exported to EnergyPlus. Building operating conditions, such as load information, system, and zoning operation schedules, were implemented. Figure 1 shows the building model designed with DesignBuilder. System information is generated after a detailed survey of the ECE department. We used the MLE+ toolbox for the co-simulation of MATLAB and EnergyPlus. MLE+ interfaces EnergyPlus software with MATLAB/Simulink to implement control schemes for building energy management. It permits the co-simulation of two programs on a time-step level. Inputs, output objects, schedules, setpoints, and control actuators are created in EnergyPlus '.idf' file. The MATLAB code, after reading outputs from EnergyPlus, determines new inputs for every time step.

A. BUILDING ENVELOPE INFORMATION

The external envelope of the building is made up of brick walls, glass doors, and single-panel glass windows. The wall is composed of 9.0-inch brick and a 1.25-inch cement layer. The U-value for the exterior wall is 0.331 Btu/ft^2.F. For the roof, the U-value is 0.516 Btu/ft^2.F, and for the floor, the U-value is 0.137 Btu/ft^2.F. The glass for the single and double windows is single-pane, with a U-value of 1.09 Btu/ft^2.F. The windows to external walls ratio of the building is 16.60%.

B. BUILDING ZONES

The building has a total of 28 rooms, which include lecture rooms, faculty offices, storage rooms, bathrooms, and laboratories. Figure 2 shows the zone structure on the first floor and Figure 3 shows the ground floor.

Solar gains, internal gains, and envelope gains are factors that cause the temperature to vary over time. Each thermal zone is efficiently controlled by a single thermostat.

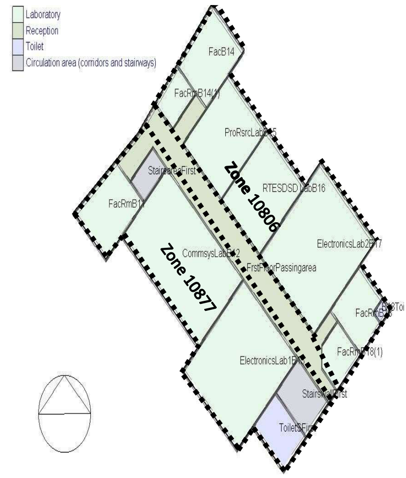

FIGURE 2. Zone structure of the first floor.

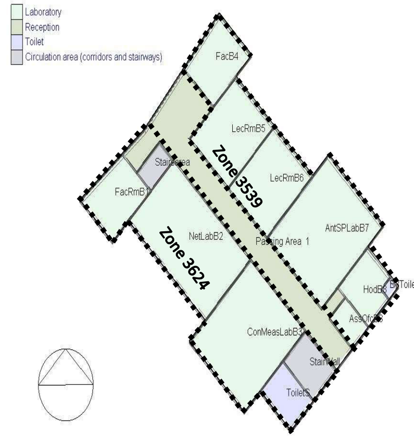

FIGURE 3. Zone structure of the ground floor.

Zone 3624 is composed of rooms located on the left side of the ground floor, while zone 3539 is composed of rooms located on the right side of the ground floor. Similarly, rooms on the left side of the first floor are grouped as Zone 10877, and rooms on the right side of the first floor are grouped as Zone 10806.

1) SCHEDULES

Lighting, equipment, and occupancy schedules are in the load portion of the input file.

- **Occupancy**: The office hours for the building are between 8:30 am and 8:30 pm. After 5:30 PM, occupancy levels are reduced to 60%. Occupancy is at 20% of the maximum between 2:30 pm and 5:30 pm on weekends.
- **Lighting**: The lighting level is at 90% from 8:30 am to 5:30 pm. At night, the lighting level is reduced to 95% of the maximum lighting load. The lighting load is reduced to 80% during weekends.
- **Equipment**: The equipment load varies between 40% to 80% of the full load from 8:30 am to 5:30 pm. At night,

it is reduced to 80% of the full load. During the weekend, the equipment load operation remains at 5%.

IV. CONTROL SYSTEM DESIGN AND SIMULATION

The system architecture of the proposed smart controller for HVAC is shown in Figure 4. The smart controller consists of two modules: 1) PMV-based Setpoint Estimator for Heating/ Cooling and 2) MPC/SMC controller for estimating the supply air temperature for HVAC. The PMV-based setpoints for heating/cooling and supply air temperature are supplied to the HVAC controller for maintaining a comfortable indoor environment and reducing the energy consumption of HVAC. The sensor node for each zone measures the zone's air temperature, humidity (RH), mean radiant temperature (MRT), and calculates the average PMV values. The user provides the metabolic rate/activity level, air velocity, preferred PMV index, and clothing insulation. The control scheme is explained in the subsections.

A. PMV-BASED SETPOINTS ESTIMATOR

The ANN is utilized to model the PMV-based temperature setpoint estimator. Kang et al. proposed a thermal comfort control technique that is based on the PMV index. This method uses inverse computation of the PMV index to adjust the setpoints of the thermostatic controller according to consumer-defined PMV and variations in indoor climate [28]. Our main objective is to maintain a thermally comfortable indoor environment by maintaining PMV-based temperature setpoints. For PMV inverse calculation, the dataset is collected from the ASHRAE thermal comfort index website, and then the ANN is trained with input variables (PMV, zone mean radiant temperature, air velocity, clothing insulation, metabolic rate, and zone relative humidity). The thermostat setpoint is taken as the output variable. The general structure of the ANN model is shown in Figure 5.

The ANN is trained with different hidden layers and training functions. The transfer function tangent sigmoid is used in this training. The data is divided into such manner: 85% training data, 10% validation data, and 5% test data. The training results for Levenberg Marquardt (LM) and Bayesian Regularization (BR) training algorithms with different hidden neurons are shown in 6. Figure 6 shows the regression and MSE values of each configuration. Based on rigorous testing, we selected the ANN model (with 30 hidden neurons) trained with the BR training function for the prediction of PMV-based heating and cooling setpoints.

B. MODELING OF ON/OFF CONTROLLER IN EnergyPlus

A simple ON/OFF controller is established with an EnergyPlus building model to determine the feasibility of the co-simulation framework of MATLAB/Simulink and EnergyPlus to execute a multi-zone control scheme. Its thermal comfort and power consumption performances are taken as benchmarks.

The PMV is used as a thermal comfort control criterion, which is calculated through six parameters: zone mean radiant temperature, zone air temperature, zone relative humidity, metabolic rate, air velocity, and clothing insulation. The mean radiant temperature, air temperature, and relative humidity are computed at each iteration in EnergyPlus. Further details about the simulation environment are described in Table 1.

TABLE 1. Assumptions for Simple ON/OFF Controller, SMC, and MPC.

HVAC Operation Timing	Weekdays 8:00 AM - 8:30 PM Weekends 2:00 PM - 5:00 PM
PMV setpoints	[-0.5,0.5]
PMV variable assumptions	Metabolic rate = 1.2 Met, air velocity = 0.12 m/s, clothing insulation during summers = 0.5 clo, clothing insulation during winters=1 clo
Weather and Schedules	TMY3- Lahore Pakistan, Design case occupancy lighting and equipment schedules

In the heating and cooling modes, the thermostat constantly compares the room air temperature with the setpoint temperature and offset temperature. When the zone air temperature reaches the upper limit of the cooling temperature setpoint (offset of 1°C), cooling starts and continues until it ranges at the lower limit of the setpoint. When a lower limit is reached, cooling stops until the room air temperature reaches the higher limit of the setpoint again.

The energy management system (EMS) module provides high-level, superintendent control, which overrules certain features of EnergyPlus program modeling techniques. The EMS is established assuming one building with four zones, which are heated and cooled by ON/OFF heating and cooling coils. The cooling and heating setpoints are enabled in the EnergyPlus file (IDF) known as an input data file.

The ON/OFF control scheme written in the EMS module is incorporated into EnergyPlus by overruling the portion of the EnergyPlus section that generates the HVAC activity status. The EMS can operate the HVAC in full-on mode, partially on mode, and fully off mode based on the heating and cooling setpoints of the zone air temperature.

C. MODEL PREDICTIVE CONTROLLER DESIGN IN EnergyPlus

The principle of the EnergyPlus model-based predictive controller is to keep the PMV comfort in range and optimize the supply air temperature of the AHU to minimize the power consumption of the HVAC system. The objective function $O(x,t)$ of the proposed MPC is:

$$O(x,t) = \min\big(Q_{\text{chiller}}(x,t) + Q_{\text{biogas}}(x,t) + Q_{\text{bioelc}}(x,t) + Q_{\text{fan}}(x,t) + Q_{\text{pump}}(x,t)\big) \tag{1}$$

Subject to

$$|\text{PMV}| \leq 0.5 \tag{2}$$

$$\begin{Bmatrix} 12.8 \leq T_s(x,t) \leq 13, & \text{CC} = 1 \\ 15 \leq T_s(x,t) \leq 16, & \text{HC} = 1 \end{Bmatrix} \tag{3}$$

where symbols used in equations are described in Table 2.

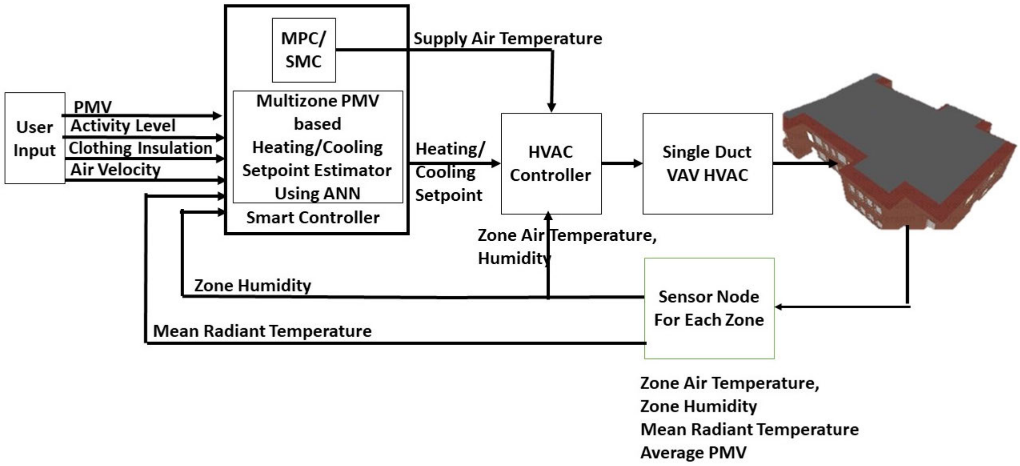

FIGURE 4. **Proposed control system architecture.**

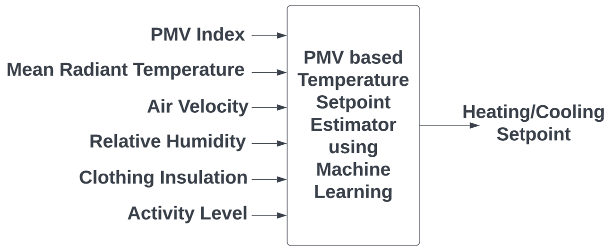

FIGURE 5. **PMV-based temperature setpoint estimator using ML.**

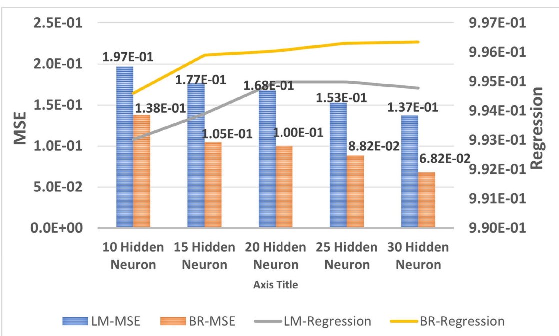

FIGURE 6. **ANN training results in different Training Functions & Hidden Layers. The left y-axis shows MSE while the right y-axis shows the Regression.**

Equation (1) shows that the optimization problem has two parameters that should be isolated into two distinctive enhancement modes; the first one is the cooling mode and the second is the heating mode. Optimization is accompanied by two modes utilizing outdoor temperature separately.

$$\begin{Bmatrix} O = \min\left(f_{\text{power}}(x,t)\right), & \text{If (2) is satisfied.} \\ O = \min\left(\left|f_{\text{PMV}}(x,t)\right|\right), & \text{Otherwise} \end{Bmatrix} \tag{4}$$

Equation (4) ensures thermal comfort is preferred over reducing energy consumption. If the thermal comfort constraint described in (2) is fulfilled, then this algorithm reduces the usage of power. Constraint selections in (2) between the PMV limit and power limit can shift during the same horizon.

TABLE 2. **Description of Symbols used in MPC Equations.**

Symbol	Description
t	time in seconds
x	optimized supply air temperature setpoint
O(x,t)	the total HVAC system power in Watts (W) at time t,
$Q_{chiller}$(x,t)	chiller power (W) at time t,
Q_{biogas}(x,t)	boiler gas power (W) at time t,
Q_{bioelc}(x,t)	Boiler electric power (W) at time t,
Q_{fan}(x,t)	fan power (W) at time t
Q_{pump}(x,t)	hot water & chilled water pump power (W) at time t,
CC	Cooling coil, CC=1 mean Coil ON, CC=0 mean Coil Off
HC	Heating coil, HC=1 mean Coil ON, HC=0 mean Coil Off
T_s(x,t)	the supply air temperature (^{o}C) at time t

The prediction horizon of the MPC is two hours, while the control horizon is one hour. Optimized supply air temperature setpoints are determined by the MPC through Average PMV, zone air temperature, and HVAC system power demand data from EnergyPlus at every execution horizon. The controller updates the supply air temperature and thermal comfort-based heating/cooling setpoints after every hour. The control scheme of the MPC is shown in Figure 7. In the simulation layer, heating and cooling setpoints, and the supply air temperature setpoint of the AHU are inputs for the EnergyPlus model, while HVAC system power demand, air temperature of rooms, relative humidity of rooms, mean radiant temperature, and real simulation time (which is utilized for the time synchronization between EnergyPlus and MATLAB/Simulink) are the outputs of EnergyPlus.

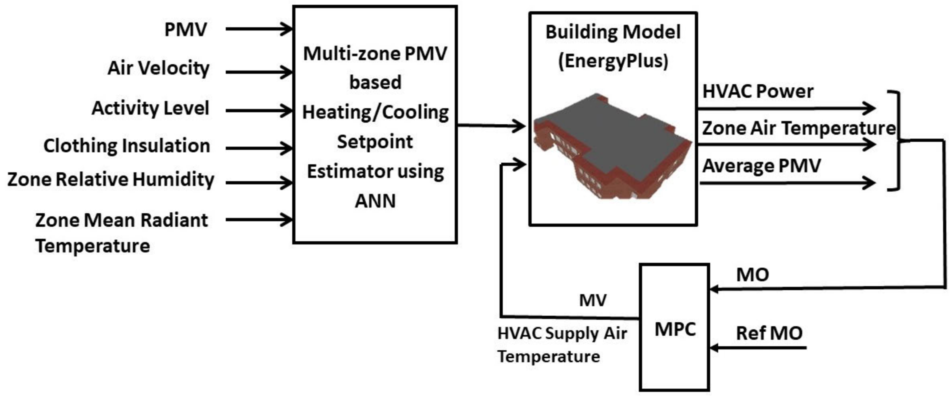

FIGURE 7. MPC control scheme.

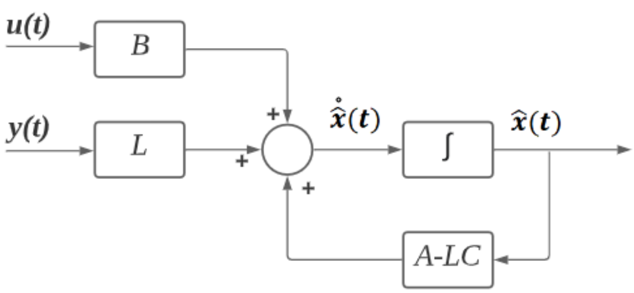

FIGURE 8. Observer design.

D. SLIDING MODE CONTROLLER DESIGN IN EnergyPlus

Figure 8 shows a full order observer design, which is used to estimate unavailable states for the model.

$$\hat{x}(t) = (A - LC)\hat{x}(t) + (B - LD)u(t) + Ly(t) \tag{5}$$

Let's consider a general plant system

$$\dot{x}(t) = f(x, t) + g(x, t)u \tag{6}$$

The basic notion of the SMC is to define a sliding surface, then by using control law, enforce the system states to remain on a sliding surface. Consider the tracking error

$$e = x_d - x_1 \tag{7}$$

$$\dot{e} = \dot{x}_d - \dot{x}_1 \tag{8}$$

x_d is the desired signal. The sliding mode function can be written as

$$s(t) = ce(t) + \dot{e}(t) \tag{9}$$

Hurwitz condition must be satisfied by c, $c > 0$. Tracking errors and their derivatives are defined as

$$\begin{aligned} \dot{s}(t) &= c\dot{e} + \ddot{e} \\ \dot{s} &= c(\dot{x_d} - \dot{x}) + (\ddot{x_d} - \ddot{x}) \\ \dot{s} &= c(\dot{x_d} - \dot{x}) + (\ddot{x_d} - \ddot{x}) \end{aligned} \tag{10}$$

By using reaching law

$$\begin{aligned} \dot{s} &= -k|s|^a sign(\frac{s}{\varphi}) \\ k &> 0, 1 < a < 0 \end{aligned} \tag{11}$$

For analysis of stability, the Lyapunov function is considered as:

$$V = \frac{1}{2}s^2 \tag{12}$$

$$\dot{V} = s\dot{s} \tag{13}$$

The fourth-order state-space model of the building used for SMC is represented by (14).

$$\begin{aligned} \dot{x}_1 &= k_{1q}x_1 + k_{2q}x_2 + k_{3q}x_3 + k_{4q}x_4 \\ \dot{x}_2 &= m_{1q}x_1 + m_{2q}x_2 + m_{3q}x_3 + m_{4q}x_4 \\ \dot{x}_3 &= n_{1q}x_1 + n_{2q}x_2 + n_{3q}x_3 + n_{4q}x_4 \\ \dot{x}_4 &= p_{1q}x_1 + p_{2q}x_2 + p_{3q}x_3 + p_{4q}x_4 \end{aligned} \tag{14}$$

The fourth-order state-space model of the building is obtained by using Matlab State Space Identification Toolbox which uses data from EnergyPlus software. The matrix form of (14) is shown in (15).

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} k_{1q} & k_{2q} & k_{3q} & k_{4q} \\ m_{1q} & m_{2q} & m_{3q} & m_{4q} \\ n_{1q} & n_{2q} & n_{3q} & n_{4q} \\ p_{1q} & p_{2q} & p_{3q} & p_{4q} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \tag{15}$$

where k_{iq}, m_{iq}, n_{iq},and p_{iq} are constants obtained from the Matlab state space identification toolbox. Equation (16) is obtained by substituting the values of constants in (15).

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} 38.36 & 12.9 & 8.86 & 126.5 \\ 1.38 & 4.07 & 6.48 & 30.28 \\ 30.79 & 19.55 & 1.26 & 157.93 \\ 67.20 & 44.9 & 130.56 & 250.23 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \tag{16}$$

Input and state variables of the system model are described as:

u as supply air temperature of HVAC system
x_1 state as zone 3539 air temperature
x_2 state as zone 3624 air temperature
x_3 state as zone 10805 air temperature
x_4 state as zone 10877 air temperature

Errors are defined in (17) to track all the states to their reference values,

$$\begin{aligned} e_1 &= x_1 d - x_1 \\ e_2 &= x_2 d - x_2 \\ e_3 &= x_3 d - x_3 \\ e_4 &= x_4 d - x_4 \end{aligned} \tag{17}$$

where $x_1 d$ is the zone temperature setpoint.

For stability, Lyapunov candidate function V has to be negative definite, since

$$\begin{aligned} \dot{s_1} &= -k|s_1|^a sign(s/\varphi) \\ k &> 0 \\ 1 &< a < 0 \end{aligned} \tag{18}$$

$$sign(s_1) = \begin{Bmatrix} 1, & if\ s_1 > 0 \\ -1, & if\ s_1 < 0 \end{Bmatrix} \tag{19}$$

and sign(0)$\epsilon[-1,1]$
Substituting (18) in (13) yields

$$\begin{aligned} \dot{V_1} &= -s_1 k|s_1|^a sign(\frac{s_1}{\varphi}) \\ \dot{V_1} &= -k|s_1|^a \varphi sign(\frac{s_1}{\varphi}) \end{aligned} \tag{20}$$

where $k > 0$, $1 < a < 0$
Since $\frac{s_1}{\varphi} sign(\frac{s_1}{\varphi}) = |\frac{s_1}{\varphi}|$

$$\dot{V_1} = -k|s_1|^a \varphi |\frac{s_1}{\varphi}| \tag{21}$$

As $|\varphi| = \varphi$ for $\varphi > 0$, substituting in (21)

$$\dot{V_1} = -k|s_1|^{(a+1)} \tag{22}$$

$\dot{V_1}$ is negative definite. Formulate u

$$\begin{aligned} u = -k|s|^a sign(\frac{s}{\varphi}) - c_1(\dot{x}_{1d} - \dot{x}_1) - c_2(\dot{x}_{2d} - \dot{x}_2) \\ - c_3(\dot{x}_{3d} - \dot{x}_3) - c_4(\dot{x}_{4d} - \dot{x}_4) \end{aligned} \tag{23}$$

In our simulation, the controller updates the supply air temperature and thermal comfort-based heating/cooling setpoints after every 1 hour. The modulation gain of the SMC is designed based on the error signal and is chosen as 10 to ensure the sliding mode is enforced. The fixed gain is used to make sure that the error converges to zero in the shortest possible time asymptotically. The control scheme of SMC is shown in Figure 9.

E. RESULTS AND DISCUSSIONS

In this work, we compared the performance of SMC, MPC, and ON/OFF controllers. Firstly, we evaluated the performance of MPC-based optimized supply air temperature and heating/cooling setpoints. Secondly, we used MPC-optimized heating and cooling setpoints in a simple ON/OFF controller. Additionally, we evaluated the performance of MPC when external weather parameters such as disturbances are included on the output side. The simple ON/OFF controller is simulated with different fixed heating and cooling setpoints, PMV-based heating and cooling setpoints, and MPC-optimized heating and cooling setpoints.

F. COMPARATIVE ANALYSIS for MAINTAINING HEATING SETPOINTS DURING WINTERS

A simple ON/OFF controller, an EnergyPlus model-based model predictive controller, and a sliding mode controller are simulated for one week during the winter season (January 23-January 30) using typical meteorological year data for Lahore, Pakistan. Figure 10 shows the outdoor air temperature for the winter season. Figure 11 represents the supply air temperature estimated by MPC. In a simple ON/OFF controller, the supply air temperature is fixed at 16°C, while in the MPC, it is optimized and regulated between 15°C to 16°C for the heating season.

The MPC can regulate a lower average supply air temperature than the baseline during the winter mode. From January 23 to January 24, the outdoor temperature increases, and therefore, the supply air temperature regulated by the MPC is the lowest during this period. Figure 12 and Figure 13 show the air temperature of Zone3539 maintained by a simple ON/OFF controller at heating setpoints of 22°C and 23°C, respectively. Figure 14 shows the air temperature of Zone3539 maintained by the MPC for the PMV-based heating setpoints, while the air temperature maintained by the SMC for PMV-based heating setpoints is shown in Figure 15. It shows the MPC removes the temperature overshoots and stabilizes it more efficiently. The SMC removes overshoot more efficiently than a simple ON/OFF controller. However, the HVAC system energy consumption is higher than other controllers. The HVAC system turns ON or OFF depending upon the heating setpoint. The operating mode has values in fractions, which means the HVAC system can be partially ON. When the room air temperature is below than lower heating setpoint, the HVAC system will be ON until the room air temperature reach at its heating setpoint. Upon reaching the heating setpoint, the HVAC turns OFF until the air temperature reaches the lower heating setpoint.

Figure 14 shows the air temperature for the zone 3539 room maintained by MPC while Figure 15 shows the air temperature for zone 3539 using SMC. At the starting point, SMC failed to obtain good thermal comfort as shown in Figure 15; the temperature is lower than the lower heating setpoint. The MPC achieved better air temperature than a simple ON/OFF controller and the SMC. We have also tested the performance of a simple ON/OFF controller for maintaining the PMV-based setpoints. Figure 16 shows the air temperature of zone 3539 maintained by a simple ON/OFF controller at PMV-based heating setpoints. Room air temperature performance is better than a simple ON/OFF controller and it efficiently rejected disturbances when the PMV-based setpoints are used for simple ON/OFF controller simulation. The accuracy of the controller increased using the PMV-based setpoints than fixed setpoints.

Figure 17 shows thermal comfort performance (PMV) for zone 3539 in different cases respectively. To minimize energy,

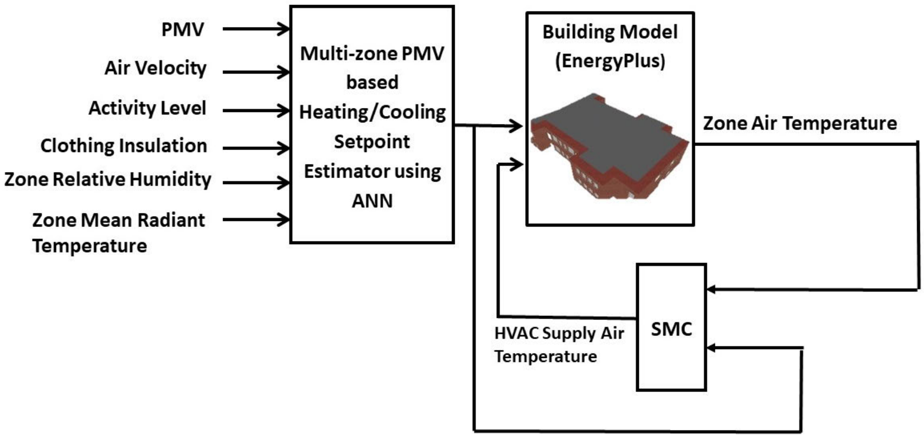

FIGURE 9. SMC control scheme.

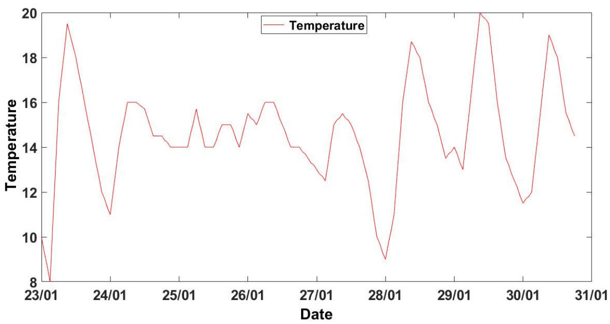

FIGURE 10. Outside air temperature in winters.

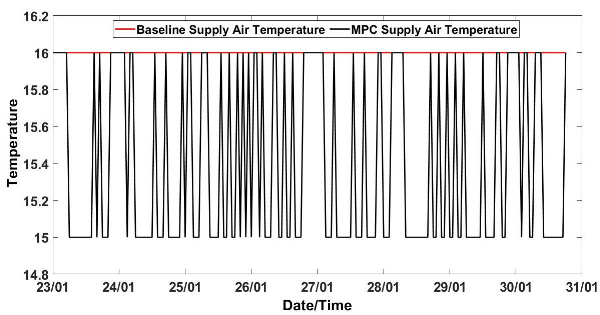

FIGURE 11. Supply air temperature in winter season.

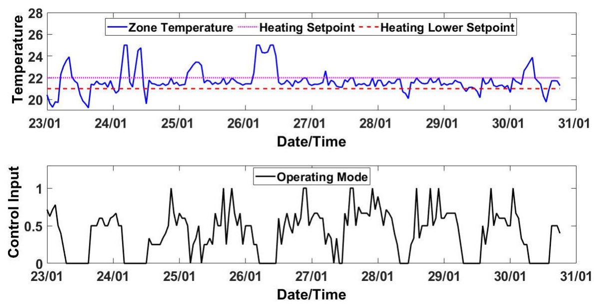

FIGURE 12. Air temperature of Zone3539 maintained by Simple ON/OFF controller at heating setpoint of 22°C.

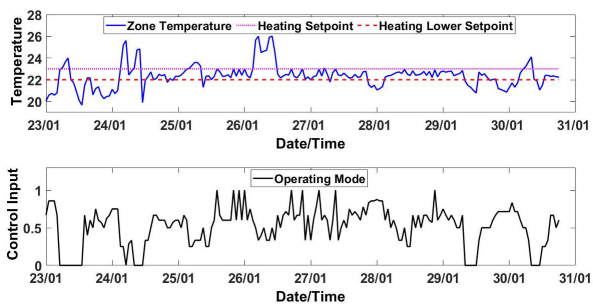

FIGURE 13. Air temperature of Zone3539 maintained by Simple ON/OFF controller at Heating Setpoint of 23°C.

MPC pushes PMV near boundaries. For example, on the first day in the heating season, the PMV value is nearer to the minor constraint boundary, while on the next day i.e., (in mid of 27th and 28th of January) is close to the upper constraint boundary for the zone 3539.

The average air temperature maintained by different controllers during winters in different zones is summarized in Table 3. The power consumption of HVAC with different controllers is described in Table 4. Total power consumption is calculated by adding boiler gas power, boiler electric power, fan power, and hot water pump power. MAE parameters are calculated for checking the control accuracy of selected controllers. A comparison of MAE for maintaining the setpoints in the winter season is shown in Table 5. The average PMV values in all zones maintained by different controllers are shown in Table 6. MPC outperformed other controllers in terms of average PMV value. MPC maintained thermal comfort between −0.3 to 0.3. Similarly, the average PPD% in the different zone is summarized in Table 7.

G. COMPARATIVE ANALYSIS for MAINTAINING COOLING SETPOINTS DURING SUMMERS

The EnergyPlus model-based model predictive controller, sliding mode controller, and Simple ON/OFF controller are

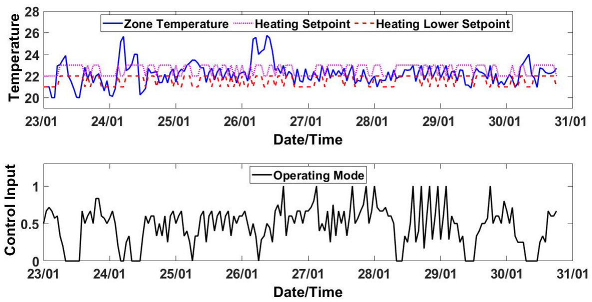

FIGURE 14. Air temperature of Zone3539 maintained by the MPC at the PMV-based setpoints during Winter Season.

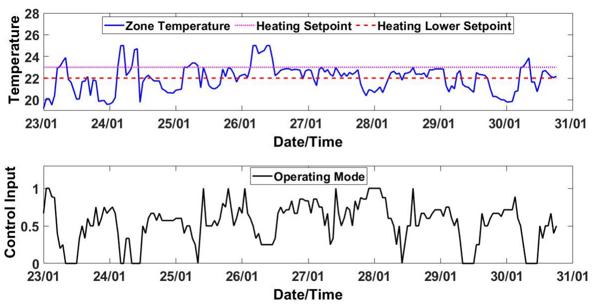

FIGURE 15. Air Temperature of Zone3539 maintained by the SMC at Heating Setpoint of 23°C.

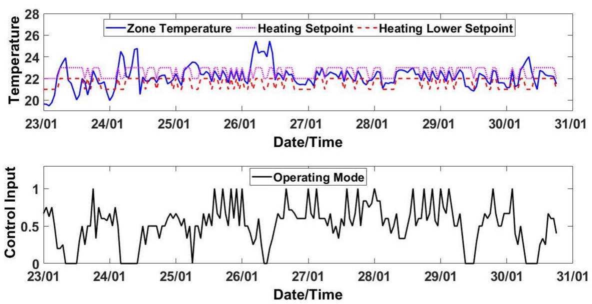

FIGURE 16. Air temperature of Zone3539 maintained by ON/OFF control at PMV-based setpoints.

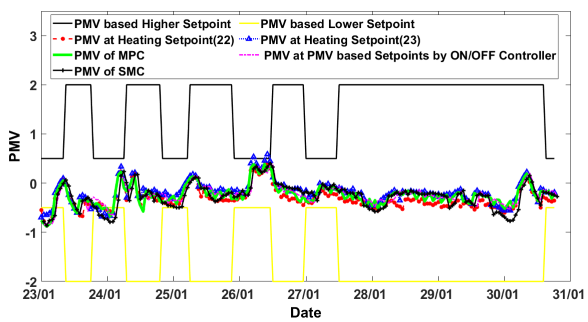

FIGURE 17. Thermal comfort comparison of Simple ON/OFF, MPC, and SMC during Winter season.

simulated from (3rd April to 10th April) summer time using a typical meteorological year, Lahore Pakistan. Supply air temperature varies between 12.8°C to 13.0°C for MPC while supply air temperature remains fixed at 12.8°C for simple ON/OFF controller.

TABLE 3. Comparison of Average Air Temperature maintained by different controllers during Winters.

Zone	Simple ON/OFF at HSP 22^oC	Simple ON/OFF at HSP 23^oC	MPC	SMC	Simple ON/OFF with PMV-based setpoints
3539	21.69	22.30	22.39	22.34	22.12
3624	22.29	23.07	22.71	22.0	22.69
10806	21.27	21.92	22.84	21.97	21.75
10877	21.88	22.69	22.97	22.70	22.32

TABLE 4. Comparison of HVAC Power Consumption (KW) during Winter Season.

	Simple ON/OFF at HSP 22^oC	Simple ON/OFF at HSP 23^oC	MPC	SMC	Simple ON/OFF with PMV-based setpoints
Total Power (KW)	1676	2262	1930	2314	2001

TABLE 5. Comparison of MAE during the Winter Season.

Zone	Simple ON/ OFF at HSP 22^oC	Simple ON/ OFF at HSP 23^oC	MPC	SMC	Simple ON/ OFF with PMV-based set-points	MPC with distur-bances
3539	0.83	1	0.97	0.32	0.92	0.96
3624	0.62	0.4668	0.71	0.37	0.60	0.68
10806	0.78	1	0.50	0.62	0.96	0.93
10877	0.48	0.46	0.71	0.50	0.56	0.59

TABLE 6. Comparison of Average PMV during the Winter Season.

Zone	Simple ON/ OFF at HSP 22^oC	Simple ON/ OFF at HSP 23^oC	MPC	SMC	Simple ON/OFF with PMV-based set-points Life	MPC with distur-bances
3539	0.32	0.20	-0.25	-0.27	-0.24	-0.34
3624	0.071	0.080	0.00	0.08	0.0	-0.08
10806	0.41	0.28	-0.32	-0.38	-0.32	-0.41
10877	0.18	0.02	-0.095	-0.03	-0.09	-0.18

TABLE 7. Comparison of Average PPD during Winter Season.

Zone	Simple ON/ OFF at HSP 22°C	Simple ON/ OFF at HSP 23°C	MPC	SMC	Simple ON/ OFF with PMV-based set-points	MPC with distur-bances
3539	8.09	6.98	7.32	7.88	7.27	8.28
3624	6.28	6.01	5.80	5.84	6.17	6.09
10806	9.10	7.49	7.89	9.30	7.94	9.18
10877	6.69	5.85	6.18	5.97	6.16	6.64

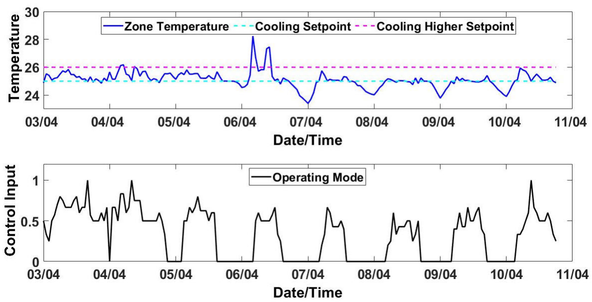

FIGURE 18. Air temperature of Zone3539 maintained by Simple ON/OFF controller at cooling setpoint of 25°C.

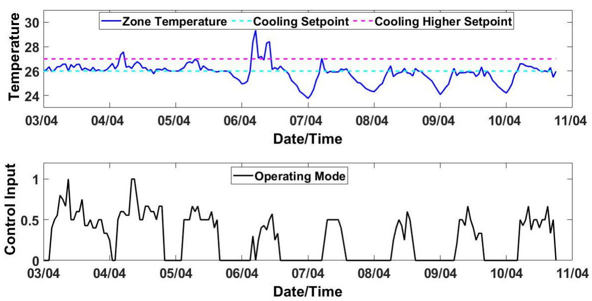

FIGURE 19. Air temperature of Zone3539 maintained by Simple ON/OFF controller at cooling setpoint of 26°C.

Figure 18 and Figure 19 show air temperature at cooling setpoints of 25°C and 26°C respectively. The room air temperature maintained by MPC for cooling setpoints is shown in Figure 20 while the air temperature of zone 3539 maintained by SMC is shown in Figure 21. MPC removes the overshoots and maintains temperature proficiently as in the graph for Zone 3539 on the 6th of April afternoon. When external weather parameters are included as disturbances, MPC efficiently rejects the effect of disturbances and provides a better comfort level with a reduction in energy consumption. Figure 22 shows the performance of a simple ON/OFF controller when PMV-based setpoints are used for simulation. Figure 23 shows the PMV values. At some points for Zone 3539 on the 4th and 6th of April afternoon MPC has

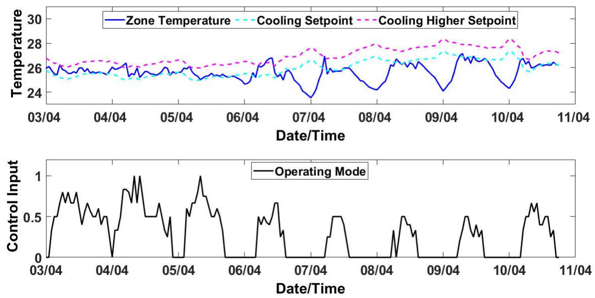

FIGURE 20. Air temperature of Zone3539 maintained by the MPC at the PMV-based setpoints during summer season.

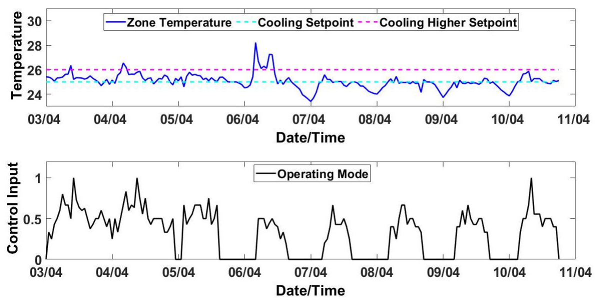

FIGURE 21. Air temperature of Zone3539 maintained by SMC at cooling setpoint of 25°C.

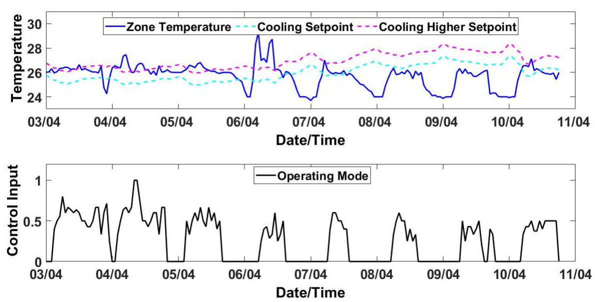

FIGURE 22. Air temperature of Zone3539 maintained by Simple ON/OFF controller at PMV-based Setpoints during summer season.

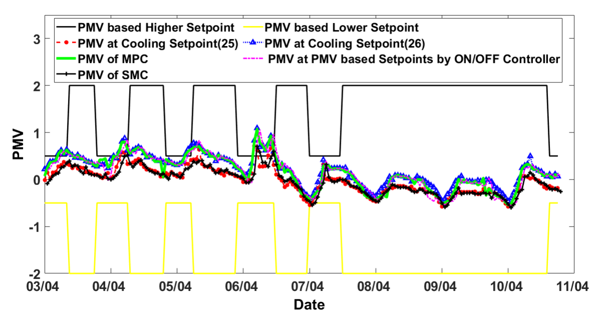

FIGURE 23. Comparison of thermal performances of controllers in summer season.

a higher PMV value for energy-saving purposes as compared to a simple ON/OFF controller.

TABLE 8. Comparison of average air temperature maintained by different controllers during summers.

Zone	Simple ON/OFF at CSP 25°C	Simple ON/OFF at CSP 26°C	MPC	SMC	Simple ON/OFF with PMV-based setpoints
3539	25.10	25.87	25.05	25.61	25.68
3624	25.38	26.18	25.349	25.98	25.94
10806	25.06	25.86	25.00	25.60	25.65
10877	25.22	26.05	25.19	25.88	25.81

TABLE 9. Comparison of HVAC power consumption (KW) during the summer season.

	Simple ON/OFF at CSP 25°C	Simple ON/OFF at CSP 26°C	MPC	SMC	Simple ON/OFF with PMV-based setpoints Life
Total Power (KW)	2004	1698	1710	1942	1757

TABLE 10. Comparison of MAE during the summer season.

Zone	Simple ON/ OFF at CSP 25°C	Simple ON/ OFF at CSP 26°C	MPC	SMC	Simple ON/ OFF with PMV-based set-points	MPC with distur-bances
3539	0.39	0.54	0.53	0.41	0.48	0.60
3624	0.51	0.55	0.66	0.49	0.59	0.78
10806	0.37	0.50	0.50	0.36	0.45	0.55
10877	0.4	0.53	0.60	0.42	0.53	0.69

TABLE 11. Comparison of average PPD during the summer season.

Zone	Simple ON/ OFF at HSP 25°C	Simple ON/ OFF at HSP 26°C	MPC	SMC	Simple ON/ OFF with PMV-based set-points	MPC with distur-bances
3539	6.53	7.99	6.08	7.57	8.24	8.04
3624	8.77	10.49	5.47	7.03	10.40	10.44
10806	7.93	9.01	6.10	6.66	9.08	9.03
10877	10.56	11.52	8.58	7.57	11.46	11.51

The average air temperature maintained by different controllers in different zones is summarized in Table 8, while

TABLE 12. Comparison of average PMV during the summer season.

Zone	Simple ON/ OFF at HSP 25°C	Simple ON/ OFF at HSP 26°C	MPC	SMC	Simple ON/ OFF with PMV-based set-points	MPC with distur-bances
3539	0.01	0.20	0.16	-0.03	0.15	0.19
3624	0.17	0.40	0.34	0.15	0.33	0.38
10806	0.05	0.28	0.24	0.03	0.22	0.26
10877	0.18	0.42	0.37	0.16	0.358	0.41

HVAC power consumption for cooling is shown in Table 9. The MAE parameter is used for checking the accuracy of all controllers. MAE for maintaining cooling setpoints in all zones by different controllers is shown in Table 10. Similarly, average PPD and average PMV values in all zones with different controllers are summarized in Table 11 and Table 12, respectively.

Results showed that MPC consumes 11.94% less power than SMC and 14.68% less than a simple ON/OFF controller (fixed cooling setpoint of 25°C). For cooling setpoint 26°C, the simple ON/OFF controller consumes 0.70% less than MPC but provides more discomfort hours than MPC. A simple ON/OFF controller for maintaining PMV-based setpoints reduced the power consumption by 3.48% than simple ON/OFF controller with fixed setpoint and thermal comfort is also improved.

V. CONCLUSION AND FUTURE WORK

In this work, three control techniques, namely (a) Simple ON/OFF controller, (b) SMC, and (c) MPC are compared in terms of thermal comfort, MAE performance index, and energy consumption. Simple ON/OFF controller produced more overshoots in air temperature at fixed setpoints and PMV-based setpoints. While the MPC performance for maintaining comfortable room air temperature is better compared to a simple ON/OFF controller. Moreover, the MPC controller efficiently rejects the effect of disturbances while accurately maintaining indoor air temperature.

During summers, the MPC saves 11.94% more energy than SMC and 14.68% more energy than a simple ON/OFF controller at fix cooling setpoint of 25°C. For a cooling setpoint of 26°C, the power consumption of a simple ON/OFF controller was 0.70% lower than MPC but provides more discomfort hours. The PMV-based setpoints reduce 3.48% power consumption when used in a simple ON/OFF controller while maintaining a thermal comfort level. In terms of control accuracy, the SMC outperformed MPC and ON/OFF controller.

During winter, the MPC consumes 13.16% more energy than a simple ON/OFF controller at 22°C. However, the thermal comfort of the ON/OFF controller was inferior to MPC.

The MPC consumes 17.20% less energy than the ON/OFF controller at the heating setpoint 23°C and thermal comfort was also superior to the ON/OFF controller. Similarly, the MPC consumed 19.89% less energy than SMC and 3.67% less energy than PMV-based setpoints. In terms of control accuracy, the SMC outperformed ON/OFF and MPC.

In this work, the MPC and SMC are based on the state-space model of the physical building. For the future prospect of this work, another effective approach is to use deep learning techniques for building modeling and HVAC control. Another future aspect of this work is the hardware implementation of a smart controller. The SMC-based smart controller can be implemented using a microcontroller. However, in SMC, the sign function is approximated as a sigmoidal function to avoid high-frequency switching (chattering). The controller can be used to regulate the supply air and zone air temperature for a single duct VAV system with reheat. On the other hand, the MPC controller requires a building model and optimization techniques to determine the optimal variables using an objective cost function equation. Due to its higher computational burden compared to SMC and Simple ON/OFF controllers, MPC is better suited for implementation on a Raspberry Pi board.

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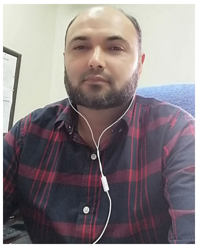

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