

Adaptive Motion-Based Tracking Optimization for HVAC (Heating, Ventilating, and Air Conditioning) System Efficiency Enhancement

Mr. Kaushikkumar K. Patel¹, Dr. Piyush R. Patel²

Ph.D. Scholar, Electrical Department, Faculty of Engineering and Technology,

Sankalchand Patel University, Dist.-Mehsana, Visnagar, Gujarat¹

kaushikp1234@gmail.com¹

Associate Professor (Electrical), School of Engineering,

Indrashil University, Rajpur, Kadi, Gujarat²

dr.piyushpatel22@gmail.com²

Abstract

The Heating, Ventilated, and Air conditioning (HVAC) system is mandatory to ensure a comfortable indoor environment in buildings, which controls high temperature ups and downs. However, high installation costs, energy consumption and noise production are considered as the boundaries of the HVAC system, which shows the impact on the efficiency of the building. Therefore, the research work employs speed-based tracking optimization HVAC System (MBTO-HVAC) to adapt to the proportional-intended (PI) controller parameters of the HVAC system. In addition, the energy consumption and thermal comfort index of the HVAC system is improved and economic cost function is estimated to reduce computational requirements. Customized controller increases economic performance and assesses thermal conditions of indoor and external temperature. The optimal set point temperature is obtained to increase the energy efficiency performance of the AC system. In particular, the developed algorithm promotes the global optimal value and ignores the local optima to increase the convergence speed, which increases the system efficiency. Eventually, the MbTO-HVAC system receives AC power, air flow rate, CO₂ level, and humidity and temperature values.

Keywords: Air Conditioning, Proportional-Integral Controller, Motion-based Tracking Optimization, control system.

1. Introduction

In recent years, scientific and technological progress have played an important role in the development of the thermal control technology [9] of the air conditioning system. The environment temperature and moisture content are regulated by AC, which is used to increase air quality and thermal comfort. Three primary environment of domestic, commercial and industrial systems used air conditioning systems [10]. In addition, the optimal temperature, humidity, and air quality of the car's interior are maintained by the motor vehicle AC system, which helps to keep a comfortable cabin [11] [2]. Energy-skilled HVAC systems are used to meet energy demands and to reduce carbon footprints. In smart building technologies, advanced artificial intelligence techniques are integrated into energy management. In addition, customized building energy consumption is obtained from learning deep reinforcement (DRL) and the optimal strategies were obtained from environmental interactions to create efficient

tools [12] [1]. Energy consumer devices are combined with HVAC system [13], which is used for energy waste stagnation by incorporating intelligent operations. In addition, problems of malfunction are addressed to find solutions to low energy consumption [14] [15] [16] [8].

HVAC's space heating and cooling system are used to meet the need for living thermal comfort, which reduces building energy and GHG emissions [3]. Mathematical models were used for quantitative model-based methods, which are based on basic laws of physics to provide process behaviour. Various process variables established analytical excesses, functional, underlying or artificial excesses. In addition, a set of algebraic or temporary relations of the system of the system, input and output introduced excess [4]. In addition, stochastic control algorithm behaves with uncertainty in cooling load measurement and cooling capacity of chillers. The energy efficiency of the Child Water Plant is maximized by a model-free optimization strategy, which uses the extremes demanding control to adjust control input based on total power consumption. In addition, non-provided power consumption functions are considered by collaborative neuro dynamic adaptation method [6]. In each HVAC system, energy consumption is influenced by the driving style and expands the range of developed vehicles [17] [2].

The main contribution of research is to design the HVAC system to maintain the air quality of the indoor manufacturing sector and is used to regulate temperature, pressure and humidity. In the HVAC system, the cooling water flow rate decreases to improve energy efficiency and maintain the desired temperature. In addition, temperature control is managed by the PI controller and the sponge control of the cooling system is considered to regulate the temperature of the building area, which leads to energy efficiency. The control mechanism of the PI controller adjusts the heating or cooling output to regulate the temperature, which monitors room temperature and determines the error between the evaluated temperature and the desired set point temperature. The major contribution of research has been discussed in this way,

Motion-based Tracking Optimization (MbTO) algorithm:

The MbTO algorithm is utilized to improve the performance of HVAC system, which optimizes the control parameters of PI controller to find the optimal solutions effectively. Population diversity and phase balancing are maintained by the optimal solutions, which increases the convergence speed and improves the system efficiency. The MbTO algorithm resolves different problems through different convergence behaviors, which exploits high convergence rate in the multi-model test functions. Moreover, the developed algorithm is focused to move towards local optima avoidance and improves the global exploration ability under low dimensional condition.

2. Literature Review

In the literature review section, various existing methods and their boundaries are discussed to prove the efficacy of MBTO-HVAC. Juan Yang et al. [1] deep reinforcement learning (DRL) approach developed, which is used to customize the HVAC system. In addition, extensive number of areas can be managed by HVAC control strategy. Multi-phase training and attention mechanisms were included to enhance the stability and scalability performance of the model. However, irregular calibration created complication in the maintenance of accuracy and the relevance of the model in real -world data. Abubakar Unguwanrimi Yakubu Et al. [2] The temperature control plan and fuzzy logic control (FLC) presented to analyze the reaction of the automated air conditioning (AAC) system. In addition, the control strategy improved performance in thermal comfort, stable-state errors and temperature control. However, poor adjustment caused temperature effects.

Jaesung park et al. [3] Initiated the real-time-based HVAC control method to assess indoor and outdoor thermal conditions. In addition, real -time energy can be adapted by adjusting the HVAC set point temperature. In addition, real -time forecasted mean vote (PMV) values were calculated by variables. In hot and dry climatic conditions, cooling energy in residential buildings was reduced. However, accurate estimation of mean radiant temperature (MRT) values is challenging. Hesam hassanpour et al. [4] Hybrid modeling method developed to detect mistakes in HVAC system and increase isolation. In addition, heating and cooling air valves were used to maintain supply air and temperature. However, the lack of hidden pattern extraction was considered as a limit to represent common and defective situations.

Francesco M. Solinas et al.[5] In addition, the trained model building uses thermal response and deep determinant policy shield (DDPG) agent. However, the control of temperature and air mass flow rate introduced complexity in the system. J.A. Borja-Kande et al. [4] to reduce computational requirements, suggested the controller of QP-based economic future. In addition, the operation and economic costs were reduced by the controller. However, two chiller units were required to provide high cooling supply.

2.1 Problem statement

The HVAC system consists of heating, ventilating and air conditioning system to control the temperature and air circulation in the building area. Moreover, the HVAC system contains air conditioners, furnaces, heat pumps and duct works. In the HVAC system, proper heating is maintained to provide ventilation air and moisture, and dust is removed by the air-conditioning unit. Moreover, the controller is essential in an HVAC system, which acts as a central nervous system of HVAC, which regulates the heating temperature to attain high energy efficiency. PI controller is used to determine the current temperature errors and to address the accumulated past errors. The system is ensured to maintain the desired set point temperature, even when faced with external disturbances.

Moreover, the controller improved the comfort and energy efficiency of the building. Let the building's heat gain (O_{AC}) provided by the HVAC system is modelled as follows,

$$O_{AC} = y_a w_a (x_s - x_r) \quad (1)$$

where, y_a is the mass flow rate, x_s is the supply air temperature, return air temperature is represented as x_r and the specific heat of supply air is indicated as w_a respectively. HVAC system requires identification and control strategy to reduce computational effort; hence the system considers the adaptive PI controller to improve the system efficiency. Moreover, the mathematical expression for the transfer function ($A(S)$) of the HVAC system is represented as follows,

$$A(S) = \frac{M(S)}{T(S)} = \frac{K_s}{I_s + 1} e^{-I_d s} \quad (2)$$

where, transfer function for building area is denoted as $M(S)$, transfer function for the time is denoted as $T(S)$, K_s , I_d and I_s are the plant gain, dead time and time constant respectively. Moreover, complex frequency variable is indicated as s . The heat transfer rate in the evaporator and condenser is denoted as,

$$J_{ev} = (\varepsilon D_{\min})_{ev} (X_{in, ev} - X_6) = y(i_7 - i_6) \quad (3)$$

$$J_{cd} = (\varepsilon D_{\min})_{cd} (X_3 - X_{in, cd}) = y(i_2 - i_3) \quad (4)$$

where, heat transfer rate of the evaporator is denoted as J_{ev} , heat transfer rate of condenser is expressed as J_{cd} , the thermal capacitance rate of the heat exchanger is represented as D_{\min} , fluid temperature in the evaporator is indicated as $X_{in, ev}$. Moreover, the condenser fluid temperature is denoted as $X_{in, cd}$, the effectiveness of the heat exchanger is denoted as ε and the fluid temperature at points of three and six is denoted as X_3 and X_6 respectively. The mass flow rate of fluid is represented as $y(\)$. PI controller is a kind of linear controller, which composes the controller error based on the setting point and process output. Moreover, the controller output depends on the proportion and integral error values. At the time ' t ', the control signal is determined for a PI controller and is derived mathematically as follows,

$$s(t) = k_p e(t) + k_i \int_0^t e(t) dt + s_0 \quad (5)$$

where, $s(t)$ is the controller output, s_0 is the initial output of the controller, the proportional parameter is indicated as k_p and the integral parameter is expressed as k_i , respectively. Moreover, $e(t)$ is the error at the time 't' respectively. Moreover, the PI controller transfer function is formulated as below,

$$A(S) = \frac{M(S)}{E(S)} = k_p + \frac{k_i}{s} \quad (6)$$

where, complex frequency variable in the Laplace transform domain is represented as S . Transfer function for the energy is represented as $E(S)$, respectively. Moreover, the MbTO algorithm provides optimal tuning of PI controller parameters improves the efficiency of the HVAC system and reduces the computational complexity of the system respectively.

3. Proposed Methodology

Air duct, refrigeration cycle and cooling water system are included in the HVAC system. Moreover, the evaporator, compressor and condenser are insisted in the refrigeration cycle. Furthermore, the fluid heat exchanger acts as a condenser and the refrigerant pipelines are connected with the throttle. The evaporator is placed near the air duct inlet valve and the condenser is placed near the outlet of the air duct. A cooling tower is included in the cooling water system, which is used to provide the cooling water to the condenser and exchanger. In the cooling water system, water pumps and pipelines are utilized to transfer the water into the system. In the air duct, the airflow is driven by the fan and the air is converted into two parallel channels in the three-fluid condenser. In an HVAC system, dampers are used to control the airflow to different zones of a building, allowing for precise temperature regulation in each area, which ultimately provides improved comfort and energy efficiency by directing air only where it is needed, preventing unnecessary heating or cooling in unoccupied spaces. In the HVAC system, a "gain controller" refers to the "proportional gain" thing within a PI controller, which determines how strongly the system reacts to a measured temperature difference (error) between the current room temperature and the desired set point; essentially, it controls the speed and responsiveness of the heating or cooling process by adjusting the output signal based on the error, with a higher gain leading to faster adjustments but potentially causing overshooting if not properly tuned. Hence, sea horse optimization [19] and slap swarm optimization [20] are employed in the gain controller for the perfect tuning purpose, which enhances the system performance. Moreover, controlled flow rate, cooling and heating rate and air mass flow rate will be considered as the expected performance metrics and the developed method is implemented on the MATLAB platform. Schematic diagram of the MbTO-HVAC system is represented in figure 1.

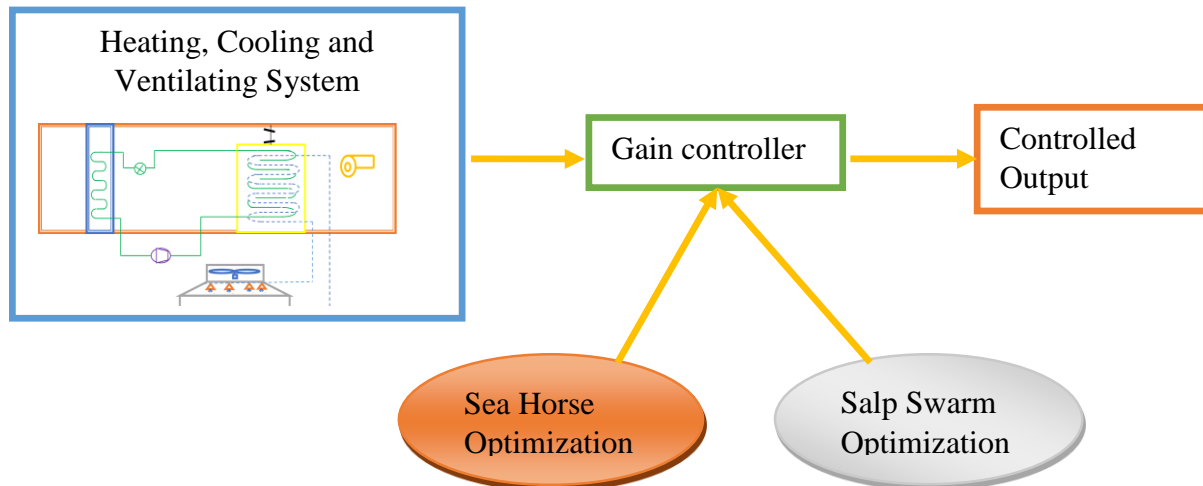


Figure 1. Schematic diagram of proposed methodology

3.1 Mathematical model

The mathematical model of the temperature regulation performance can be derived as follows,

$$T_{reg} = \frac{M_{a,c}}{M_{a,s}} \quad (7)$$

where, T_{reg} is the temperature regulator, $M_{a,c}$ is the air mass flow rate and $M_{a,s}$ is the total supply air mass flow rate respectively.

3.1.1 Refrigerant

3.1.2 Compressor

3.1.3 Condenser

3.1.4 Evaporator

3.1.5 Fan and Pumps

According to the cooling load ratio, the rated air mass flow rate is calculated to balance the energy consumption of the fan and compressor. Moreover, the energy consumption of the compressor and water pump is balanced to determine the rated water mass flow rate. The mathematical expression for the energy consumption of the fan (E_F) and water pump (E_{pump}) is calculated below,

$$E_F = \frac{x_a I_F}{1000 \rho_a \eta_f} \quad (8)$$

$$E_{pump} = \frac{x_w m w_{pump}}{1000 \eta_{pump}} \quad (9)$$

where, mass flow rate and air density are represented as x_a and ρ_a respectively. Moreover, the fan head is represented as I_F , fan efficiency is represented as η_f . Moreover, x_w is the water mass flow rate, m is the gravitational acceleration, head of the pump is indicated as w_{pump} and the pump efficiency is illustrated as η_{pump} respectively. Under varying operating conditions, the indoor load ratio is changed with the air volume and the rate of cooling water flow is changed with respect to their demand. Moreover, the square relationships between air and water flow rates are utilized to calculate the flow rates of fan and pump heads, which are expressed in mathematical terms as follows,

$$I_F \approx \left(\frac{x_a}{x_{a,rated}} \right)^2 \quad (10)$$

$$w_{pump} \approx \left(\frac{x_w}{x_{w,rated}} \right) \quad (11)$$

Where, flow rate of fan is denoted as I_F , flow rate of pump head is represented as w_{pump} , rated mass flow rates of air and water are represented as $x_{a,rated}$ and $x_{w,rated}$ respectively.

3.1.6 Heat Exchanger

The heat exchanger is utilized for the heating and cooling purposes of HVAC system, which transfers the heat between the fluid and the source. Moreover, the heat exchanger is connected to the air conditioning unit by the diminutive end. Identical functions are performed by the expansion valve and are affected by the temperature, while the fixed orifice tube diameter. Two fluids are utilized in the heat exchanger, one is flown through the tubes and the other fluid flows around the tubes. In addition, the solid wall can be utilized to separate the fluids and the heated or cooled fluid flows through the tubes. In the heat exchanger, the mathematical expression for the heat transfer is calculated as below,

$$\varepsilon = \frac{1 - \exp \left[-N_{tu} \left(1 - \frac{d_{\min}}{d_{\max}} \right) \right]}{1 - \frac{d_{\min}}{d_{\max}} \exp \left[-N_{tu} \left(1 - \frac{d_{\min}}{d_{\max}} \right) \right]} \quad (12)$$

$$N_{tu} = \frac{EW}{d_{\min}} \quad (13)$$

where, \exp is the exponential factor, the heat transfer efficiency of the heat exchanger can be represented as ε and the number of heat transfer units is represented as N_{tu} respectively. Moreover, d_{\min} and d_{\max} is the heat capacities of smaller and larger fluid capacities. In addition, the heat transfer coefficient is indicated as E and the heat exchanger area is represented as W respectively.

3.2 Mathematical model of PI controller

A PI-controller is simulated to find more required control parameters. Moreover, the refrigerator and freezer components track the internal temperature of the refrigerator by setting the ambient temperature, which is used for temperature-controlling purposes. The controllers improved the accuracy and control level, which were used to evaluate the temperature change of the refrigerator, speed changes and humidity control of the compressor. When the refrigerator attains a specific temperature, a small oscillation occurs in the temperature of the refrigerator, which is used to visualize the speed of the compressor. Moreover, the integral effect is eliminated by the inefficient PI controller. In addition, the oscillation effect is eliminated by the control system, which increases their convergence to the desired temperature. Electric systems of PI controllers are widely used in DC and AC applications to control constant or slowly variable quantities. Figure 2 indicates the schematic diagram of PI controller.

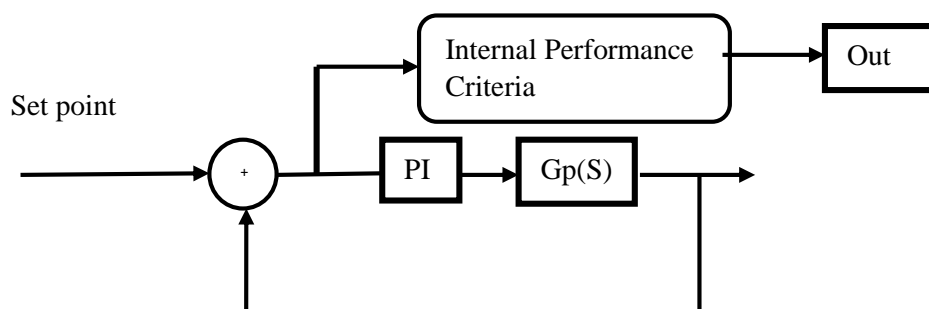


Figure 2. Schematic diagram of PI controller

The electrical systems utilized the PI controller to optimize the integral and proportional gains in the alternating obediently, which can be mathematically formulated as follows,

$$v(t) = K_p e(t) + K_i \int e(t) \quad (14)$$

where, the proportionality factor is denoted as K_p and the integration factor is represented as K_i respectively. The difference between the input signal and output signal is referred to as error, which is denoted as $e(S)$ and is mathematically represented as follows,

$$e(t) = o(t) - l(t) \quad (15)$$

where, $o(t)$ is the output signal, $l(t)$ is the input signal and $e(t)$ is denoted as the error signal. Suitable control parameters are determined by developing the integral performance condition, which depends on the error in the control system. IAE is expressed as the integral absolute error is expressed by,

$$IAE = \int_0^{\infty} |e(t)| dt \quad (16)$$

Most appropriate solutions are selected from the current situations, which is done by the MbTO algorithm. The optimization process begins by entering initial values in controller parameters. When the smallest error value is reached, the optimization process provides the most suitable controller parameters.

3.3 Motion-based Tracking Optimization

PI control parameters of proportional gain (k_p) and integral gain (k_i) are used to determine the response of controller and are adjusted to optimize the performance of HVAC system. The meta-heuristic algorithm of the MbTO algorithm is inspired by the feeding patterns and intricate movement patterns. Moreover, search space and optimal solutions are determined by improving the search capabilities. Moreover, positive information about the solutions is maintained to increase the population diversity and balance the exploration, and exploitation phases respectively.

Inspiration

The MbTO algorithm is inspired by the characteristics of the salp swarm and sea horse optimization [20] behaviours. Salp-chain forms a chain form for moving together, which is suggested for locomotion and the seahorse optimization utilized in the exploration and predation phase. In the exploration phase, spiral movement and Brownian motion with sea waves have occurred to explore better solutions. Moreover, the food capture scenario is taken in the predation phase and the concept of seahorse is included in the salp-swarm optimization. The mathematical models are used to explore and exploit the search spaces both stationary and search regions. Moreover, local optima avoidance is outperformed by the MbTO algorithm and true global optimum values are obtained by the sample points distribution.

Initialization

The whole population of search solutions in the search space of the problem is denoted as,

$$Y_i = \begin{bmatrix} Y_1' \dots Y_1^{\dim} \\ \dots \dots \dots \\ Y_{pop}' \dots Y_{pop}^{\dim} \end{bmatrix} \quad (17)$$

where, pop is represented as population, dim is denoted as the dimension, Y_i' is the solution, and Y_i is the initial solution. Each solution is randomly generated between the lower and upper bound of a specific problem denoted by,

$$Y_i^j = q_1 \cdot (Y_U - Y_L) + Y_L \quad (18)$$

where, q_1 is the random value in between 0 and 1, Y_i^j is the solution of j^{th} dimension in the i^{th} individual, i is the positive integer, which insists in the range from 1 to pop and j is the positive integer, which insists in the range of $[1, dim]$ respectively. Moreover, Y_U, Y_L are the upper and lower bounds.

Fitness function

The individual with minimum fitness is regarded as an elite individual and is expressed mathematically as follows,

$$f(Y_i) = \min(\text{Integral Absolute Error}) \quad (19)$$

$$Y_{elite} = \arg \min[f(Y_i)] \quad (20)$$

Therefore, Y_{elite} is the leader solution, $f(\cdot)$ represents the objective function value of a given problem.

Phase (i): Movement phase

In order to trade-off between exploration and exploitation performance, q_2 is considered as the cut-off point. This defines the solutions that need to be involved in local mining or global search scenarios respectively. Here, $q_2 = randn()$, which is a normal random number between $(-1 \text{ to } 1)$ and used to differentiate multiple cases.

Case 1: Local exploitation phase - (if $q_2 > n_f$)

If the cut-off point is greater than the nought factor, the local exploitation phase takes place in the case. Where, q_2 is the cut-off point and n_f is the nought factor. The solution involves in local exploitation based on the spiral motion. The levy flight is employed to simulate the movement step size of solutions, which makes the algorithm to move towards the optimal position, while considering the quality of the present solution. The solution follows the leader's solution and the position of leader is updated based on the best region. The positional update is defined as,

$$Y_{pop}^{(t+1)} = Y_i^{j(t)} + \text{levy}(\lambda)(Y_{elite}' - Y_i^{j(t)}) \bullet \text{abc} Y_{elite}' \quad (21)$$

where, $Y_{pop}^{(t+1)}$ is the updated solution, $Y_i^{(t)}$ is the current solution, three-dimensional components of coordinates under the spiral movement are represented as a, b and c , respectively. The levy flight distribution function is denoted as $levy(\lambda)$.

$$a = \rho \cos(\theta) \quad (22)$$

$$b = \rho \sin(\theta) \quad (23)$$

$$c = \rho \theta \quad (24)$$

where, $\cos(\)$ and $\sin(\)$ are the cosine and sine factors, length of stems are represented as ρ and is mathematically represented as,

$$\rho = he^{\theta g} \quad (25)$$

where, θ is the random value between $[0, 2\pi]$, h and g are the logarithmic spiral constants and the leader solution is derived in mathematical form as below,

$$Y_{elite}' = \begin{cases} K_j + u_1(Y_U - Y_L)u_2 + Y_L & u_3 \geq 0 \\ K_j - u_1(Y_U - Y_L)u_2 + Y_L & else \end{cases} \quad (26)$$

where, optimal position in j^{th} dimension is represented as K_j , u_1 and u_2 are the balancing coefficient factor, u_3 is the random number, which used to categorize the elite solutions position. Moreover, the mathematical model for the balancing coefficient factor is formulated as below,

$$u_1 = 2e^{-\left(\frac{4t}{t_{max}}\right)^2} \quad (27)$$

$$u_2 = \left(1 - \frac{t}{t_{max}}\right) \left(2 \frac{t}{t_{max}}\right) \quad (28)$$

where, t is the iteration and t_{max} is the maximum iterations. Thus, the solution's movement strategy based on levy flight and the leader-based updation makes the algorithm to move towards the best exploiting region respectively.

Case 2: Brownian Follow-up Phase- (if $q_2 \leq n_f$)

The algorithm enables the exploration to find the regions in the movement phase. When the q_2 value is located at the left side of the cut-off point. In this scenario, the solution makes Brownian motion and along with introduces the follower solution in which the other following

solutions. Move-up is considered for overall improvement of the population and thus algorithm enables the maximum number of possible values with minimum fitness values respectively. The mathematical expression for the case is denoted as,

$$Y_i'^{t+1} = Y_i'^t + q_3 \cdot L \cdot \alpha_t (Y_i' - \alpha_t Y_{elite}') \quad (29)$$

where,

$$Y_i'^t = \frac{1}{2} (Y_i^t + Y_k^t) \quad (30)$$

where, k^{th} nearest solution is represented as Y_k^t and the position of the followers' solution is indicated as $Y_i'^t$, which makes the algorithm to move with the nearest possible solutions respectively. Moreover, the exponential factor of q_3 is represented in mathematical form as follows,

$$q_3 = \frac{1}{1 + e^{-t/t_{max}}} \quad (31)$$

where, L is the constant coefficient, which is considered as the value of 0.05. Moreover, the random walk coefficient of Brownian movement is represented as α_t and is mathematically represented as,

$$\alpha_t = \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-t}{2}\right) \quad (32)$$

$$Y^{t+1} = \frac{1}{2} (Y_i^t + Y_k^t) + q_3 \cdot L \cdot \alpha_t \left(\frac{1}{2} (Y_i^t + Y_k^t) - \alpha_t Y_{elite}' \right) \quad (33)$$

Phase 2: Looting Phase

Phase 1 solutions are utilized to execute the algorithm, which considers the probability of solutions to provide the best values. Here, two types of scenarios are obtained. The looting phase makes to stay with the current optimal or needs to make global exploration of finding any other presence of optimal values and the mathematical expression can be derived as follows,

$$Y^{2(t+1)} = \begin{cases} \beta(Y_{elite}^1 - q_3 \cdot Y^{1t}) + (1 - \beta)Y_{elite}^1 & \text{if } q_4 > 0.1 \\ (1 - \beta) \cdot (Y^{1(t)} - q_3 Y_{elite}) + \beta \cdot Y(t) & \text{otherwise} \end{cases} \quad (34)$$

where, q_4 is the random solution, which insists in the range between 0 and 1 respectively. Moreover, β decreases linearly with iterations to adjust the moving step size of the solution and is mathematically represented as below,

$$\beta = \left(1 - \frac{t}{t_{\max}}\right)^{\left(\frac{2t}{t_{\max}}\right)} \quad (35)$$

Thus, the overall algorithm enables the controller to provide the maximum gain with the minimum objective function for the HVAC system respectively.

4. Simulation setup

The MbTO-HVAC model is implemented on the MATLAB R2024b platform, which has the memory of 16GB RAM. The programming language of MATLAB computes with matrices and arrays, which are used for the data analysis. Moreover, plot functions and data are derived from the implementation platform.

4.1 Simulation diagram

Figure 3 indicates the simulation diagram for building a model with the HVAC system. Moreover, the Simulink diagram contains the building system and control system of the HVAC system.

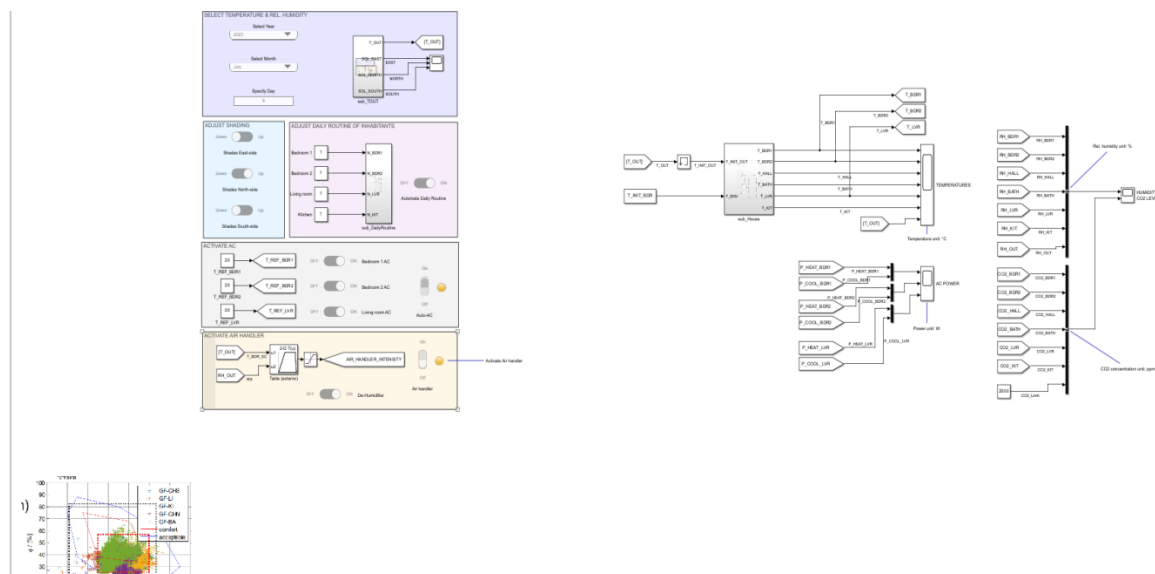


Figure 3. Simulation diagram for building model with HVAC system

4.2 Comparative Methods

In the research work, the comparative methods of DRL[1], FLC[2], MPC-RL [3], SSO-HVAC[20] and SHO-HVAC [19] methods are compared with the MbTO-HVAC system to prove the model efficacy. The comparative methods outperformed the AC power, air flow rate, CO₂ level, humidity and temperature values, which are compared with the developed system.

4.3 Comparative analysis

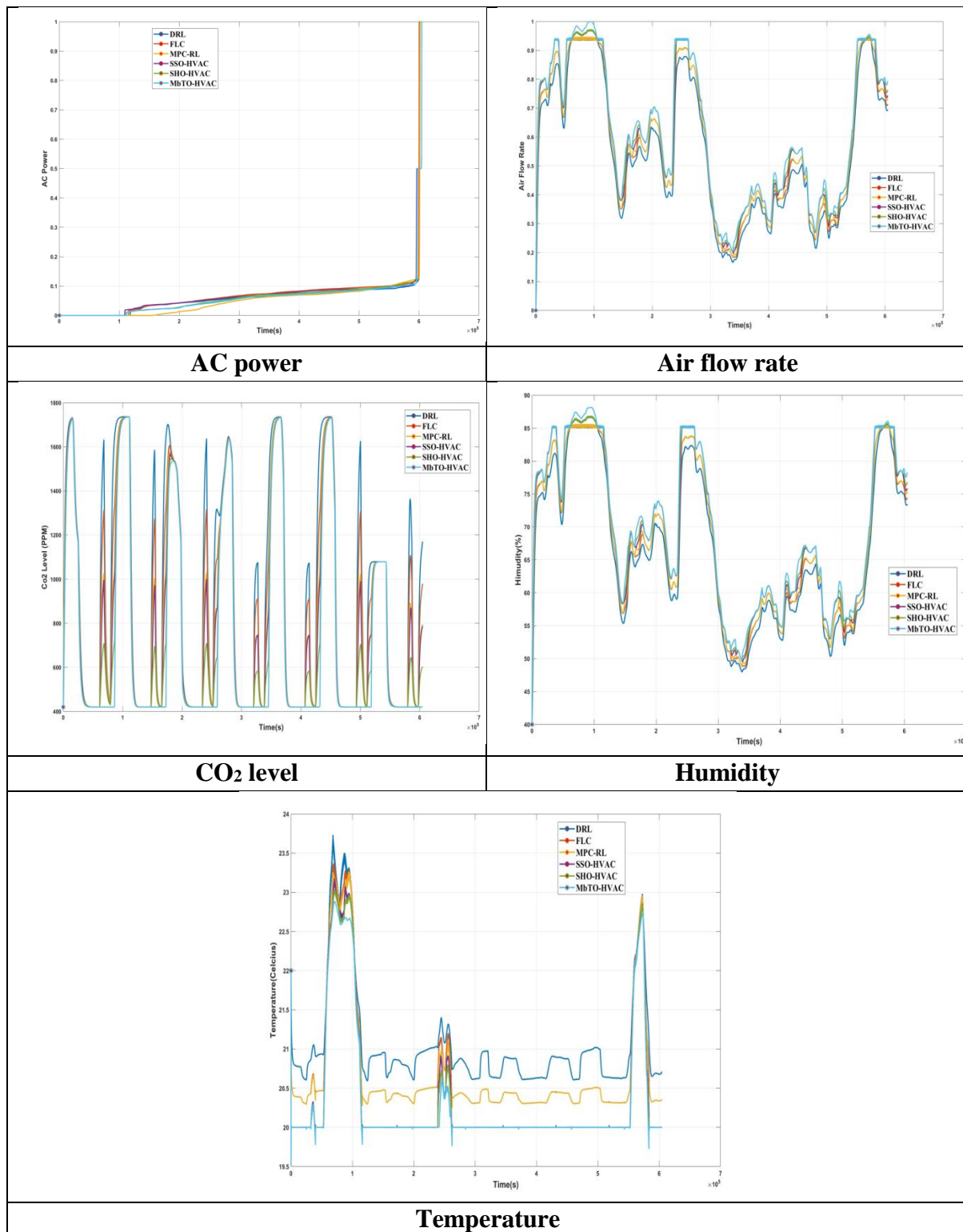


Figure 4. Comparative analysis of MbTO-HVAC system for room-1

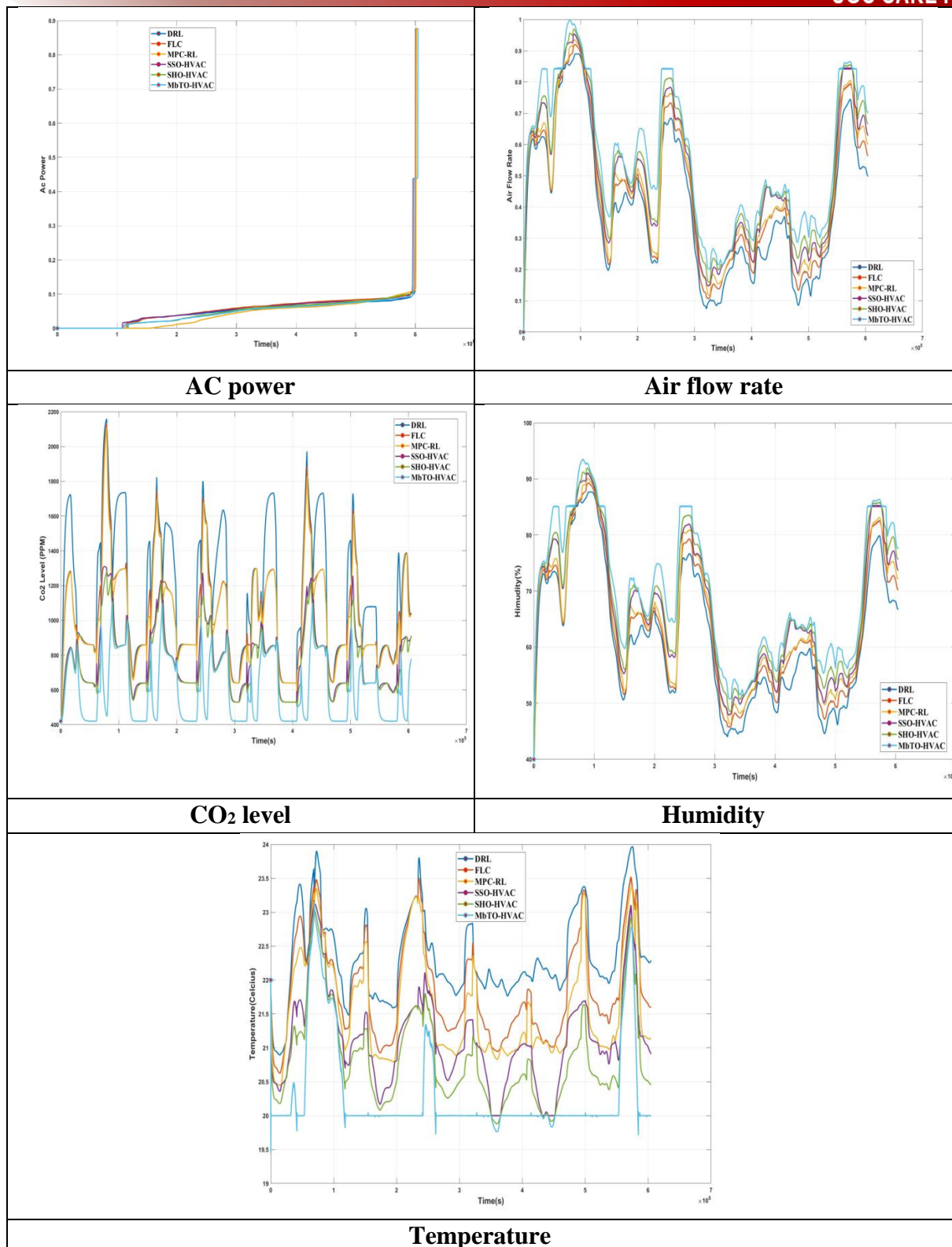


Figure 5. Comparative analysis of MbTO-HVAC system for room-2

4.4 Comparative Discussion

Table 2. Comparative Discussion Table for Room-1

Methods	AC power (KW)	Air flow rate (m^3/hr)	CO ₂ level (ppm)	Humidity (%)	Temperature (°C)
DRL	10.250	72.293	977.27	74.83	22.804
FLC	10.992	74.158	813.98	75.72	22.787
MPC-RL	12.062	76.023	698.64	76.62	22.769
SSO-HVAC	11.27	76.249	650.69	76.73	22.707
SHO-HVAC	11.483	78.113	535.35	77.63	22.69
MbTO-HVAC	10.608	80.204	420	78.64	22.61

Table 3. Comparative Discussion Table for Room-2

Methods	AC power (KW)	Air flow rate (m^3/hr)	CO ₂ level (ppm)	Humidity	Temperature (°C)
DRL	8.987	52.586	1163.7	67.99	22.28
FLC	9.638	59.674	1111.6	71.61	21.65
MPC-RL	10.576	63.139	1059.5	74.64	21.14
SSO-HVAC	9.881	66.762	881.26	75.24	21.01
SHO-HVAC	10.068	70.227	829.16	78.26	20.51
MbTO-HVAC	9.3	73.691	598.84	81.29	20

5. Conclusion

In warm and dry climatic conditions, cooling energy efficiency and increase of indoor comfort are mandatory for residential buildings. In addition, HVAC set point temperature is used to maintain indoor thermal comfort behaviour and evaluate cooling energy savings. Therefore, the MBTO algorithm is applied to the PI controller, which is used to customize the control parameters of the HVAC system. In addition, computational requirements are reduced by estimating the economic cost ceremony. Thermal conditions of indoor and outdoor temperature are assessed by customized PI controller, which improves system efficiency. In particular, the convergence speed increases by global optimal values and controls the temperature, pressure and humidity of the HVAC system. The overall building temperature is maintained at the desired temperature by reducing the flow rate of cold water. Ultimately, the MBTO-HVAC system receives AC power, air flow rate, CO₂ level, and humidity and temperature values respectively.

6. References

- [1] Yang, J., Yu, J. and Wang, S., “Heating ventilation air-conditioner system for multi-regional commercial buildings based on deep reinforcement learning,,” *Advanced Control for Applications: Engineering and Industrial Systems*, pp.190.
- [2] Yakubu, A.U., Xiong, S., Jiang, Q., Zhao, J., Wu, Z., Wang, H., Ye, X. and Wangsen, H., “Fuzzy-based thermal management control analysis of vehicle air conditioning system,,” *International Journal of Hydrogen Energy*, vol.77, pp.834-843, 2024.
- [3] Park, J., Kim, T., Kim, D., Alghimlas, F., AlRagom, F., Choi, H. and Cho, H., “Field test of machine-learning based mean radiant temperature estimation methods for thermal comfort-integrated air-conditioning control improvement and energy savings,,” *Energy Reports*, vol.11, pp.5682-5702, 2024.
- [4] Hassanpour, H., Hamed, A.H., Mhaskar, P., House, J.M. and Salsbury, T.I., “A hybrid clustering approach integrating first-principles knowledge with data for fault detection in HVAC systems,,” *Computers & Chemical Engineering*, vol.187, pp.108717., 2024.
- [5] Solinas, F.M., Macii, A., Patti, E. and Bottaccioli, L., “An online reinforcement learning approach for HVAC control,,” *Expert Systems with Applications*, vol.238, pp.121749, 2024.
- [6] Borja-Conde, J.A., Nadales, J.M., Ordonez, J.G., Fele, F. and Limon, D., “Efficient management of HVAC systems through coordinated operation of parallel chiller units: An economic predictive control approach,,” *Energy and Buildings*, vol.304, pp.113879, 2024.
- [7] Xie, X., Merino, J., Moretti, N., Pauwels, P., Chang, J.Y. and Parlikad, A., “Digital twin enabled fault detection and diagnosis process for building HVAC systems,,” *Automation in Construction*, vol.146, p.104695, 2023.
- [8] Movahed, P., Taheri, S. and Razban, A., “A bi-level data-driven framework for fault-detection and diagnosis of HVAC systems,,” *Applied Energy*, vol.339, pp.120948, 2023.
- [9] Fanger, P.O., “Human requirements in future air-conditioned environments; Menschliche Anforderungen an zukuenftigzuklimatisierendeUmgebungen,,” *Ki Luft-und Kaeltetechnik*, vol.36, 2000.
- [10] Hu, D., Qiu, C., Lu, D., Xue, H., Huang, H. and Wang, J., “Thermal comfort control for intelligent air conditioning of fuel cell vehicles,,” *Available at SSRN 4646930*.
- [11] Tijjani, I. and Bashir, H.A., “Fuzzy based temperature control analysis for automotive air conditioning system,,” *Nigerian Journal of Engineering*, vol.28., no.1, pp.1-1, 2021.

- [12] Wei, T., Wang, Y. and Zhu, Q., “Deep reinforcement learning for building HVAC control.” In *Proceedings of the 54th annual design automation conference*, pp. 1-6, 2017, June.
- [13] Ahmadi, A., Talaei, M., Sadipour, M., Amani, A.M. and Jalili, M., “Deep federated learning-based privacy-preserving wind power forecasting,” *IEEE Access*, vol.11, pp.39521-39530, 2022.
- [14] Chakraborty, D. and Elzarka, H., “Early detection of faults in HVAC systems using an XGBoost model with a dynamic threshold,” *Energy and Buildings*, vol.185, pp.326-344, 2019.
- [15] Beghi, A., Brignoli, R., Cecchinato, L., Menegazzo, G., Rampazzo, M. and Simmini, F., “Data-driven fault detection and diagnosis for HVAC water chillers,” *Control Engineering Practice*, vol.53, pp.79-91, 2016.
- [16] Mansour, S. and Raeesi, M., “Performance assessment of fuel cell and electric vehicles taking into account the fuel cell degradation, battery lifetime, and heating, ventilation, and air conditioning system,” *International Journal of Hydrogen Energy*, vol.52, pp.834-855, 2024.
- [17] Rasmussen, M.H., Lefrançois, M., Schneider, G.F. and Pauwels, P., “BOT: The building topology ontology of the W3C linked building data group,” *Semantic Web*, vol.12., no.1, pp.143-161.,2021.
- [18] Jung, D. and Sundström, C., “A combined data-driven and model-based residual selection algorithm for fault detection and isolation,” *IEEE Transactions on Control Systems Technology*, vol.27., no.2, pp.616-630., 2017.
- [19] Hashim, F.A., Mostafa, R.R., Khurma, R.A., Qaddoura, R. and Castillo, P.A., 2024. A new approach for solving global optimization and engineering problems based on modified sea horse optimizer. *Journal of Computational Design and Engineering*, 11(1), pp.73-98.
- [20] Lou, Y., Shi, Y., Yang, K., Zhou, L., Yang, T., Zhang, P., Qin, B. and Qian, Z., 2024. Modified tuna swarm optimization algorithm for brain stroke imaging with electrical impedance tomography. *Engineering Analysis with Boundary Elements*, 165, p.105786.