HVAC system modeling and control methods: a review and case study

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Improving the air quality and preserving the residents' comfort are the main tasks of HVAC (heating, ventilation, and air conditioning) systems in different buildings. A large number of control methods have been applied to HVAC systems to adjust the indoor temperature of buildings and at the same time to minimize the energy consumption and the energy cost, to reduce the peak load of the grid, and to provide ancillary services such as frequency regulation. This paper reviews different techniques proposed for HVAC systems modeling. Then, the HVAC system control methods are reviewed comprehensively and the main features of them are extracted. Furthermore, an HVAC system model is proposed and the performance of it is compared with the RLF (residential load factor) model with and without applying the Takagi-Sugeno Fuzzy (TSF) controller. The simulation results are obtained and analyzed for the proposed HVAC system and the RLF model from different aspects. The results demonstrate the efficiency and robustness of the proposed model. Moreover, the energy consumption of an HVAC system, controlled by a TSF controller, along a day is evaluated. The results show an energy saving of 10.06% of the proposed HVAC system as compared with the RLF model.

keywords: *HVAC system, control methods, takagi-sugeno fuzzy method, residential load factor, energy saving.*

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NOMENCLATURE

HVAC	Heating, ventilation, and air conditioning.
ANN	Artificial neural network.
SVM	Support vector machine.
TS	Takagi-Sugeno.
ANFIS	Adaptive network-based fuzzy inference system.
ARX	Autoregressive exogenous model.
ARMAX	Autoregressive moving average exogenous model.
ARIMA	Autoregressive integrated moving average model.
MIMO	Multi input Multi output.
SISO	Single input single output.
LQR	Linear quadratic regulator.
RNN	Recurrent neural network.
CBR	Case-based reasoning.
PSO	Particle swarm optimization.
GP	Genetic programming.
EP	Evolutionary programming.
CI	Computational intelligence.
SCM	Soft computing method.
DRL	Deep reinforcement learning.
RLS	Recursive least square.
EMS	Energy management system.
DX	Direct expansion.
MPC	Model predictive controller.
RMS	Root mean square.
ODE	Operation decision environment architecture.
KBS	Knowledge-based system.
GA	Genetic algorithm.
SNN	Static neural network.
DMM	Decision-making method.
PPD	Predicted percentage of dissatisfaction.
PSTC	Predictive smart thermostat controller.
PID	Proportional integral derivative.
CANN	Convolutional artificial neural network.
AI	Artificial intelligence.
RLF	Residential load factor.

ES Evaluation strategy.
DE Differential evolution.
ACO Ant colony optimization.
FCM Fuzzy cognitive map.
K_{nn} K-nearest neighbor.
HMM Hidden Markov model.
RLF Residential load factor.
ARXNN Autoregressive model with exogenous inputs neural network.
RBF Radial basic function.
MASRL Multi-agent system reinforcement learning.
DEMPC Distributed economic model predictive control.
AHU Air handling unit.

1. INTRODUCTION

A. Motivation and background

In recent years, energy consumption has grown rapidly causing various environmental and economic challenges worldwide. Pollution and global warming are examples of these challenges. Buildings are one of the most energy-exhaustive industries and the highest greenhouse gas (GHG) emitters, contributing to around 40% of total energy demand and 30% of GHG emission [1], [2]. To reduce energy consumption in buildings, efforts are being made to improve energy efficiency through greater design. Efficient HVAC systems can be presented to considerably reduce energy consumption and carbon emission in buildings [3]. Given the importance of models and appropriate control methods for the HVAC systems, the present paper addresses these two issues.
HVAC systems are becoming more widespread in the residential, commercial, and industrial sectors, increasing pollution and global warming. At the same time, the demand for HVAC systems is on the rise over the world while their demand rises worldwide.
One of the most challenging tasks concerning HVAC systems is plant modeling due to their complex nature. The energy consumed by an HVAC system is around 70% of the total energy of a building and 10% to 20% of the energy consumption in the developed countries [4]. These systems play a significant role in buildings because they provide the desired comfort conditions for the inhabitants. In recent years, researchers have focused on finding different strategies for controlling HVAC systems. The primary motivation behind these studies is to provide the occupants' desired comfort levels and demand-side management simultaneously, i.e., to reduce energy consumption, energy cost, carbon emission, and (demand response) peak shaving [5].
Improving the HVAC system models and utilizing proper control strategies can provide a more efficient way for energy saving and preserving thermal comfort levels. The available HVAC system models are reviewed and categorized as white-box, black-box, or gray-box models in this work. In a white-box model, the physical relationships, linked input(s), and HVAC system outputs can be described by several mathematical equations. In contrast, a black-box model implements statistical estimation approaches, and requires data collected from the input(s)/output(s), developing without knowledge of the structure, elements, or control approach. A mixture of a white-box and a black-box model provides a gray-box model.
Several control schemes are found in the literature [6]. In this paper, HVAC system control methods are classified into five groups: feedback control methods, feed-forward control methods, nonlinear control methods, artificial intelligent control methods, and hybrid control methods. Then, the advantages of these groups are separately highlighted such as achievement of super performance, fast response, credible prediction, and environment adaptation. The disadvantages of each group are also presented; for instance, some of them are inappropriate for real-time HVAC system applications, requiring large amounts of training data, and influence model stability. Moreover, a comparison is made between the advantages and disadvantages of these groups of control methods.
In addition, an HVAC system model is proposed based on the heating effects only, regardless of the impacts of air humidity and simulation results are analyzed to evaluate the performance of the proposed HVAC system and RLF model.
Then, a TSF controller is developed to examine the efficiency and robustness of the proposed HVAC system model. Actual worldwide building and weather data (real outdoor/indoor conditions) for the city of Basrah, in the south of Iraq, are used in the verification process of the model validity. Finally, a comparison is made for the simulation results to demonstrate the better performance of propose HVAC system as compared to the RLF model.

B. Contributions

In summary, the significant contributions of this paper can be highlighted as follows.
1- Different HVAC system models are presented. Moreover, various HVAC system control techniques are reviewed and categorized into different groups, and a comparison is made between their advantages and drawbacks from other aspects.
2- An HVAC system model is proposed with new relationships based only on thermal effect and control volume. A comparison is made between the presented model and the RLF model in different conditions. The two models are also tested under the TSF controller to demonstrate that the adopted HVAC system model provides a better response than the complex-structure RLF model due to its simplicity, more remarkable energy-saving, and robustness.

C. Paper organization

The paper is organized as follows. Section 2 gives a review of the different methods of HVAC system modeling. The following is an overview of the control techniques available for HVAC systems in Section 3. Section 4 presents a case study of a new HVAC system model. Section 5 reports the simulation results, analyzes, and discusses them, along with a comparison between the peresented model and the RLF model under different conditions. Conclusions and suggestions for future works are made in Section 6.

2. HVAC SYSTEM MODELING

To represent the behavior of real HVAC systems, they are modeled in distinct ways, which can be categorized into three basic types based on their structures. The first type structure is the white-box (mathematical or physical) model, which consists of two subtypes, the lumped and distributed parameter models. The second type structure is the gray-box (semi-physical) model,

and the third is the black-box model. A discussion about the advantages and shortcomings of the models mentioned above reveals that the gray-box (hybrid) model is distinctive because it involves several features closely representing the real behavior of the HVAC system [7]. By modifying the black-box or the white-box model of an HVAC system to a gray-box model, its prediction accuracy and robustness can be improved, and training time can be reduced [8].
Afram et al. reported and reviewed three modeling methods: data-driven (black-box), physics-based (white-box), and gray-box modeling techniques. They concluded that gray-box models combine the benefits of the other two types. The white-, black-, and gray-box models can be categorized as discrete/continuous [9], static/dynamic [10], [11], linear/nonlinear [12], [13], deterministic/probabilistic, and explicit/implicit models [14], [15]. Compared to data-driven models, gray-box models provide perfect generalization capabilities. According to the studies conducted on the major data-driven models, they are more precise than physics-based, shown in Fig. 1 [16].
Table 1 shows a summary of several related works. A review of various modeling strategies, used in HVAC system models, along with their advantages and disadvantages was developed in [17]. The physical model approach helps to divide the HVAC system into subsystems to reduce its complexity so that the components of an HVAC system such as cooling and heating coils, steam humidifiers, hydraulic systems, humidity and temperature sensors, pumps, mixing boxes, and fans can be modeled and described separately [18], [19].
Based on the energy conservation principle, the HVAC system mathematical model has been generated with several assumptions [20]. Arendt et al. [21] compared the performance of white-box, black-box, and gray-box models to predict the indoor temperature in a building. In most cases, the black-box models outperformed the white- and gray-box models, but the gray-box models provided a reasonable alternative for the black-box models in terms of accuracy. Using the SISO and MIMO black-box modeling techniques and the ARMAX and ARX structures, the modeling of AHU has been presented and its parameters have been identified [22]. The results demonstrated that the MIMO ARMAX model is the most efficient [22].
Afram et al. presented a white-box and gray-box model for the HVAC system and its subsystems, including the buffer tank (BT), energy recovery ventilator (ERV), radiant floor heating (RFH) system, AHU, zone, and ground source heat pump (GSHP), based on energy balance equations [23].

3. CONTROL METHODS FOR HVAC SYSTEMS

Generally, the design of a controller for an HVAC system is a complex problem. Using a proper control method for HVAC systems improves their efficiency while maintaining occupants' thermal and air quality comfort levels. The literature on HVAC control methods consists of several research papers and reports, technical articles, and numerous textbooks [24], [25]. In this paper, a comprehensive overview has been provided to classify the major optimal and supervisory control approaches and sophisticated optimization methods for the HVAC systems; Fig. 2 shows the categorization of HVAC systems control methods. These control methods have been divided into five main categories: feedback control methods, feed-forward control methods, nonlinear control methods, hybrid control methods, and Artificial Intelligent (AI) control methods [26]. This paper has focused on the AI control systems, especially on the reinforcement learning (RL) control method, which comprises a subset of machine learning, and the multi-agent system (MAS) control method.

A. Feedback control methods

Feedback is a control system in which an output is used as feedback to adjust the system's performance. It can be classified as: P, PI, PID, On-Off, LQR, and MPC. A review presented in [50] comprehensively has been summarized and compared the standard technologies and implementations available for control methods.
The most common control approach used in the HVAC system industry is the PID method because of its simplicity, efficiency in different operation conditions, and ease of implementation [51].
On the other hand, PID control methods suffer drawbacks such as a trial-and-error process to determine the optimal PID parameters. It is difficult to maintain control variables close to set-point values due to changing operating conditions. To manage these problems, there are three conventional approaches used for the regulation of the hybrid (PI/PID) controller in HVAC systems: self-tuning, manual, and adaptive control methods. PID controllers can be combined with other feedback controllers, feed-forward controller, cascade controller, and common controller structures of the three types mentioned in [51], [52]. A combination of the feed-forward controller and a SISO PI decentralized feedback controller has been used to progress the step reference tracking behavior of rate evaporator temperature, simultaneous with the decreasing coupling influence of other input channel changes. The results have demonstrated a reduction of Root Mean Square (RMS) control system error [52].
Meanwhile, to improve energy efficiency in buildings of Energy Technological Institute (ETI), PID controllers have been used for enhancing the HVAC system control [53]. The only aim of the On/Off controller is to provide two outputs for the HVAC system: maximum (On) and minimum (zero) (Off). The advantage of this controller is that it is low-cost and straightforward, but it fails to provide sufficient quality and accuracy [54]. An energy management system (EMS) has been evolved in Energy Plus (EP) that allows simulation of the residential DX-HVAC system on/off cycling. The results exhibited improvements in different ways [55]. The predictive control is important because it contains a model for future troubles and disturbances [50], [56]. Many studies have demonstrated that predictive controllers can reduce energy consumption if provided with occupancy predictions, real-time measurements, and information on weather circumstances [57], [58]. Parisio et al. designed a stochastic MPC method by proposing a randomization strategy obtaining suboptimal solutions to the problem of non-convex stochastic MPC [59], [60].
Several studies have been found in the literature for applying the MPC to HVAC systems [61], [62]. A simple controller has been proposed in [63], [64] that uses a pulse width modulation technique to turn the HVAC system on/off according to the optimal decisions made by MPC. The controller has been referred to as a predictive smart thermostat controller (PSTC), which saves energy and is cheap and straightforward. The Linear Quadratic Regulator (LQR) is a conventional control method that computes the state feedback gain and optimizes a function of the quadratic cost of inputs and states. Several articles focused on LQR have been presented in [65].

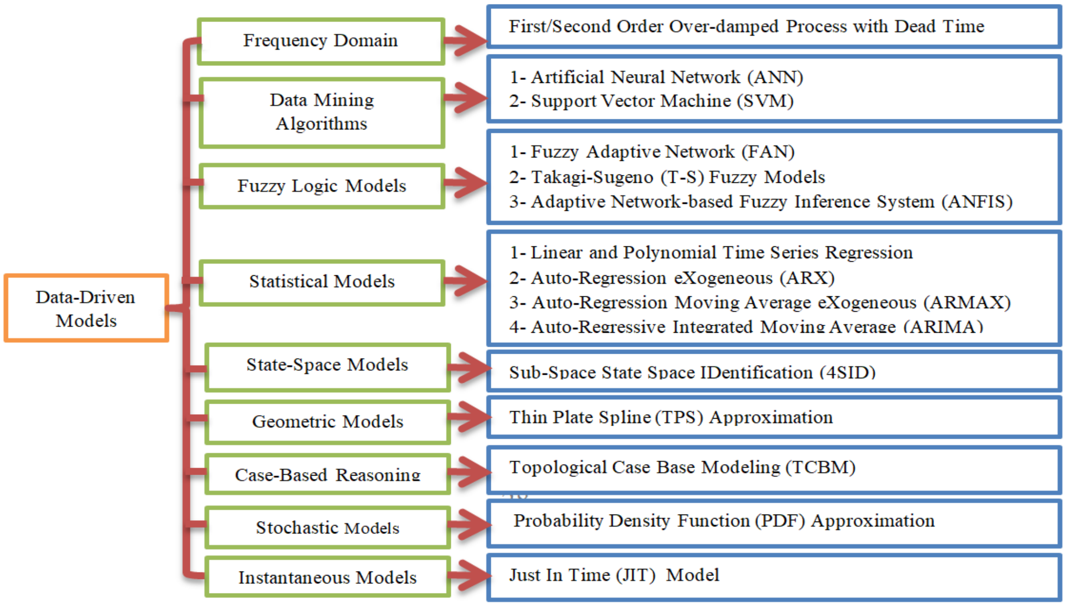

Fig. 1. Data-driven modeling strategies.

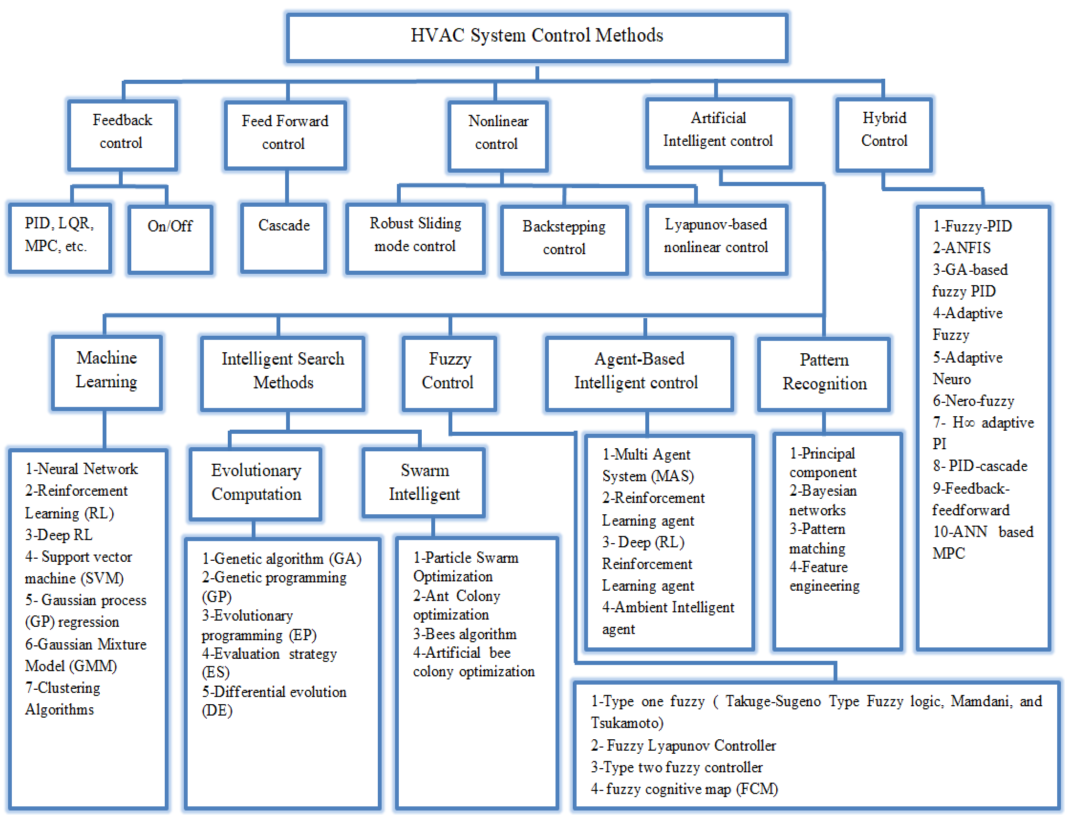

Fig. 2. Classification of the control methods of HVAC systems.

B. Feed-forward control methods

The feed-forward principle is used to forecast a forthcoming weather variation indicated by future changes in certain parameters [66]. Cascade control is an example of the feed-forward control methods, used to control the temperature in HVAC systems [67]. The set-point response of a new controller proposed in [67] has been planned according to the robust control H2 performance specification. Several research papers have been found on the performance of feed-forward and cascade control methods [68], [69]. Genetic Algorithm (GA) has been used in [70] for simultaneous tuning of control parameters in the outer (PID) and inner (PI) loops of a cascade HVAC system. Kianfar et al. [71] have designed the inner and outer loops of a cascade

Table 1. Summary of previous research closely related to HVAC system modeling.

Year	HVAC Model Type	Objective Function	Advantages	Ref.
2020	White-Box	Enhancing thermal efficiency by maintaining the region thermal comfort limits	Precision, explainability, and reliability	[27]
2020	White-Box (Energy Plus)	Developing energy model simulation	Development of indoor environment quality that is directly associated with occupant productivity	[28]
2020	White-Box (Energy Plus)	Controlling demand response in an entire building	Energy-saving while maintaining occupants? thermal comfort levels and meeting the demand response target	[29]
2019	White-Box(TRNSYS)	Investigating the impacts of interzonal airflow, air leakage, and ventilation	Low price and convenient access to numerous building types	[30]
2019	White-Box (Energy Plus)	Estimating, evaluating, and diagnosing electrical energy exhaust, measuring energy maintenance, and estimating annual CO2 emission	A simple reflection of system performance	[31]
2019	White-Box (TRNSYS)	Forecasting the efficiency of desiccant-based thermal/cooling systems	An individual-friendly, interactive, components-based software package involving the developing demands of the various users	[32]
2017	White-Box (ESP-r)	Implementing a two-node thermoregulatory framework	Strength, versatility, and home energy maximization	[33]
2016	White-Box (Energy Plus)	Modeling HVAC running faults	Simple execution, high capacity, versatility, and applicability	[34]
2015	White-Box (Energy Plus)	Reducing HVAC energy consumption by preserving thermal comfort for the occupants	Excellent sophistication and verification and continuous modification of the energy simulation system for entire buildings	[35]
2020	Gray-Box	Predicting the AHU supply air temperature for two buildings	Virtual calibration and measurement with HVAC fault detection	[36]
2020	Gray-Box	Optimizing HVAC energy consumption	Applicability to buildings with more complicated HVAC systems	[37]
2017	Gray-Box	Thermal building modeling	More efficient representation of building dynamics	[38]
2016	Gray-Box	Generating low-order models for analysis and control of surveyed buildings	Possibility to exchange inputs and outputs by maintaining problem balance	[39]
2015	Gray-Box Fourier series model (FSM)	Modeling lighting plug sub-meter energy consumption in modern commercial buildings	Simplicity and possibility to directly copy to other buildings of the same type	[40]
2020	Black-Box (ARX-NN)	Predicting indoor temperature in buildings	Accurate simulation of the building thermal behavior with limited data	[41]
2020	Black-Box	Presenting an energy-saving-oriented air-balanced approach	Absence of knowledge requirements on the duct parameters and minimization of the air balancing computational costs in large-scale duct systems	[42]
2018	Black-Box (ARX, ANN)	Specifying the best behavior and performance of residential HVAC models	Low parameter requirements and short computation time	[43]
2017	Black-Box (ANN)	1- Identifying abnormality from the unexpected residual model 2- Comparing benchmarking efficiency among identical equipment running under different conditions	Quick identification of deviations in performance and suggestion of appropriate maintenance tasks before possible failures	[44]
2016	Black-Box	Monitoring the performance of the HVAC system	Minimization of energy wastage and peak load.	[45]
2015	Black-Box (ARX, ARMAX, Box-Jenkins, and Output Error (OE))	Identifying the main inputs and the downstream and upstream neighbors within each subsystem to determine the parameter values before performing regression analysis	Management of the building structure complexity, selection of the subsystem inputs, and solution of the input collinearity problem	[46]
2014	Black-Box	Estimating thermal conduct in different buildings	Reusability	[47]
2013	Black-Box	Optimizing the operating costs in buildings using a small collection of data	Comprehensiveness, simplicity, and incremental operation	[48]
2012	Black-Box (ANN)	Modeling the non-linear data relationships	Low parameter requirements	[49]

controller to control both superheat temperature and two-phase flow length in an HVAC evaporator using the sliding mode.

C. Nonlinear control methods

A control system with at least one nonlinearity is called a nonlinear controller. This article briefly describes three example nonlinear control methods such as robust sliding mode control (SMC), backstepping control, and Lyapunov-based nonlinear control has been provided. Several papers have applied robust control methods to improve efficiency and airflow precision in HVAC systems [72]. Sliding-mode control is assumed to be robust for linear and nonlinear nondeterministic systems [72]. The robustness analysis of sliding-mode schemes, mainly dynamic schemes, requires more significant consideration for cases of deterministic nonlinear systems. Shah et al. [73] have designed and compared SMC with a PID controller to ensure the robust presentation of AHU for the achievement of low energy consumption in buildings. In a nonlinear system, there is differential input/output plus higher uncertainty; and the system order and relative order are not essentially equivalent. The sta-

bility analysis and solution existence of a closed-loop system are dependent on a generalized Lyapunov theorem. For the provision of the nonlinear model of an HVAC-refrigeration system, a robust control method based on a super-twisting sliding-mode controller has been designed and implemented [74]. The simulation results demonstrated that the super-twisting algorithm does not suffer the chattering problem in the standard sliding mode, and is robust against parameter uncertainty [74]. In [75], a feedback linearization for an MIMO HVAC system has been provided and the state variables have been decupled from disturbances. Then the backstepping method was applied to the HVAC system and compared to the PID controller. The results demonstrated its effectiveness in output regulation, disturbance decoupling in the existence of slowly time-varying loads, oscillation removals, and offset. A new method has been presented for capacity control and superheat of HVAC-refrigeration systems [76]. A nonlinear low-order evaporator model has been presented and used in a backstepping controller.
Through Lyapunov analysis, the stability of the method has been demonstrated theoretically [76]. In [77], a comprehensive description of the nonlinear control system design, sliding control mode, and fundamental of the Lyapunov theorem has been provided.

D. Hybrid control methods

By combining two or more control methods, a hybrid control approach can be developed. Several hybrid controllers have been proposed for the control of HVAC systems such as Linear Quadratic Tracking (LQT)-PID control [78], PI-neural control [79], Fuzzy-PID control [80], Artificial Neural Network (ANN)-based MPC [81], and Learning-Based Model Predictive Control (LBMPC) [82].
Fiorentini et al. have been developed a hybrid MPC method that uses a new high-level/low-level technology for the overall predictive control of residential buildings equipped with the HVAC system [83]. The results demonstrated that the controller could select an appropriate operating mode to achieve various desired objectives [83].
A new adaptive PI controller for HVAC systems has been presented in [84] where a first-order plus dead-time model has been adopted for the HVAC system. The recursive least squares (RLS) method has been used to update the HVAC system model parameters along with exponential forgetting and zero-frequency model-matching. Compared to the adaptive PI controller based on the Ziegler-Nichols (Z-N) tuning strategy and the H∞ adaptive PI controller, the new adaptive control method is powerful, stable, and fast in response [84]. A combined PID cascade control method developed with industrial PID has been designed to achieve better performance in the central air conditioning system compared with the Ziegler-Nichols method [85]. The simulation results demonstrated that the controller is adaptive to system changes, and provides fast responses [85]. A hybrid model used for controlling indoor thermal comfort in HVAC systems has been presented in [86], [87]. By combination of neural networks (NNs) and fuzzy system methods, a new method called FCM (fuzzy cognitive maps) has been developed in [88], and [89], which benefits from both approaches.

E. Artificial Intelligent control

This type of control method has been discussed as a general case, focusing on the unique case of Machine Learning (ML) methods, especially RL and MAS.

E.1. General case

Three intelligent control methods, neural networks, knowledge-based systems, fuzzy logic, and numerous combinations thereof have been used widely to control HVAC systems [90–93]. Chen et al. have been presented information concerning the evolution of AI methods from 1997 to 2018 for upgrading the performance of HVAC systems [90] (including the operation decision environment (ODE) architecture, knowledge-based system (KBS) for predictive control, native fuzzy KBS at the supervisory level [91], GA, SNN, ANN [92] [93], hybrid fuzzy-PID control [94], adaptive fuzzy PID control, fuzzy neural network, adaptive ANN model, fuzzy multi-criteria decision-making method (DMM), support vector machine (SVM), MAS, combination of rough set (RS) theory and ANN for cooling load prediction, combination of evolutionary programming (EP) and particle swarm optimization (PSO), convolutional artificial neural network (CANN), linear RL control, regression model development for prediction, recurrent neural network (RNN), ward-type ANN [95], optimization via RNN, fuzzy-PID schema development for model predictive control (MPC) [96], ANFIS [97], wavelet-based ANN [98], GA-based fuzzy PID control, principal component analysis (PCA), multi-objective GA, autoregressive model with exogenous terms (ARX), radial basic function (RBF) network, supervisory control and data acquisition plus home intelligent management system, hidden Markov model (HMM), layered HMM, user-oriented control based on behavior prediction, case-based reasoning (CBR) model, nonlinear multiclass SVM, HMM, and kNN model, short-term smart-learning electrical load algorithm, bottom-up approach, deep reinforcement learning (DRL)-based algorithm [99], Elman neural network, distributed economic model predictive control (DEMPC) [100], MAS [101], and CBR for energy management and decision-making) [9]. Kozák has presented advanced control methods and constructions based on optimality, intelligence, and robustness. The significant ideas that have been noted in his article included optimal predictive, hybrid predictive, neural network, robust, and fuzzy logic control [102]. Dounis has focused on designing a multi-agent control system (MACS) in HVAC systems [6]. The results demonstrated that the MACS could successfully manage the user's preferences for indoor air quality, energy conservation, thermal, and illuminance comfort [6]. A review of intelligent control methods for HVAC systems has been presented in [103].
Ahmad et al. have classified computational intelligence (CI) methods based on their applications in HVAC systems [104]. They have reviewed some of them by removing their hybrid techniques from their diagrams to maintain clarity. They have found that metaheuristic algorithms, such as GA PSO and ACO, are the most common CI methods due to their various specifications and search capabilities [104].
Yuan et al. have investigated and briefly reviewed an RL technique on the control of HVAC system energy [105]. RL can function in both model-free and model-based environments. The common advantage of RL is that the agent (learner) can take optimal actions using trial-and-error standards regardless of the supervisor (teacher), which fits the purpose of the control problem [106].

E.2. Agent-based RL control methods

The indoor conditions interact with the field operation of an autonomous agent to control the HVAC system [107], [108]. References [109], [110] have proposed a novel deep RL framework to optimize HVAC system control [111], [112]. Agent-based [28], [113] and multi-agent control [114], [115] methods have

been applied in many fields comprising control applications and buildings [116], [117]. An intelligent agent is a structure that can understand things in its environment (e.g., from a sensor) and then applies some simple or complex rules to take various actions [118], [119]. These agents are capable of working together (cooperate/compete) either directly via negotiation and communication or indirectly via action on the environment [120], [121]. The idea of agent-based control is best understood through assurance of the best results by MAS in HVAC system control [122]. Al-Daraiseh et al. have provided a platform structure for MAS control of HVAC systems [123].
The results of several studies have shown that the HVAC system could maintain the desired room temperature upon selecting the heat supply with the most cost-effective heat generation process. The main features of MAS, including the autonomous nature, learning capability, cooperation, and intrinsic distributed nature, have been summarized in references [124], [125]. Timilehin et al. [126] have presented the scope for an MA-coordinated possession disclosure system for demand-driven control applications in buildings, including HVAC, to obtain higher system energy efficiency and to realize the smart grid.
To investigate the application of the RL control method to building energy, a review has been presented in [127]. Fig. 3 shows how MAS can be used for building energy control [128]. The Markov decision process (MDP) property of MASRL has been explained widely in matrix game-playing [129], [130].
The advantages of MASRL include information exchange, flexibility, skill-learning among several agents, communication and distribution of experience, and autonomy. Moreover, if one or more agents fail to function in the system, the remaining agents will still react optimally [131]. The research and studies associated with the application of multi-agent systems to HVAC control in buildings have been comprehensively reviewed in [132]. The authors have concluded that MAS provides an essential change in how automation problems and building HVAC controls can be approached. MAS is a common technique for the realization of distributed control/services [133].
MAS offers a chance to implement a diversity of new software-based techniques, providing far greater flexibility in building processes. Table 2 summarizes the advantages and limitations of some of the HVAC control methods.

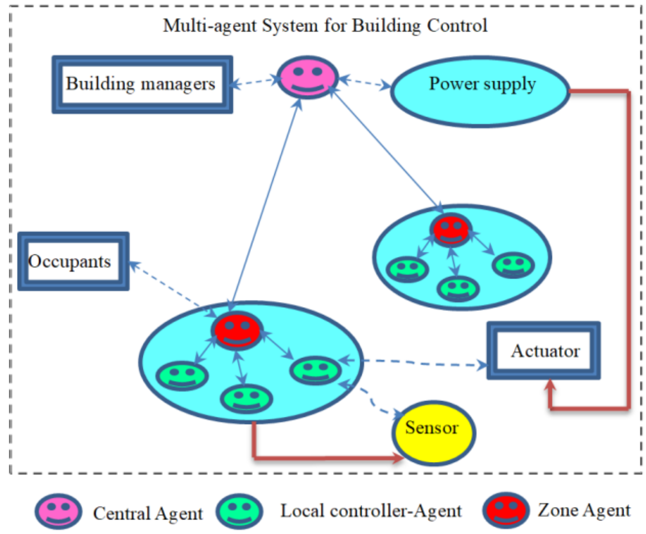

Fig. 3. MAS for building energy control.

4. MODELLING OF WIDE AREA FUZZY CONTROLLER IN THE SYSTEM UNDER STUDY

This section presents the proposed HVAC system model in detail, along with a block diagram of its MATLAB subsystems applied to residential buildings. The TSF controller is applied to the presented HVAC system model for evaluation of its performances.

A. HVAC system model

In this paper, the HVAC system RLF model is used to evaluate the performance of the proposed HVAC system model. The RLF model is an accurate hybrid model with many variables that controls temperature and air humidity conditions. It combines the physical and empirical modeling methods using the residential heat balance (RHB). However, in the proposed HVAC model, only the temperature is controlled and the air humidity conditions effects are ignored. This minimizes the sub-blocks of the proposed HVAC model, simplifies the system, and eliminates the temperature-humidity decoupling problem. The performance of the proposed HVAC model is compared with by the RLF model in terms of thermal conditions only. Moreover, the TSF controller is applied to the proposed model and the RLF model and the results are compared with each other.
To model the performance of an HVAC system in a thermal study, one must apply the energy conservation law, where the rate of energy in the overall storage system can be defined as:

$$\frac{dE_s}{dt} = \sum_i \dot{E}_{in} - \sum_i \dot{E}_{out} \quad (1)$$

The right side of Eqn. 1 indicates the net energy transfer rate. The HVAC system model can be represented by many nonlinear partial differential equations related to heat transfer, including partial derivatives with respect to time and space. Most of these equations are very difficult to solve and need to be simplified [134]. The proposed HVAC system model comprises two subsystem models: the heat exchange and the conditioned building space model. These two models are simulated using the equations derived in detail, as shown in Appendix (A).

B. Block diagram of the model

The complete block diagram of the model can be obtained using the connection of all the subsystem. The combination of the subsystem block diagrams is shown in Fig. 4.
According to Fig. 4, the number of input and output variables are six, and one, respectively, as listed below.
Input variables.
The flow rate of chilled water supply to the heat exchanger.
1. $D_{rr}(s)$: Damper ratio for return air.
2. $D_{rf}(s)$: Damper ratio for fresh air.
3. $T_o(s)$: Perturbations in outside temperature.
4. K_1: Open/Closed windows and doors.
5. K_2: On/Off lights.
6. $T_s(s)$: Supply temperature.
Output variable.
$T_r(s)$: Room temperature or conditioned space temperature.
In Fig. 4, the mathematical descriptions for the block diagrams $G_{1,1}$,$G_{1,3}$, $G_{2,1}$, and $G_{2,4}$ are given in the appendix (A).

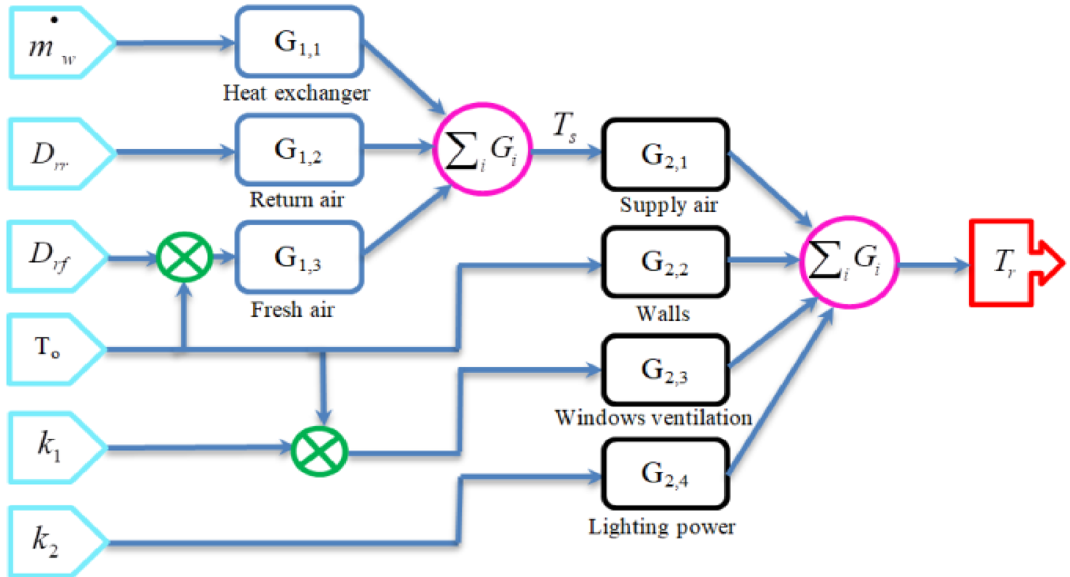

Fig. 4. Subsystems model of the HVAC system block diagram.

B.1. Application of the model to a residential building

For implementing the model transfer function, the parameters of the HVAC system are assumed to be known, as shown in Table 3. The plan of the building, shown in Fig. 5, is used for the evaluation the performance of the HVAC system model [135].

B.2. TSF controller model

Many studies have used fuzzy logic controllers for HVAC systems to enhance the occupants' comfort levels and energy-saving purposes [137], [138]. In this paper, the TSF controller is used due to its main advantages such as decreasing overshoot, reducing tuning time, online auto-tuning, and speeding up system response [139], [140]. The TSF controller is applied to both types of the HVAC system (the proposed and RLF model). The TSF control tuning process is carried out with two inputs: 1) the error: Error=$(T_{r(desired)} - T_{r(feedback)})$ where $T_{r(desired)}$ the desired set-point temperature T_r, and $T_{r(feedback)}$: the measured indoor temperature and 2) the error variation: $\Delta\text{Error} = \frac{d(\mathrm{T_r(desired)} - \mathrm{T_r(feedback)})}{dt}$.
Moreover, the TSF controller has a single output, i.e. supplied chilled water (Ch.W.Flow), obtained from summation of the chilled water coming from both main cooling and pre-cooling coils for the RLF model and the supplied chilled water coming from the main cooling coil for the presented HVAC model. The general schematic for control of an HVAC system is shown in Fig. 6. Three linguistic variables are used for the TSF membership functions (Big Negative, Zero, and Big Positive). The algorithm inputs/outputs, membership functions, and rules of the TSF controller are generated using the MATLAB M-file code. The input membership functions are shown in Fig. 7, and the controller rules are presented in Table (4). As shown in Fig. 7, the membership functions for input variables are triangular.
The output membership functions include a first-order polynomial form, i.e., the Takagi-Sugeno first-order fuzzy model. A singleton with the vector [a b c] is the resulting fuzzy inference model. For tuning the fixed parameters of the [a b c] vector, the Gauss-Newton method is used, where c is the shifted parameter, and a and b are the TSF input parameters.

5. RESULTS AND DISCUSSIONS

For performance evaluation of the proposed model, a residential building has been selected. The building model is the typical single-zone house that has a simple construction. The overall area is 220 m_2, and the volume of the whole house is 616 m_3, excluding the garage. The climatic data and information of this building are related to Basra's city in southern Iraq [141].
The conditions of natural ventilation (HVAC system off mode) have been applied to the house model. Therefore, the indoor conditions have been influenced only by the outdoor weather conditions. For every hour within 24 hours, the indoor temperature behavior of the HVAC system models have been obtained and compared with the indoor temperature [87], The results are shown in Fig. 8. As shown in Fig. 8, the simulated indoor temperature for two HVAC system models can track the variation of outdoor temperatures.

The $T_r(t)$ variable, the plant output that is the simulated of the indoor temperature, is shown in Fig. 9, for the proposed HVAC system and RLF, where the outdoor temperature, $T_o(t)$, is considered to be 36($^\circ$C). The TS fuzzy controllers have been applied to the two types HVAC system models. Fig. 10 shows the TS fuzzy surfaces for both models. The HVAC systems have been operated by the TS controllers to follow the indoor temperature (T_r) set-points, which has changed from 22 to 24 ($^\circ$C) in 8.334 hrs within the 24 hrs of the day, as shown in Fig. 11. It can be seen that both HVAC system models have satisfactory behavior results under indoor temperature variations, while the proposed HVAC system model has a better performance as compared with the RLF model.

The cooling coil valve position signals for the RLF and proposed HVAC models have been used to compute their energy consumption. Fig. 12 shows chilled water valve position (open%) for the RLF and proposed HVAC models. The energy consumption can be calculated using iterative methods in MATLAB. The cumulative consumed energy has been calculated using Eqns. (5) and (6), explained in Appendix (A), for the proposed HVAC system model. for the RLF model, the cumulative consumed energy has been computed using the equations pre-

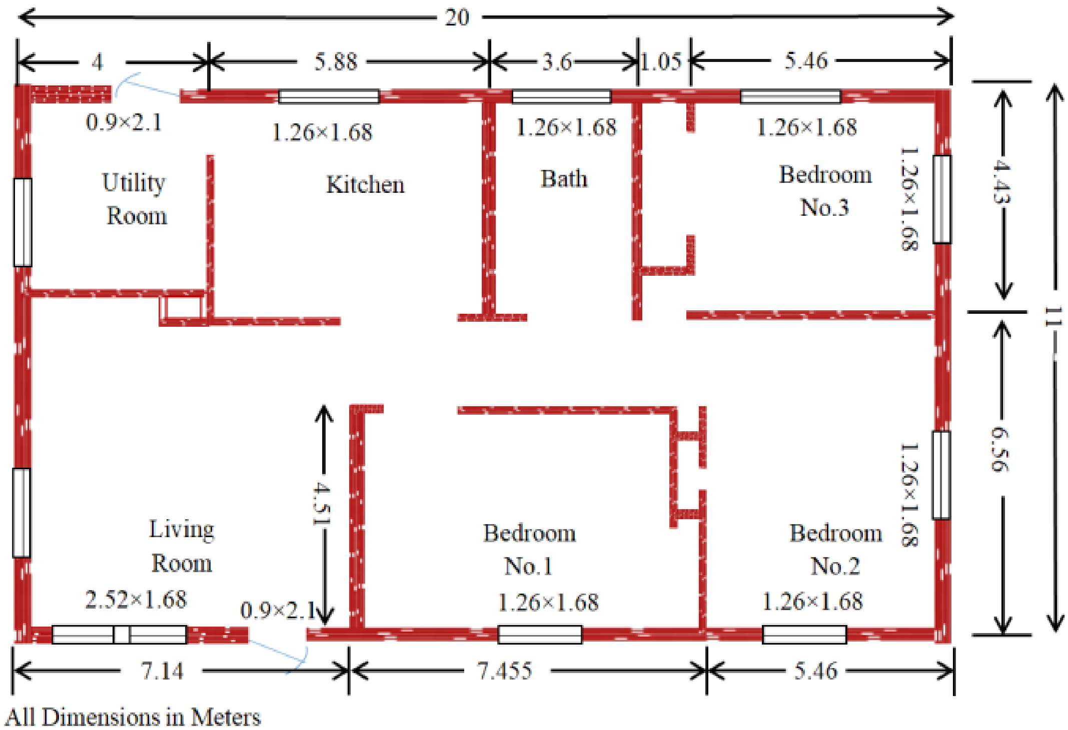

Fig. 5. Plan of the selected building [134].

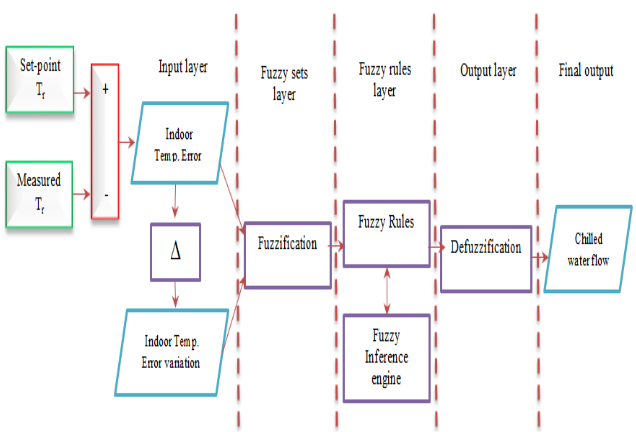

Fig. 6. General schematic used to control an HVAC system.

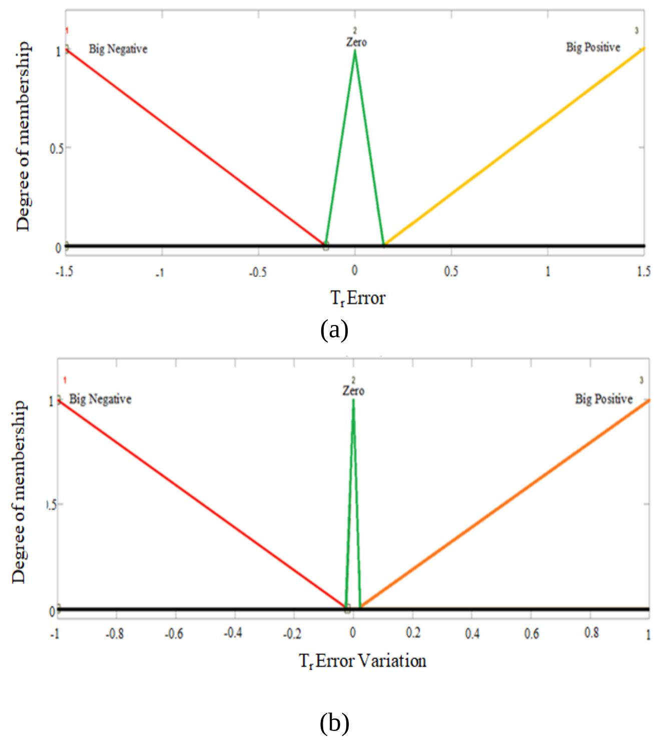

Fig. 7. TSF controller input membership functions: (a) First input (Error), (b) Second input (ΔError).

sented in [142].

It can be seen from Fig. 12, that the valve signals for two models have been saturated in the period of 13 to 15 hrs.

The simulation results for the cumulative consumed energy of two models are shown in Fig. 13. As shown in Fig. 13, the RLF system model has exhibited higher energy consumption than the proposed HVAC system model. This is due to uninterrupted process of cooling to meet the indoor thermal comfort demands. In the RLF model, the chilled water supplied is divided between two coils, including the main cooling coil and the pre-cooling coil. This set has high energy consumption. Whereas in the proposed HVAC, only one cooling coil is used for the heat exchanger, the same as the main cooling coil.

According to Fig. 13, the energy consumptions within 24 hrs for both models in usual conditions are: 148 kWh/day for the RLF

Table 2. A general comparison among HVAC system control strategies.

Control method	Advantages	Disadvantages
Hybrid control	Finding solutions to problems that cannot be handled by individual controllers.	The intelligent control requires a large amount of data for the training process, causing the challenge to tune the other control methods.
	Mixing the advantages of intelligent/soft control methods and others.	
	Obtaining superior control as compared to separate use of each control method.	
AI control	Providing HVAC systems with high accuracy, fast operation, and high efficiency.	The number of input variables is limited
	Handling enormous amounts of data and large numbers of input variables.	Performance estimation requires an enormous amount of data.
	Allowing the exact model to be unnecessary.	Stability is nondeterministic.
	Making credible predictions.	Processing is carried out with long runtime.
		The method is sometimes inappropriate for real-time HVAC applications.
Feed-forward control	Providing indemnity for disruptions before affecting the process results	The steady-state offset is so hard to remove.
	Maintaining the stability of the control system.	A model and a sensor are necessary for handling disturbances.
Feedback control	Providing fast response, low cost, wide application, and a very simple structure.	The method is inefficient, as the set-point cannot always be properly tracked.
	Providing efficiency with all disruptions.	In the long run, flexibility and efficiency are lost.
	Functioning with minimal system model knowledge.	The stability of closed loops is influenced.
		Maintenance is required.
		Parameter setting is extremely difficult.
		The method is not appropriate for complex models or nondeterministic data systems.
		Performance is low.
Nonlinear control	Covering nonlinear models.	There are complexities in obtaining Lyapunov functions.
	Handling the parameters of slowly time-varying/nondeterministic systems models.	Difficulties are involved in the integration of the nonlinear observer with HVAC.
		The method is sensitive to parameter changes.
		The operational range of state feedback is limited.
		Stability is hard to prove.
		There need to be calculations or additional measurements for all state variables.
		The method is appropriate only to stable processes.
		If all state variables are not measurable, nonlinear observers are required.

system and 133.114 kWh/day for the proposed HVAC system. The simulation results also indicate that the proposed HVAC system model has achieved an energy-saving of 10.06% compared with RLF model, which demonstrates that the proposed HVAC model is more energy-saving, and more efficient than the RLF model.

Table 3. HVAC system model components [136].

Component	Value	Component	Value	Component	Value
$\dot{m}_a$	0.84 kg/sec.	M_{He}	10kg	ΔT_w	$5°C$
cp_a	1.005J/kg.°C	cp_{He}	0.4 J/kg.°C	cp_w	4200 J/kg.°C
K	0.7	A	173.6m^2		
Δx	0.4m	♯ of lamps	50 lamps		

Table 4. TSF rules.

Δ Error / Error	Big Negative	Zero	Big Positive
Big Negative (1)	Big Negative	Big Negative	Zero
Zero (2)	Big Negative	Zero	Big Positive
Big Positive (3)	Zero	Big Positive	Big Positive

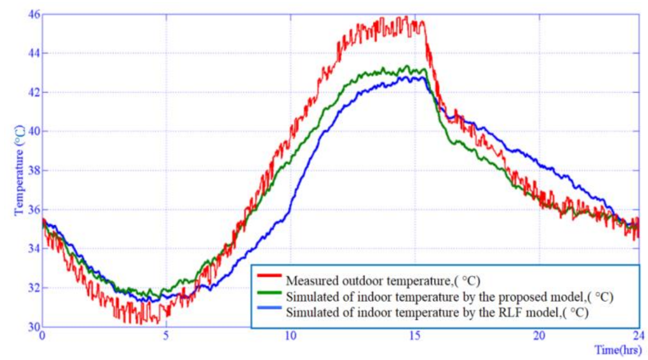

Fig. 8. Changes in indoor temperature concerning a variety of outdoor temperatures.

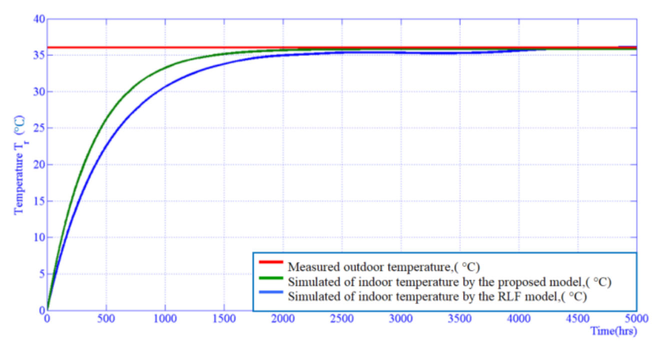

Fig. 9. The indoor temperature T_r concerning the constant outdoor temperature.

6. CONCLUSION

In this paper, various modeling of HVAC is examined, and their characteristics are categorized and compared. Then, the HVAC control methods have been reviewed comprehensively. By presenting a new categorization for various control approaches of HVAC systems, their main features have been extracted and compared to each other from different aspects.
Meanwhile, an HVAC system model has been proposed, and

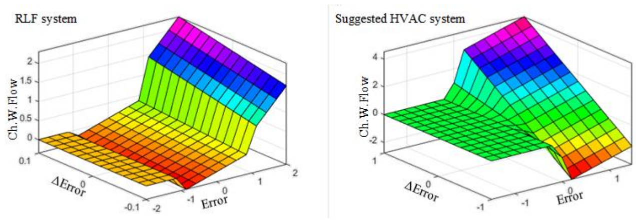

Fig. 10. TSF controller surfaces for the RLF and proposed HVAC systems.

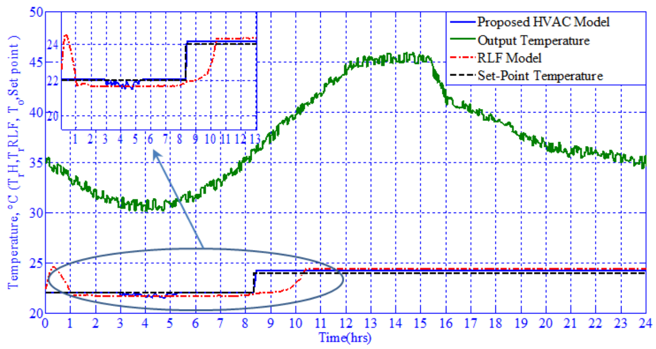

Fig. 11. Comparison of the RLF and proposed HVAC in terms of the indoor temperature Tr under the TSF controller.

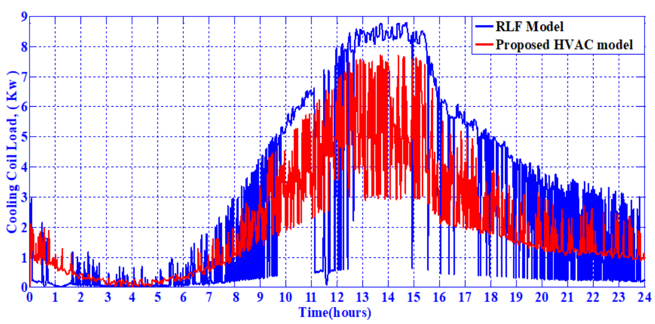

Fig. 12. Chilled water valve position for the RLF and proposed HVAC system models.

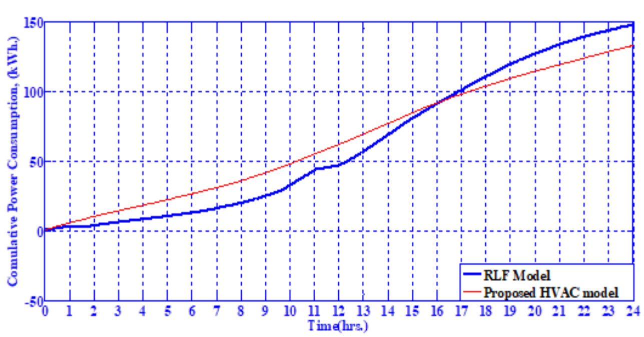

Fig. 13. Energy consumed by the RLF and proposed HVAC models.

simulations have been made to apply the Takagi-Sugeno fuzzy approach to the two types of HVAC system models: the proposed HVAC system and the RLF models. The simulation results for the proposed HVAC system and the RLF models have been analyzed from different aspects. The results demonstrate the efficiency and robustness of the proposed HVAC system model compared to the RLF model in terms of energy saving.

REFERENCES

1. G. Pierre, H. Steinfeld, B. Henderson, A. Mottet, C. Opio, J. Dijkman, A. Falcucci, and G. Tempio, "Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities,". Food and Agriculture Organization of the United Nations (FAO), vol. 14, no. 2, 2013.
2. R. Z. Homod, K. S. Gaeid, S. M. Dawood, A. Hatami, and K. S. Sahari, "Evaluation of energy-saving potential for optimal time response of HVAC control system in smart buildings," Appl. Energy, vol. 271, no. August, p. 115255, 2020.
3. P. Octavian, L. F. Tutunaru, F. Bode, A. C. Abrudan, and M. C. Balan. "Energy efficiency of PCM integrated in fresh air cooling systems in different climatic conditions," Applied energy, vol.212, pp.976-996, 2018.
4. R. Z. Homod, "Analysis and optimization of HVAC control systems based on energy and performance considerations for smart buildings, " Renew. Energy, vol. 126, pp. 49–64, 2018.
5. R. Z. Homod, and S. SM Khairul. "Intelligent HVAC control for high energy efficiency in buildings: achieving energy savings with developed nonlinear control strategies of central air-condition for intelligent buildings, " LAP LAMBERT Academic Publishing, 2014.
6. A. I. Dounis and C. Caraiscos, "Advanced control systems engineering for energy and comfort management in a building environment — A review ", Renewable and Sustainable Energy Reviews. vol. 13, pp. 1246–1261, 2009.
7. R. Z. Homod, "Review on the HVAC System Modeling Types and the Shortcomings of Their Application," Journal of Energy, 2013.
8. R. Z. Homod, "Modeling and Fault-Tolerant Control Developed for HVAC Systems". LAP LAMBERT Academic Publishing, 2014.
9. W. Sheng-wei, J. Wang, and J. Burnett., "Mechanistic model of centrifugal chillers for HVAC system dynamics simulation," Build Serv Eng Res Technol, pp.73–83., 2000.
10. C. Xiao, Q. Wang, and J. Srebric, "A data-driven state-space model of indoor thermal sensation using occupant feedback for low-energy buildings, " Energy Build J., 91, pp. 187–198, 2015.
11. Z. Dongliang, X. Xia, and N. Cai, "A dynamic simplified model of radiant ceiling cooling integrated with underfloor ventilation system, "Appl. Therm. Eng.Journal, 106, pp.415-422, 2016.
12. M. Giorgio, J. Chen, and G. Lowry. "Development of room temperature and relative humidity linear parametric models for an open office using BMS data." Energy and Buildings, vol.42, no.3, pp.348-356, 2010.
13. K. Andrew, M. Li, and F. Tang, "Modeling and optimization of HVAC energy consumption," Applied Energy, vol.87, no.10, pp.3092-3102, 2010.
14. M. Yudong, J. Matuško, and F. Borrelli. "Stochastic model predictive control for building HVAC systems: Complexity and conservatism," IEEE Transactions on Control Systems Technology, vol. 23, no.1, pp.101-116. 2014.
15. G. Ali, C. Tang, and B. Becerik-Gerber. "An online learning approach for quantifying personalized thermal comfort via adaptive stochastic modeling," Building and Environment, vol. 92, pp. 86–96, 2015.
16. A. Afram and F. Janabi-Sharifi, "Review of modeling methods for HVAC systems" , Applied Thermal Engineering, vol. 67, 2014.
17. G. H. Afroz, GM Shafiullah, T. Urmeea, "Modeling techniques used in building HVAC control systems: A review," Renew. Sustain. Energy Rev., pp. 1–21, 2017.
18. J. Rehrl, D. Schwingshackl, and M. Horn, "A modeling approach for HVAC systems based on the LoLiMoT algorithm," IFAC Proceedings ,vol.47, no. 3, 10862-10868. 2014.
19. M. Barbosa and N. Mendes, "Combined simulation of central HVAC sys-

tems with a whole-building hygrothermal model," Energy and Buildings, vol.40, no. 3, pp.276-288, 2008.

20. I. Ursu, I. Nastase, S. Caluianu, A. Iftene, and A. Toader, "Intelligent control of HVAC systems. Part I: Modeling and synthesis, " INCAS Bull., vol. 5, no. 1, pp. 103–118, 2013.
21. K. Arendt, M. Jradi, H. R. Shaker, C. T. Veje, and S. Denmark, "Comparative Analysis Of White- , Gray- And Black-Box Models For Thermal Simulation Of Indoor Environment: Teaching Building Case Study General description, " In Proceedings of the 2018 Building Performance Modeling Conference and SimBuild co-organized by ASHRAE and IBPSA-USA, Chicago, IL, USA, pp. 26-28. 2018.
22. J. C. Yiu and S. Wang, "Multiple ARMAX modeling scheme for forecasting air conditioning system performance," Energy Conversion and Management, vol. 48, pp. 2276–2285, 2007.
23. A. Afram and F. Janabi-Sharifi, "Gray-box modeling and validation of residential HVAC system for control system design, " Appl. Energy, vol. 137, pp. 134–150, 2015.
24. Z. Yi, and V. I. Hanby, "Model-based control of renewable energy systems in buildings," HVAC&R Research vol.12, no. S1, pp.739-760, 2006.
25. J. E. Braun, "A general control algorithm for cooling towers in cooling plants with electric and/or gas-driven chillers, " HVAC&R Res., pp. 581–598, 2007.
26. S. Andreas, G. Zucker, and R. Hofmann. "Automatically creating HVAC control strategies based on Building Information Modeling (BIM): Heat provisioning and distribution." Energies, vol. 13, no. 17, pp.4403, 2020.
27. A. Niccolo, M. Manfren, and G. Marenzi, "Building Automation and Control Systems and performance optimization: A framework for analysis," Renewable and Sustainable Energy Reviews, vol.75, pp. 313–330., 2017.
28. D. Picard and L. Helsen, "Cloud-based implementation of white-box model predictive control for a GEOTABS office building: A field test demonstration," J. Process Control, vol. 88, pp. 63–77, 2020.
29. M. Jia, “Building Performance Evaluation Using Coupled Simulation of EnergyPlus TM and an Occupant Behavior Model,” , Sustainability, vol.12, no.10, pp.4086.2020.
30. D. Azuatalam, W. Lee, F. De Nijs, and A. Liebman, "Reinforcement Learning for Whole-building HVAC Control and Demand Response, " Energy AI, p. 100020, 2020.
31. K. Eydner, M. Toufek, B. Henzler, and T. Stergiaropoulos, "Investigation of multizone building with HVAC system using a coupled thermal and airflow model, " CLIMA, vol. 111, pp. 1–8, 2019.
32. J. Woods and E. Bonnema, "Regression-based approach to modeling emerging HVAC technologies in EnergyPlus: A case study using a Vuilleumier-cycle heat pump, " Energy Build., vol. 186, pp. 195–207, 2019.
33. Jani, D. B., K. Bhabhor, M. Dadi, S. Doshi, P. V. Jotaniya, H. Ravat, and K. Bhatt, "A review on use of TRNSYS as simulation tool in performance prediction of desiccant cooling cycle," Journal of Thermal Analysis and Calorimetry, vol.140, no. 5, pp.2011-2031, 2020.
34. R. Mohamad, and N. Kelly, "Toward better estimation of HVAC Loads: integrating a detailed human thermal model into building simulation," Energy Procedia vol. 122, pp. 1147–1152, 2017.
35. R. Zhang, T. Hong, and L. Berkeley, "Modeling And Simulation Of Operational Faults Of Hvac Systems Using Energyplus, " ASHRAE and IBPSA-USA SimBuild, Building Performance Modeling Conference Salt Lake City, UT, August 8-12, 2016.
36. P. Taylor, J. Zhao, K. P. Lam, B. E. Ydstie, and O. T. Karaguzel, "EnergyPlus model-based predictive control within design–build–operate energy information modelling infrastructure, " J. Build. Perform. Simul., pp. 37–41, 2015.
37. S. Ahamed, R. Zmeureanu, N. Cortrufo, and J. Candanedo, "Gray-box virtual sensor of the supply air temperature of air handling units, " Sci. Technol. Built Environ., pp. 1–12, 2020.
38. W. Xiong and J. Wang, "A semi-physical static model for optimizing power consumption of HVAC systems," Control Eng. Pract., vol. 96, p. 104312, 2020.
39. K. Saurav, "Gray-Box Approach for Thermal Modelling of Buildings for Applications in District Heating and Cooling Networks," In Proceedings of the Eighth International Conference on Future Energy Systems, pp. 347-352. 2017.
40. R. D. Coninck, F. Magnusson, J. Åkesson, and L. Helsen, "Toolbox for development and validation of grey-box building models for forecasting and control," J. Build. Perform. Simul., vol. 9, no. 3, pp. 288–303, 2016.
41. Y. Ji and P. Xu, "Model Based Indirect Submetering Method of HVAC End-use in Existing Office Building," Procedia Eng., vol. 121, no. 114, pp. 1705–1712, 2015.
42. B. Delcroix, J. L. Ny, M. Bernier, M. Azam, B. Qu, and J. S. Venne, "Autoregressive neural networks with exogenous variables for indoor temperature prediction in buildings, " Build. Simul., 2020.
43. C. Cui, X. Zhang, and W. Cai, "An energy-saving oriented air balancing method for demand controlled ventilation systems with branch and black-box model," Appl. Energy, vol. 264, p. 114734, 2020.
44. A. Afram, A. S. Fung, F. Janabi-Sharifi, and K. Raahemifar, "Development and performance comparison of low-order black-box models for a residential HVAC system, " Journal of Building Engineering, vol. 15, pp. 137–155, 2018.
45. H. B. Gunay, W. Shen, and C. Yang, "Blackbox modeling of central heating and cooling plant equipment performance Blackbox modeling of central heating and cooling plant equipment performance, " Science and Technology for the Built Environment, vol.24, no. 4, p.396-409, 2017.
46. C. K. Sara, and C. Kallus, "Data-driven methodology for energy and peak load reduction of residential HVAC systems," vol. 145, pp. 852–859, 2016.
47. R. H. Chintala, and B. P. Rasmussen, "Automated Multi-Zone Linear Parametric Black Box Modeling approach For Building HVAC Systems," In Dynamic Systems and Control Conference, American Society of Mechanical Engineers, vol. 57250, pp. 1–10, 2015.
48. S. Royer, S. Thil, and T. Talbert, "Black-box modeling of buildings thermal behavior using system identification," IFAC Proceedings, vol. 47, no.3, pp.10850-10855, 2014.
49. K. Macek, G. Kontes, and V. Dimitrios, "Black-Box Optimization for Buildings and Its Enhancement by Advanced Communication Infrastructure Optimization in Buildings," Advances in Distributed Computing and Artificial Intelligence Journal, vol.2, no.2, pp.53, 53–64, 2013.
50. H. Fock, E. Mara, T. A. Lauret, and A. J. Boyer, "Black-Box Modelling Of HVAC System: Improving The Performances Of Neural Networks Eric Fock," arXiv Prepr. arXiv1212.5594., 2012.
51. A. Almabrok, M. Psarakis, and A. Dounis, "Fast tuning of the PID controller in an HVAC system using the Big Bang-Big Crunch algorithm and FPGA technology," Algorithms, vol. 11, no.10, 2018.
52. M. Imal, "Design and implementation of energy efficiency in HVAC systems based on robust PID control for industrial applications," J. Sensors, 2015.
53. C. Blasco, J. Monreal, and I. Ben, "Modelling and PID Control of HVAC System According to Energy Efficiency and Comfort Criteria," In Sustainability in Energy and Buildings, pp. 365–374, 2012.
54. G. Ulpiani, "Comparing the performance of on / off, PID and fuzzy controllers applied to the heating system of an energy-efficient building," Energy and Buildings, vol.116, pp.1-17, 2016.
55. K. Cetin, M. H. Fathollahzadeh, and N. Kunwar, "Development and validation of an HVAC on/off controller in EnergyPlus for energy simulation of residential and small commercial buildings," Energy Build., 2018.
56. S. J. Salsbury, T. Mhaskar, P., & Qin, "Predictive control methods to improve energy efficiency and reduce demand in buildings," Comput. Chem. Eng., vol. 51, pp. 77-85, 2013.
57. A. Almusaed, A. Almssad, R.Z. Homod, and I. Yitmen, "Environmental Profile on Building Material Passports for Hot Climates", Sustainability, vol. 12, no. 9, p. 3720, 2020.
58. A. Maytham, A. Mohamed, R. Z. Homod, H. Shareef, and K. Khalid, "Awareness on energy management in residential buildings: A case study in Kajang and Putrajaya," Journal of Engineering Science and Technology, vol. 12, no. 5, pp. 1280–1294, 2017.
59. A. Parisio, D. Varagnolo, D. Risberg, G. Pattarello, M. Molinari, and K. H. Johansson, "Randomized Model Predictive Control for HVAC

Systems," In Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings, pp. 1-8. 2013.
60. R. Carli, G. Cavone, S. Ben Othman, and M. Dotoli, "IoT based architecture for model predictive control of HVAC systems in smart buildings, " Sensors (Switzerland), vol. 20, no. 3, pp. 1–18, 2020.
61. M. Amin, and B. Dong. "Occupancy behavior based model predictive control for building indoor climate—A critical review," Energy and Buildings, vol. 129, pp. 499–513., 2016.
62. A Afram and F Janabi-Sharifi , "Theory and applications of HVAC control systems-A review of model predictive control (MPC)," Building and Environment, vol.72, pp. 343-355, 2014.
63. D. P. I. Hazyuk, C. Ghiaus, "Model predictive control of thermal comfort as a benchmark for controller performance," J. Autom. Constr., pp. 98–109, 2014.
64. M. Soudari, V. Kaparin, and S. Srinivasan, "Predictive smart thermostat controller for heating, ventilation, and air-conditioning systems,", Proceedings of the Estonian Academy of Sciences, vol.67, no. 3, pp. 291–299, 2018.
65. G. R. Gonc, A. S. Bazanella, and C. Lorenzini, "Data-Driven LQR Control Design," IEEE control systems letters, vol.3, no.1, pp.180-185, 2018.
66. B. Thomas, M Soleimani-Mohseni, P Fahlén, "Feed-forward in temperature control of buildings," Energy Build. Sci. Direct, vol.37, no. 7, pp.755-761, 2005.
67. J.J. Wang, C.F. Zhang, Y.Y. Jing, "Research of Cascade Control with an Application to Central Air-Conditioning System, ", In 2007 International Conference on Machine Learning and Cybernetics, IEEE, vol. 1, pp. 498-503., 2007.
68. N. Jain, R. J. Otten, and A. G. Alleyne, "Decoupled Feedforward Control for an Air-Conditioning and Refrigeration System," In Proceedings of the 2010 American control conference, IEEE, pp. 5904–5909, 2010.
69. C. H. Mayr, N. Euler-Rolle, M. Kozek, C. Hametner, and S. Jakubek, "Control Engineering Practice Engine control unit PID controller calibration by means of local model networks," Control Eng. Pract., vol. 33, pp. 125–135, 2014.
70. D. Ivanova, N. Valov, and M. Deyanov, "Application of the genetic algorithm for cascade control of a HVAC system," MATEC Web Conf., vol. 292, pp. 01064, 2019.
71. K. Kianfar and M. Saif, "Cascaded Control of Superheat Temperature of an HVAC System Via Super Twisting Sliding Mode Control", IFAC, vol. 47, no. 3., 2014.
72. C. Lin and F. Hsiao, "Applied Sciences Proportional-Integral Sliding Mode Control with an Application in The Balance Control of A Two-Wheel Vehicle System," Applied Sciences, vol.10, no. 15, pp.5087., 2020.
73. A. Shah, D. Huang, Y. Chen, X. Kang, and N. Qin, "Robust sliding mode control of air handling unit for energy efficiency enhancement, " Energies, vol. 10, no. 11, 2017.
74. O. H. Hameed, J. J. Faraj, and M. S. Alwan, "A Review of Intelligent Control Approaches in Heating Ventilation and Air Conditioning Systems," J. Mech. Eng. Res. Dev., vol. 43, no. 6, pp. 135–166, 2020.
75. E. Semsar-Kazerooni, M. J. Yazdanpanah, and C. Lucas, "Nonlinear control and disturbance decoupling of HVAC systems using feedback linearization and backstepping with load estimation," IEEE Trans. Control Syst. Technol., vol. 16, no. 5, pp. 918–929, 2008.
76. Z. Wang and G. Hu, "Economic MPC of nonlinear systems with non-monotonic Lyapunov functions and its application to HVAC control," Int. J. Robust Nonlinear Control, vol. 28, no. 6, pp. 2513–2527, 2018.
77. L. Zheng and L. Cai, "A distributed demand response control strategy using Lyapunov optimization," IEEE Trans. Smart Grid, vol. 5, no. 4, pp. 2075–2083, 2014.
78. C.G. Rieger and D.S. Naidu, "Demonstration of a Hybrid Intelligent Control Strategy for Critical Building HVAC Systems," J. Control Intell. Syst., pp. 1-22., 2010.
79. C. Guo, Q. Song, and W. Cai, "A neural network assisted cascade control system for air handling unit," IEEE Trans. Ind. Electron., vol. 54, no. 1, pp. 620–628, 2007.
80. K. M. and A. H. Soyguder S, "Design and simulation of self-tuning PID-type fuzzy adaptive control for an expert HVAC system," Expert Syst Appl., pp. 4566–73., 2009.
81. A. Afram, F. Janabi-Sharifi, A. S. Fung, and K. Raahemifar, "Artificial neural network (ANN) based model predictive control (MPC) and optimization of HVAC systems: A state of the art review and case study of a residential HVAC system," Energy Build., vol. 141, pp. 96–113, 2017.
82. A. Aswani, M. Neal, T. Jay, K. Andrew, C. David, and T. Claire, "Energy-efficient building HVAC control using hybrid system LBMPC." IFAC Proceedings, vol.45, no.17, pp.496-501, 2012.
83. M. Fiorentini, P. Cooper, Z. Ma, and D. A. Robinson, "Hybrid model predictive control of a residential HVAC system with PVT energy generation and PCM thermal storage," Energy Procedia, vol. 83, pp. 21–30, 2015.
84. J. Bai and X. Zhang, "A new adaptive PI controller and its application in HVAC systems," Energy Conversion and Management, vol. 48, pp. 1043–1054, 2007.
85. R. Z. Homod, T. M. I. Mahlia, and H. A. F. Mohamed, "PID-Cascade for HVAC System Control for HVAC System Control" In International Conference on Control, Instrumentation and Mechatronic Engineering (CIM09,), pp. 598-603, 2009.
86. J. Aguilar, "A survey about fuzzy cognitive maps papers," International journal of computational cognition, vol.3, no. 2 pp. 27–33., 2005.
87. R. Z. Homod, K. Salleh, M. Sahari, H. A. F. Almurib, and F. Ha, "RLF and TS fuzzy model identification of indoor thermal comfort based on PMV/PPD," Building and Environment, vol.49, pp.141-153., 2012.
88. F. Behrooz, R. Abdul Rahman, and S. Khairulmizam, "A survey on applying different control methods approach in building automation systems to obtain more energy efficiency," International Journal of Physical Sciences vol.6, no. 9, pp. 2308–2314., 2011.
89. C.D. Stylios and P.P. Groumpos, "Fuzzy cognitive maps in modeling supervisory control systems," J.Intell. FuzzySyst., vol.8, no.1, pp. 83–98., 2000.
90. C.C. Cheng and D. Lee, "Artificial intelligence-assisted heating ventilation and air conditioning control and the unmet demand for sensors: Part 1. Problem formulation and the hypothesis," Sensors, vol.19, no.5, p.1131, 2019.
91. J.K.W. Wong, H. Li, S.W. Wang , "Intelligent building research: A review, " Autom. Constr., vol.14, no.1, pp. 143–159, 2005.
92. S.A. Kalogirou, "Artificial neural networks in renewable energy systems applications: A review," Renew. Sustain. Energy Rev., pp. 373–401., 2001.
93. S.A. Kalogirou, G.A. Florides, C. Neocleous, and C.N. Schizas, "Estimation of daily heating and cooling loads using artificial Neural Networks," CLIMA, pp. 1–11, 2001.
94. F. Calvino, M. La Gennusa, G. Rizzo, and G. Scaccianoce, "The control of indoor thermal comfort conditions: introducing a fuzzy adaptive controller," Energy Build., pp. 97–102., 2004.
95. P.A. González and J.M. Zamarreno, "Prediction of hourly energy consumption in buildings based on a feedback artificial neural network," Energy Build., vol.37, no.6, pp. 595–601, 2005.
96. B. Paris, J. Eynard, S. Grieu, and M. Polit, "Hybrid PID-fuzzy control scheme for managing energy resources in buildings," Appl. Soft Comput., pp. 5068–5080., 2011.
97. Ö. A. Dombayci, "The prediction of heating energy consumption in a model house by using artificial neural networks in Denizli–Turkey," Advances in Engineering Software, vol.41, no.2, pp. 141–147., 2010.
98. A.H. Neto and F.A.S. Fiorelli , "Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption," Energy and buildings, vol.40, no.12, pp.2169-2176, 2008.
99. K. Dalamagkidis, D. Kolokotsa, K. Kalaitzakis, and G. S. Stavrakakis, "Reinforcement learning for energy conservation and comfort in buildings," Building and environment, vol.42, no.7, pp.2686-2698, 2007.
100. M Terziyska, Y Todorov, and M Petrov, "Fuzzy-Neural model predictive control of a building heating system," IFAC, pp. 69–74., 2006.
101. M. Hadjiski, V. Sgurev, and V. Boishina, "Multi agent intelligent control of centralized HVAC systems," IFAC Proceedings, vol.39, no.19, pp.195-

200, 2006.
102. Š. Kozák, "Advanced Control Engineering Methods in Modern Technological Applications," In Proceedings of the 13th International Carpathian Control Conference (ICCC). IEEE, pp. 392–397, 2012.
103. L.S.H. Mirinejad and K.C. Welch, "A Review of Intelligent Control Techniques in HVAC Systems," In 2012 IEEE Energytech, IEEE, pp. 1-5., 2012.
104. M.W. Ahmad, M. Mourshed, B. Yuce, and Y. Rezgui, "Computational intelligence techniques for HVAC systems: A review," In Building Simulation, vol.9, no.4, pp. 359–398, 2016.
105. X. Yuan, Y. Pan, J. Yang, W. Wang, and Z. Huang, "Study on the application of reinforcement learning in the operation optimization of HVAC system," In Building Simulation, vol.14, no.1, pp. 75-87, 2021.
106. Z. M. and V. A. Ye D., "A Survey of Self-Organization Mechanisms in Multiagent Systems," IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol.47, no.3, IEEE, pp. 441–461, 2017.
107. D. Biswas, "Reinforcement Learning based HVAC Optimization in Factories," In Proceedings of the Eleventh ACM International Conference on Future Energy Systems, pp. 428-433, 2020.
108. P Stone and M Veloso, "Multiagent systems: a survey from machine learning perspective," Autonomous Robots, vol.8, no. 3, pp. 345-383, 2000.
109. L. Yu, S. Qin, M. Zhang, C. Shen, T. Jiang, and X. Guan, "Deep Reinforcement Learning for Smart Building Energy Management: A Survey," arXiv preprint arXiv:2008.05074, 2020.
110. Z. Zhang, A. Chong, Y. Pan, C. Zhang, S. Lu and K.P. Lam, "A deep reinforcement learning approach to using whole building energy model for hvac optimal control," In 2018 Building Performance Analysis Conference and SimBuild., vol. 3, pp. 22-23, 2018.
111. T. Wei, S. Member, S. Ren, and Q. Zhu, "Deep Reinforcement Learning for Joint Datacenter and HVAC Load Control in Distributed Mixed-Use Buildings," IEEE Trans. Sustain. Comput., 2019.
112. P. Davidsson, L. Henesey, L. Ramstedt, J. Törnquist, and F. Wernstedt, "An analysis of agent-based approaches to transport logistics," Transportation Research part C: emerging technologies, vol.13, no. 4, pp.255-271, 2005.
113. K. U. Ahn and C. S. Park, "Application of deep Q-networks for model-free optimal control balancing between different HVAC systems Application of deep Q-networks for model-free optimal control balancing between different HVAC systems, " Sci. Technol. Built Environ., vol. 26, no. 1, pp. 61–74, 2020.
114. R. Jia, M. Jin, K. Sun, T. Hong, and C. Spanos, "Advanced Building Control via Deep Reinforcement Learning Assessing the feasibility of using the heat demand-outdoor temperature function for a long-term district heat demand forecast, " Energy Procedia, vol. 158, pp. 6158–6163, 2019.
115. L. Yu, Y. Sun, Z. Xu, C. Shen, and S. Member, "Multi-Agent Deep Reinforcement Learning for HVAC Control in Commercial Buildings," IEEE Transactions on Smart Grid, vol.12, no.1, pp.407-419, 2020.
116. Y. Zhang, Z. Li, and Y. Zhang, "Validation and Calibration of an Agent-Based Model: A Surrogate Approach," Discrete Dynamics in Nature and Society, Hindawi, p.9, 2020.
117. X. Li, W. Mao, D. Zeng, and F.Y. Wang, "Agent-based social simulation and modeling in social computing," In International Conference on Intelligence and Security Informatics, Springer, Berlin, Heidelberg, pp. 401-412, 2008.
118. L.Klein, K. Jun-young, K. Geoffrey, J. Farrokh Jazizadeh, B.-G. Burcin, V. Pradeep, and T. Milind, "Coordinating occupant behavior for building energy and comfort management using multi-agent systems," Automation in construction, vol.22, pp. 525–536., 2012.
119. S Russell and P Norvig, "Artificial Intelligence: a modern approach," 3rd Ed. Ch. Upper Saddle River, NJ: Prentice-Hall, 2009.
120. F.L. Bellifemine, G. Caire, D. Greenwood, and F.L. Bellifemine, "Developing Multi-Agent Systems with JADE, " John Wiley & Sons,vol.7, 2007.
121. A.E.F. Seghrouchni, A.M. Florea, and A. Olaru, "Multi-Agent Systems: A Paradigm to Design Ambient Intelligent Applications," In Intelligent Distributed Computing IV, Springer, Berlin, Heidelberg, pp. 3–9., 2010.
122. A. G. Lez-Briones, F. D. L. Prieta, M. S. Mohamad, S. Omatu, and J. M. Corchado, "Multi-agent systems applications in energy optimization problems: A state-of-the-art review," Energies, vol. 11, no. 8, pp. 1–28, 2018.
123. A. Al-Daraiseh, E. El-Qawasmeh, and N. Shah, "Multi-agent system for energy consumption optimisation in higher education institutions," J. Comput. Syst. Sci., vol. 81, no. 6, pp. 958–965, 2015.
124. W. Kofler M. J., Reinisch C. and Kastner, "A semantic representation of energy-related information in future smart homes," Energy Build., pp. 169–179., 2012.
125. M Ganzha, LC Jain, D Jarvis, J Jarvis, and R Rönnquist, "Multiagent Systems and Applications," Intelligent systems reference library, Springer, 2013.
126. T Labeodan, K Aduda, G Boxem, and W Zeiler, "On the application of multi-agent systems in buildings for improved building operations, performance and smart grid interaction–A survey," Renewable and Sustainable Energy Reviews, vol. 50 , pp.1405-1414, 2015.
127. M. Han and R. May, "A review of reinforcement learning methodologies on control systems for building energy," information technology and microdata analysis, pp. 1–26, 2018.
128. R. Yang and L. Wang, "Multi-zone building energy management using intelligent control and optimization, " Sustainable cities and society, vol.6, pp. 16-21, 2013.
129. H.M. Schwartz, "Multi-agent machine learning," John Wiley Sons Inc, 2014.
130. M. Bowling and V. Manuela, "Multiagent learning using a variable learning rate," Artificial Intelligence, vol.136, no. 2, pp. 215-250, 2002.
131. R. Dominguez and S. Cannella, "Insights on multi-agent systems applications for supply chain management," Sustain., vol. 12, no. 5, pp. 1–13, 2020.
132. A. Windham, S. Treado, "A review of multi-agent systems concepts and research related to building HVAC control," Science and Technology for the Built Environment, vol.22, no.1, pp.50-66. 2017.
133. S. Wang, and M. Zhenjun, "Supervisory and optimal control of building HVAC systems: A review." Hvac&R Research, vol.14, no. 1, pp. 3–32, 2008.
134. B. Tashtoush, M. Mohammed, and A.-R. Mohammed. "Dynamic model of an HVAC system for control analysis," Energy, vol.30, no.10, pp. 1729–1745, 2005.
135. EG Pita and S Stevenson, "Air conditioning principles and systems", Columbus, OH: Prentice Hall, 1998.
136. R. Z. Homod, K. S. M. Sahari, H. A. F. Almurib, and F. H. Nagi, "Double cooling coil model for non-linear HVAC system using RLF method, " Energy Build., vol. 43, no. 9, pp. 2043–2054, 2011.
137. L. Morales Escobar, J. Aguilar, A. Garces-Jimenez, J. A. Gutierrez De Mesa, and J. M. Gomez-Pulido, "Advanced fuzzy-logic-based context-driven control for HVAC management systems in buildings," IEEE Access, vol. 8, pp. 16111–16126, 2020.
138. Z. A. Shah, H. F. Sindi, A. Ul-Haq, and M. A. Ali, "Fuzzy Logic-Based Direct Load Control Scheme for Air Conditioning Load to Reduce Energy Consumption," IEEE Access, vol. 8, pp. 117413–117427, 2020.
139. R. Z. Homod, K. Salleh, M. Sahari, H. A. F. Almurib, and F. Hafiz, "Gradient auto-tuned Takagi–Sugeno Fuzzy Forward control of a HVAC system using predicted mean vote index," Energy Build., vol. 49, pp. 254–267, 2012.
140. R. Z. Homod, H. Togun, H. J. Abd, and K. S. M. Sahari, "A novel hybrid modelling structure fabricated by using Takagi-Sugeno fuzzy to forecast HVAC systems energy demand in real-time for Basra city," Sustain. Cities Soc., vol. 56, no. June 2019, p. 102091, 2020.
141. "https://www.bbc.com/weather/99532.".
142. R. Z. Homod, K. Salleh, M. Sahari, and H. A. F. Almurib, "Energy saving by integrated control of natural ventilation and HVAC systems using model guide for comparison," Renew. Energy, vol. 71, pp. 639–650, 2014.

A. APPENDIX A

A. Heat exchanger model

Based on the energy flow, heat exchanger control volume can assess the latent energy that is absorbed by the main cooling coil using Eqn. 1.

$$M_{He}cp_{He}\frac{dT_s(t)}{dt} = \dot{m}_a\, cp_a T_m(t) - \dot{m}_a\, cp_a T_s(t) + \dot{m}_w\, kcp_w T_{win} - \dot{m}_w\, kcp_w T_{wout} \tag{2}$$

$T_{wout} - T_{win} = \Delta T = 5 - 10 = -5$

Where: M_{He} is the mass of the heat exchanger (kg), cp_{He}, cp_a, and cp_w (J/kg.°C) are the specific heat of the heat exchanger, and air and water, respectively, $\dot{m}_w$ is the mass flow rate of chilled water at time t ($kg/sec.$), $T_t(t)\&T_s(t)$ are the temperature of the mixing and out supply air at time t (°C), respectively, $T_{wout}\&T_{win}$ are water out and in heat exchanger temperature (°C), respectively, and $\dot{m}_a$ is the mass flow rate of outside air at time t ($kg/sec.$).

Taking Laplace transform on both sides of the equation, assuming zero initial conditions, and simplifying the expression, the transfer function of the heat exchanger temperature ratio of the supply air can be given as:

$$T_s(s) = \frac{T_m(s)}{(\tau_1 s+1)} + \frac{\dot{m}_w\, cp_w \Delta T_w}{\dot{m}_a\, cp_a(\tau_1 s+1)} \tag{3}$$

$\dot{m}_a = \frac{A*h*\rho*\#of.air.replaced.times(=4)}{3600} = 0.84\, kg/\sec.$

$\tau_1 = \frac{M_{He}cp_{He}}{\dot{m}_a\, cp_a} = 4.7382 \sec.$

Where: τ_1 is the time delay for the controlled object (s), and $T_m(s) = D_{rr}T_r(s) + D_{rf}T_o(s)$.

Here, D_{rr} and D_{rf} are damper ratios for return and fresh air, which are 0.75% and 0.25%, respectively. T_r and T_o are the room and output temperature at time t (°C), respectively.

$$T_s(s) = \frac{D_{rr}T_r(s)+D_{rf}T_o(s)}{(\tau_1 s+1)} + \frac{\dot{m}_w\, cp_w \Delta T_w}{\dot{m}_a\, cp_a(\tau_1 s+1)} \tag{4}$$

$$T_s(s) = \underbrace{\frac{\dot{m}_w\, 4200 * -5}{0.84 * 1.005(4.7s+1)}}_{G_{1,1}} + \underbrace{\frac{0.75 * 22}{(4.7s+1)}}_{G_{1,2}} + \underbrace{\frac{0.25T_o(s)}{(4.7s+1)}}_{G_{1,3}}$$

B. Conditioned space building model

The building construction thermal mass has a flywheel influence on the prompt load. The conditioned space is enclosed by walls, windows, ceilings, and doors. Therefore, the components include air space, lighting, furniture, and occupants generating heating load. By applying the energy and mass conservation laws to the conditioned space control volume, the heat balance in the conditioned space building is given by:

$$\dot{Q}_r = \dot{Q}_s + \dot{Q}_{wd/dr} + \dot{Q}_{wal} + \dot{Q}_{cel} + \dot{Q}_l \tag{5}$$

Where:

$\dot{Q}_r = M_{ar}cp_{ar}\frac{dT_r}{dt}$, $\dot{Q}_s = \sum_j m_{as}cp_a\,(T_s - T_r)$, $\dot{Q}_{wal} = \sum_j \frac{KA}{\Delta x}\,(T_o - T_r)$, $\dot{Q}_{wd/dr} = \sum_j m_{av}cp_a\,(T_o - T_r)$, $\dot{Q}_{cel} = 0.6\,\dot{Q}_{wal}$ and $\dot{Q}_l = 40N_{ol}$.

$m_{as} = m_{av} = \dot{m}_a$.

The simplified transfer function for the conditioned space temperature ratio of room/out air is given by:

$$M_{ar}cp_a\frac{dT_r(t)}{dt} = \sum_j m_{as}cp_a\,(T_s(t) - T_r(t)) + \sum_j m_{av}cp_a\,(T_o(t) - T_r(t)) + \sum_j \frac{KA}{\Delta x}\,(T_o(t) - T_r(t)) + 0.6 * \sum_j \frac{KA}{\Delta x}\,(T_o(t) - T_r(t)) + 40N_{ol}.$$

Taking Laplace transform on both sides of the equation, assuming zero initial conditions, and rearranging the expression, the transfer function for the conditioned space temperature ratio can be given as:

$$T_r(s) = \frac{m_{as}cp_a T_s(s)}{\left(\frac{KA}{\Delta x}+2m_{as}cp_a\right)(\tau_2 s+1)} + \frac{m_{av}cp_a T_o(s)}{\left(\frac{KA}{\Delta x}+2m_{as}cp_a\right)(\tau_2 s+1)} + \frac{KAT_o(s)(1+0.6)}{\Delta x\left(\frac{KA}{\Delta x}+2m_{as}cp_a\right)(\tau_2 s+1)} + \frac{40N_{ol}}{\left(\frac{KA}{\Delta x}+2m_{as}cp_a\right)(\tau_2 s+1)} \tag{6}$$

Where: τ_2 is the time delay for the controlled object(s).

$\tau_2 = \frac{M_{ar}cp_a}{\frac{KA}{\Delta x}+2m_{as}cp_a}$, $\tau_2 = \frac{Ab*h*\rho*cp_a}{\frac{KA}{\Delta x}+2m_{as}cp_a}$, $\tau_2 = 381.5791 \sec.$

$$T_r(s) = \underbrace{\frac{0.84 * 1005 * T_s(s)}{\left(\frac{0.7*173.6}{0.4} + 2 * 0.84 * 1005\right)(381.5791s+1)}}_{G_{2,1}} + \underbrace{\frac{0.84 * 1005 * T_o(s)}{\left(\frac{0.7*173.6}{0.4} + 2 * 0.84 * 1005\right)(381.5791s+1)}}_{G_{2,2}} + \underbrace{\frac{0.7 * 173.6 * 0.6 * T_o(s)}{0.4 * \left(\frac{0.7*173.6}{0.4} + 2 * 0.84 * 1005\right)(381.5791s+1)}}_{G_{2,3}} + \underbrace{\frac{40 * 50}{\left(\frac{0.7*173.6}{0.4} + 2 * 0.84 * 1005\right)(381.5791s+1)}}_{G_{2,4}}$$