www.rericjournal.ait.ac.th

Review on HVAC System Optimization Towards Energy Saving Building Operation

Hazlina Selamat*, Mohamad Fadzli Haniff#,1, Zainon Mat Sharif$, Seyed Mohammad Attaran^, Fadhilah Mohd Sakri&, and Muhammad Al'Hapis Bin Abdul Razak**

Abstract **–** Works on the optimization of heating, ventilation and air-conditioning (HVAC) systems have been done extensively because of its high amount of building electrical energy usage. This paper provides a review on the optimizations works of HVAC systems based on three main approaches – HVAC operational parameters optimization, HVAC controller parameters optimization and building design parameters optimization. For the system's operational parameters, the optimization is based on the HVAC's conventional and predictive energy consumption models which is clear the predictive HVAC system models can get better response to reduce energy consumption compare to conventional energy consumption model. In most works, the thermal comfort model, either indicated by the indoor air quality (IAQ) or the predicted mean vote (PMV) was included. It is be noticed that between IAQ comfort index and PMV comfort index the PMV had a better response that can get 46% reduce the energy consumption. In addition, in the HVAC's controller optimization approach, its objective is to improve the output response of the HVAC system in order to avoid unnecessary energy usage by optimizing the controller parameters that employ controllers such as Fuzzy Logic, Neural Network and Proportional-Integral-Derivative (PID) controllers. It is clear that among the different controller optimizations mentioned above the fuzzy logic tuning optimization has a better response to reduction of energy consumption rather than other controller optimization approach. Meanwhile, the optimization of building design parameters approach is done before the construction of the buildings so as to reduce the energy consumption, where factors such as HVAC system type, construction material type and window dimensions are determined through the optimization process. This paper reviews the works based on the three approaches of HVAC system optimizations with the objective of reducing energy usage without sacrificing the comfort of occupants inside the building that is recommended to use predictive HVAC system approaches with fuzzy logic controller. Moreover, comparing different tools for building parameter and design optimization including SEDICAE, EXRETopt and EneryPlus, the EXRETopt by using PMV comfort index makes to 62% reduction of energy consumption.

Keywords **–** *energy consumption, HVAC optimization, thermal comfort.*

1. INTRODUCTION

Heating, ventilation and air-conditioning (HVAC) systems are widely used in buildings all over the world and are generally responsible for the highest amount of total building energy consumption [1]-[4]. This system is essential in providing a comfortable temperature for building occupants regardless of the outdoor temperature. For HVAC systems, the coefficient of performance (COP) has been used as an indicator to assess its energy performance [5]-[7]. COP is the ratio between the produced cooling/heating energy and electrical energy input. Higher COP leads to a lower energy consumption and higher system efficiency, as shown in [8]. Based on Carnot's Theorem [5], for a cooling system, the COP of a HVAC system depends on the difference between the cold (indoor) temperature and hot (outdoor) temperature. In cooling process, the objective of HVAC is to not increase the indoor temperature. In order to increase the COP value for lower energy consumption, the indoor temperature can be increased to be closer to the outdoor temperature such that comfortable environment is provided without consuming too much electrical energy.

In this paper, only works that involve indoor thermal comfort are considered as this type of comfort is related to the effects of the use of HVAC systems in buildings. Thermal comfort levels of occupants inside a building can be measured using indicators such as the predicted mean vote (PMV) or indoor air quality (IAQ). PMV was introduced by Fanger [9], and since it is used in the ISO 7730 Standard [10], it has been widely adopted in many works on optimization of comfort

*Centre for Artificial Intelligence & Robotics, School of Electrical Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, 81310 Skudai Johor, Malaysia.

#System Engineering and Energy Laboratory (SEELab), Electrical, Electronics and Automation Section, Universiti Kuala Lumpur Malaysia Spanish Institute (UniKL MSI), Kulim Hi-Tech Park, 09000 Kulim Kedah, Malaysia.

$College of Graduate Studies, Univeriti Tenaga Nasional, Putrajaya Campus, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor Malaysia.

^Fars Science and Technology Park, Iran.

&Aerospace Section, Universiti Kuala Lumpur Malaysia Institute of Aviation Technology (UniKL MIAT), 43900 Sepang, Selangor, Malaysia.

**System Engineering and Energy Laboratory (SEELab), Manufacturing Section, Universiti Kuala Lumpur Malaysia Spanish Institute (UniKL MSI), Kulim Hi-Tech Park, 09000 Kulim Kedah, Malaysia.

*Corresponding author:
Tel: +60137121780
Email: mohamadfadzli@unikl.edu.my.

levels produced by HVAC systems [11-13]. PMV is an index that predicts the mean value of the votes of a large group of people on a 7-point thermal sensation scale ranging from '-3' (representing 'cold' sensation) to '+3' (representing 'hot' sensation). Scale '0' represent a neutral thermal sensation and the recommended PMV range is between -0.5 and +0.5. The PMV value inside a building is determined based on the air temperature (Tair), mean radiant temperature (Tmrt), activity or metabolism rate (M), air velocity (va), relative air humidity (RH) and clothing insulation (Iclo). In order to obtain a good PMV value, several combinations of these six parameters can be manipulated. However, the combination must not only able to provide a good PMV, but also able to do so without consuming too much electrical energy.

Another way of measuring the comfort inside a building is by measuring the indoor air quality (IAQ), which directly affects comfort, health and productivity of the occupants [14]. IAQ extends the thermal comfort indication by focusing on the contamination level of the air in a building. IAQ may be affected by factors such as temperature, humidity, carbon dioxide (CO_2) level, airflow rate and pressure. IAQ of a building should follow the standards set by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) in ASHRAE Standard 62.1 [15]. However, obtaining a good IAQ may results in excessive cost and so most building developers, owners and architects rarely take IAQ into consideration in their works.

For reducing building energy usage and providing good thermal comfort simultaneously, HVAC system operation needs to be optimized. This can be done using the single-objective optimization or the multi-objective optimization. In the single-objective optimization, the optimization algorithm focuses on minimizing electrical energy consumption but a minimum comfort level that must be met is imposed so as to avoid discomfort to the occupant. On the other hand, in the multi-objective optimization, the optimization algorithm finds a correct balance between minimizing electrical energy consumption and maximizing comfort level experienced by the occupants.

The aim of this paper is to provide a comprehensive review on various HVAC system optimization approaches that are used to obtain a good balance between building electrical energy consumption and thermal comfort to the occupants from classic conventional techniques to the more recent and advanced techniques. In particular, three broad optimization approaches are discussed in this paper. They are the manipulation of HVAC system's energy consumption models [16]-[21] and the predictive models [22]-[29], its controller parameters [30]-[39] and the building design parameters [40]-[42]. It also describes the advantages and limitations of every approach and recommends the suitable scenarios that are suitable for each of them.

2. METHODOLOGY

In this section the methodology of the paper is consist of different approaches as following:

I. Operational parameters optimization approach including using conventional energy consumption model and predictive HVAC system models to reduction of energy consumption.
II. Controller optimization approach including reduce tracking error, fuzzy logic tuning optimization, PID tuning optimization and neural network optimization to improve the response of HVAC system outputs in order to avoid unnecessary energy waste.
III. Building parameter and design optimization approaches to determine a low energy building designs in terms of the type of HVAC system, construction material, and etc.

3. OPTIMIZATION METHODS IN HVAC SYSTEMS

Optimization works related to HVAC systems have been done mainly with the objective of reducing the energy consumption of the system while maintaining comfortable indoor environment. The optimization of HVAC system operations had moved from the basic based-on-system model optimization to control system optimization and then to building design optimization. HVAC's operational parameter optimizations are done based on the system model in order to find suitable parameter settings for low energy consumption operation. Meanwhile, optimizations based on the control system design of HVAC systems have the purpose of improving the system response to avoid unnecessary energy usage. The building design optimizations aims to find suitable building parameters and designs that will enable efficient use of energy for the HVAC system.

3.1 HVAC Operational Parameters Optimization

To obtain good indoor environment without causing HVAC systems to consume high amount of electrical energy, suitable operational parameter settings can be determined by optimizing the parameters of the HVAC system models. Most HVAC system models represent the relationship between various operational parameters and its output parameters, such as energy consumption, temperature and humidity. The optimization of these operational parameters can be based on the conventional energy consumption models [16]-[21] or the predictive energy consumption models [23], [28]-[34], as explained in the following sections.

3.1.1 Operational parameters optimization based on the conventional energy consumption models

This method is one of the simplest ways to optimize the operational parameters of an HVAC system. It is based on the model that relates the operational parameters such as the air temperature, airflow rate and air static pressure with the energy consumption of the system. The energy consumption of an HVAC system (E_{system}) is conventionally defined as the total power usage from its components, such as the chiller ($E_{chiller}$), fan (E_{fan}), pump (E_{pump}) and the cooling tower ($E_{cooling\ tower}$), as shown in Equation 1 [16]-[19]. There are many parameters that affect the amount of energy used by these components and several are used as the optimization variables. For example, $E_{chiller}$ is affected by the coil temperature and position, while E_{fan} is affected by the air supply and return speed. In some works such as in [16] and [17], two operational parameters were considered in minimizing the energy consumption of the HVAC system. In [16], the temperature of the chilled water supply (T_{CHWS}) and the supply airflow rate (m_{SA}) were used as the optimization variables, whereas in [17], the supply air temperature set point and the air static set point were used.

$$E_{system} = E_{chiller} + E_{fan} + E_{pump} + E_{cooling\ tower} \quad (1)$$

There are also works that include more operational parameters to be optimized. For example, in [18], the optimization variables were the cooling water temperature (T_{CW}), the chilled water temperature from primary chiller ($T_{CHW,prm}$), the chilled water temperature from secondary chiller ($T_{CHW,sec}$) and the supply air temperature (T_{sa}). Meanwhile, in [19], the optimized operational parameters included the two zone temperatures (T_{z1}, T_{z2}), the humidity ratios in the zones (W_{z1}, W_{z2}), the discharge-air temperature (T_a), the temperature of chilled water (T_c), the outdoor airflow rates (m_{OA}), the supply airflow rates and the static pressure in the duct system (P). The optimized operational parameters were then sent to the local control loops such as the fan speed control loop to obtain optimized HVAC performances.

By minimizing the energy consumption of the HVAC system, the optimized operational parameter values can be obtained and can result in an energy-saving operation. Energy savings resulted from the optimization approaches in [16], [17], [18], and [19] were reported to be up to 10%, 7.66%, 11.82% and 20% respectively when compared to the non-optimized, fixed setting operation method.

In some works, the objective of reducing HVAC's energy usage is achieved by minimizing the total exergy loss of the system [20], [21]. In thermodynamics, 'exergy' is the energy that is available to be used. High exergy loss indicates low efficiency HVAC system, while low exergy loss indicates a highly efficient system. Total exergy loss (EL_{sys}) is defined by Equation 2, which is the sum of energy loss from the cooling tower water flow ($EL_{cooling\ tower}$), energy consumption of the subsystem's cooling tower ($E_{cooling\ tower}$), the chillers ($E_{chillers}$), the air handling units (E_{AHUs}) and the outflow exergy of the air handling units ($E_{AHUs,out}$). It can be seen thatby reducing the energy consumptions of the chiller, fan, pump and cooling tower (as in Equation 1), total exergy loss can be reduced too.

$$EL_{sys} = EL_{cooling\ tower} + E_{cooling\ tower} + E_{chillers} + E_{AHUs} + E_{AHUs,out} \quad (2)$$

In the approach given by [20], some of the optimized parameters were the supply cooling water temperature setpoints ($T_{CH,out}$), the supply chilled water temperature ($T_{CT,out}$), and the outdoor air flow rate (m_{OA}). Meanwhile, the work in [21] optimizes only the cooling rate (Q_{rate}) setting to reduce the exergy loss. By determining the optimized parameters, the methods proposed in [20] and [21] were able to achieve up to 12% and 9.2% reduction of the HVAC system energy consumption, respectively, when compared to a non-optimized technique. In [22], particle swarm optimization and harmony search algorithms have been used to simultaneously minimize HVAC energy consumption and room temperature ramp rate. The proposed method used similar conventional energy model and results in 15% energy saving which is considerably high because it includes the building thermal dynamics. This shows that, in modeling the energy consumption model of HVAC system for energy saving improvement, not only it can be done based on the HVAC system itself, it can also be done based on the building temperature dynamics and achieving a considerably high energy saving improvement.

Table 1 shows the summary of works on the operational parameters optimization based on the conventional energy consumption model.

3.1.2 Operational parameters optimization based on the predictive energy consumption models

To make HVAC systems more energy-efficient while providing comfort, the model predictive control has been introduced. This type of model is much simpler and easier to be applied on real-time applications compared to other models such as the dynamic model and the physical-based models [23]. Unlike the conventional models, the predictive models of HVAC systems are not restricted only to the energy models, but also for other system outputs such as temperature, humidity, CO_2 concentration level and even occupancy levels [23]. Because of these advantages, predictive models have been used in many optimization works on HVAC system operation in recent years [24]-[26], [27]. In [31] and [32], the prediction of the desired output (y) was made based on the current and/or previous values of the controlled parameters (x) and the uncontrolled parameters (v) given in Equation 3 is the time interval, x_1 is the supply air static pressure setpoint and x_2 is the supply air temperature setpoint. v_1 to v_6 refer to mixed air temperature, chilled water temperature, outside air temperature, air humidity, supply air fan speed and return air fan speed, respectively. The controlled parameters to be optimized can be the supply air temperature set point [23]-[32], the supply air static pressure set point [23]-[32] and the air and mean radiant temperature of the space which affected by the building thermal dynamics [33], [34].

Table 1. Summary of optimization works based on the conventional energy consumption model.

Reference		Optimized Parameters	Energy Saving Improvement*
[16]	i.	temperature of the chilled water supply (T_{CHWS})	10.00%
	ii.	supply air flow rate (m_{SA})	
[17]	i.	supply air temperature set point	7.66%
	ii.	air static set point	
[18]	i.	cooling water temperature (T_{CW})	11.82%
	ii.	chilled water temperature from primary chiller ($T_{CHW,prm}$)	
	iii.	chilled water temperature from secondary chiller ($T_{CHW,sec}$)	
	iv.	supply air temperature (T_{sa}).	
[19]	i.	twozone temperatures (T_{z1}, T_{z2})	20%
	ii.	humidity ratios in the zones (W_{z1}, W_{z2})	
	iii.	discharge-air temperature (T_a)	
	iv.	temperature of chilled water (T_c)	
	v.	outdoor airflow rates (m_{OA})	
	vi.	supply airflow rates	
	vii.	static pressure in the duct system(P)	
[20]	i.	supply cooling water temperature setpoints ($T_{CH,out}$)	12.00%
	ii.	supply chilled water temperature ($T_{CT,out}$)	
	iii.	outdoor air flow rate (m_{OA})	
[21]	i.	cooling rate (Q_{rate}) setting	9.20%
[22]	i.	temperature ramp rate	15%

$$y(t+d) = f(y(t), x_1(t), x_2(t), v_1(t), v_1(t - d), v_2(t), v_2(t - d), v_3(t), v_4(t), v_5(t), v_6(t) \quad (3)$$

Works based on the single-objective optimization, such as in [34], used only the predictive energy model as the objective function to find the optimized values of the two operational parameters $x_1$and x_2, and was able to reduce the energy consumption of the HVAC system by about 17.24%.

In the multiple-objective HVAC system optimization works, several predictive models were used as the objective functions for reducing energy consumption without violating the indoor air quality (IAQ). As IAQ affects the health and the human body development, any energy saving efforts must not affect IAQ in a negative manner [35]. In [23], the predictive energy consumption model along with the air temperature, air humidity and CO_2 concentration were used as the objective functions to determine the optimized parameter setting for $x_1$and x_2. One multi-objective optimization approach involved combining all the objective values into a single simple function to be minimized by the optimizer such as that given in Equation 4, where the values of four objectives y_1, y_2, y_3, and y_4 correspond to total energy (in kJ), violation of temperature (in °F), violation of humidity (in %) and violation of CO_2 concentration (in ppm). The violation of parameters are usually caused by the lack of knowledge to set the HVAC system to satisfy the thermal dynamics of the building. Their minimum and maximum values were utilized, along with the weight associated with each of the objectives (w_1, w_2, w_3, and w_4) to simplify the problem formulation. w_1, w_2, w_3, and w_4 are the weights associated with y_1, y_2, y_3, and y_4 respectively. The value of the weight of each objective was based on certain priorities or biases set by the user with $w_1 + w_2 + w_3 + w_4 = 1$. In [23], it has been reported that by using this method, about 12.4% of energy consumption can be reduced without significantly violating the IAQ constraints. Table 2 shows some of the effects of the weight values on the energy consumption and the level of violation on IAQ parameters resulted from the optimization works. The higher the weight value, the lower the violation becomes. It can also be seen that omitting IAQ in the objectives weight reduces the amount of energy consumption but results in a major violation of IAQ levels. By including the IAQ violations as optimization objective, the system is able to satisfy the comfort needs in the building without causing high energy consumption.

$$obj = w_1 \frac{y_1 - y_{1min}}{y_{1max} - y_{1min}} + w_2 \frac{y_2 - y_{2min}}{y_{2max} - y_{2min}} + w_3 \frac{y_3 - y_{3min}}{y_{3max} - y_{3min}} + w_4 \frac{y_4 - y_{4min}}{y_{4max} - y_{4min}} \quad (4)$$

Table 2. Violation of IAQ based on weight values [20].

Objectives weight				Objectives			
w_1	w_2	w_3	w_4	y_1 Total energy (kJ)	y_2 Violation of temperature (°F)	y_3 Violation of humidity (%)	y_4 Violation of CO_2 concentration(ppm)
1	0	0	0	25449.47	+0.62	-5.26	-19.28
0.5	0.5	0	0	26053.00	+0.51	-6.16	-30.11
0.5	0	0.5	0	26822.61	+0.60	-0.54	+1.45
0.5	0	0	0.5	25865.57	+0.62	-3.61	0

The HVAC optimization works based on the manipulation of its operational parameters in [30], [31] were similar to that in [23]. However, instead of using four, only three objective functions were used, where the CO_2 concentration was not included. The multi-objective optimization formulation was also similar to Equation 4. The works showed up to 13.4% energy reduction potential without much violation on the IAQ constraints. Another work using a similar multi-objective formulation has been done in [28] where only the predictive models of energy and temperature were used, and the energy consumption of the HVAC system was reduced by 18.5%. From the results of these works, it can be seen that as more objectives were included in the optimization problem formulation, the energy saving potentials were reduced due to the need to compromise energy consumption with the IAQ requirements.

In [33]-[34], the comfort index, PMV, defined by Equations 5 to 11 and Table 3, has been used instead of the IAQ. It can be seen how the air temperature (T_{air}), mean radiant temperature (T_{mrt}), activity or metabolism rate (M), air velocity (v_a), relative air humidity (RH) and clothing insulation (I_{clo}) determine the PMV value. Not all six PMV parameters can be controlled, so in optimization works only some of the six parameters are used as variable parameters. Parameters such as clothing types of the occupants, humidity and air speed in a building cannot simply be controlled but it can be set to a certain normalized or average value depending to the types of building and activity. As an example, an office building will be filled with occupants wearing smart casual attire while a restaurant building may be filled with occupants wearing thinner clothes. In [33]-[34], the optimization objective in these works was to minimize the violation of PMV in the building while reducing its energy consumption. The operating parameters that need to be optimized and controlled were the supply water temperature (T_{sw}), the air temperature (T_{air}) and the mean radiant temperature (T_{mrt}). This approach was able to reduce the HVAC system energy consumption by up to 10% while maintaining occupants' comfort. In the recent energy-comfort optimization based on the PMV model, the works in [36] and [37] managed to take the energy saving potential even higher respectively up to 46% and 33%.

$$PMV = (0.303 \,.\exp(-0.036\,.M) + 0.028)\,.L \tag{5}$$

where,

$$\begin{aligned} L = {} & (M-W) - 3.05\,.10^{-3}\,.(5733 \\ & - 6.99\,.(M-W) - p_a) \\ & - 0.42\,.((M-W) - 58.15) \\ & - 1.7\,.10^{-5}\,.M\,.(5867 - p_a) \\ & - 0.0014.M.(34 - T_{air}) \\ & - 3.96.10^{-8}.f_{cl}.((T_{cl}+273)^4 \\ & - (T_{mrt}+273)^4) \\ & - f_{cl}.h_c.(T_{cl} - T_{air}) \end{aligned} \tag{6}$$

$$\begin{aligned} t_{cl} = {} & 35.7 - 0.028.(M-W) \\ & - I_{cl}.\big(3.96.10^{-8}.f_{cl}.((T_{cl} \\ & + 273)^4 - (T_{mrt}+273)^4) \\ & + f_{cl}\,.h_c\,.\,(T_{cl} - T_{air})\big) \end{aligned} \tag{7}$$

$$h_c = \begin{cases} 2.38\,.|T_{cl} - T_{air}|^{0.25} \quad if \\ 2.38\,.|T_{cl} - T_{air}|^{0.25} \geq 12.1\,.\sqrt{v_{ar}} \\ 12.1\,.\sqrt{v_{ar}} \quad if \\ 2.38\,.\,|T_{cl} - T_{air}|^{0.25} < 12.1\,.\sqrt{v_{ar}} \end{cases} \tag{8}$$

$$f_{cl} = \begin{cases} 1.00 + 1.290\,.I_{cl} \;\; if\; I_{cl} \leq 0.078 \\ 1.05 + 0.645\,.I_{cl} \;\; if\; I_{cl} > 0.078 \end{cases} \tag{9}$$

$$P_a = \frac{P_s RH}{100} \tag{10}$$

$$P_s = \frac{C_1}{T} + C_2 + C_3 T + C_4 T^2 + C_5 T^3 + C_6 \ln T \tag{11}$$

where,

$C_1 = -5.8002206\,E+03$
$C_2 = \;1.3914493\,E+00$
$C_3 = -4.8640239\,E-02$
$C_4 = \;4.1764768\,E-05$
$C_5 = -1.4452093\,E-08$
$C_6 = 6.5459673\,E+00$

Optimization of the HVAC systems by using only conventional energy model may be able to reduce a considerable amount of energy, but for a more efficient operation, more models need to be included as the objective functions. Due to this, this basic method is still used until now and improved to more advanced versions. The use of IAQ and PMV in optimizing the HVAC system operation enables low energy consumption while maintaining the thermal comfort level in a building. While predictive models are used in most multi-objective optimization work of HVAC systems, this approach requires identification of the system model via system identification approach, which may take a significant amount of time especially if the models need to be very accurate [29]-[32].

Table 3. PMV parameters and sub parameters.

Symbol	Quantity	Typical values	Units	Description
M	Metabolic rate	46-232	W/m^2	1 met = 58.333 W/m^2
W	Effective mechanical power	≥0	W/m^2	0 W/m^2 if not assisted by mechanical power
I_{cl}	Clothing insulation	0-0.31	m^2K/W	1 clo = 0.155K/W
f_{cl}	Clothing surface area factor	0-1	-	-
T_{air}	Air temperature	10-30	℃	
T_{mrt}	Mean radiant temperature	10-40	℃	
v_{ar}	Relative air velocity	0-1	m/s	-
RH	Relative air humidity	>20	%	-
P_a	Water vapor partial pressure	0-2700	Pa	-
h_c	Convective heat transfer coefficient	0-12.1	$W/(m^2K)$	-
T_{cl}	Clothing surface temperature	10-30	℃	-

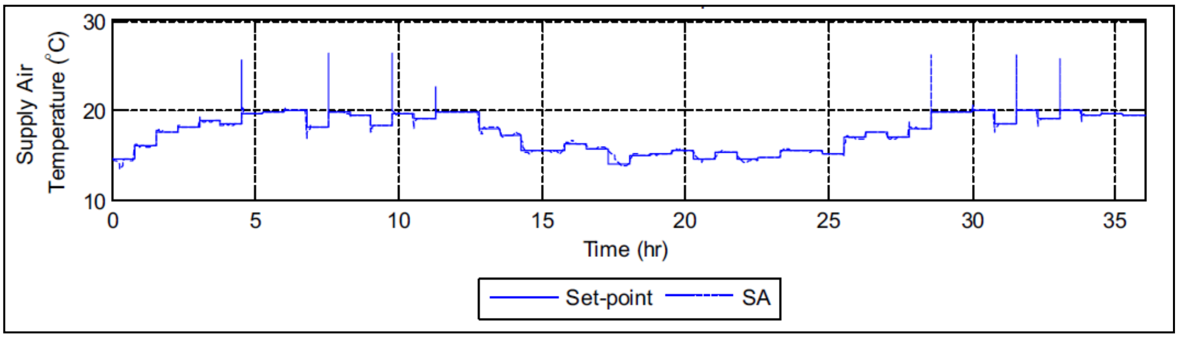

Fig. 1. Difference between the setpoint temperature and the SA temperature [42].

3.2 HVAC Controller Optimization

In ensuring good system performance, it is important that the control system of the HVAC system to be effective so as to improve the dynamic performance of the system [38], [39]. Apart from the time taken for the supply air temperature to reach the desired temperature set point, the overshoot of the supply air temperature is also an important parameter in its dynamic performance since having high overshoot of the cooling temperature will lead to electrical energy wastage [40], [41]. The overshoot of the supply air temperature can be reduced by improving the tracking error of the system response as highlighted in [42], [43], where real-time optimization techniques have been used in minimizing the tracking error of the chilled water supply temperature, the condenser water return temperature and the supply air temperature. This work was able to reduce tracking errors by more than 26% and the energy consumption of the HVAC system has been reduced by 10%. However, the main problem was the high tracking error occurrences when the value of one of the temperatures changed to a new setpoint value. Figure 1 shows that there is a small error between the supply air (SA) temperature and the setpoint temperature every time the setpoint temperature changed to a new value.

In [44], genetic algorithm (GA) has been used to optimally tune the fuzzy control rules and membership functions in controlling the set point temperature with the objective of minimizing energy consumption while providing PMV values that are within the comfortable range. This method was able to reduce up to 16% and 18% energy consumption for cooling and heating respectively when compared to the performance of a widely used control tool EnergyPlusTM. Another work related to fuzzy logic control optimization for a HVAC system was described in [45]. In this work, the fuzzy controller was set to be self-tuned using the Gauss-Newton method for nonlinear regression models with the inclusion of the PMV model so as to avoid discomfort to occupants while reducing the energy consumption. At least 30% of electrical energy usage has been reduced in this approach.

The most widely used control method for HVAC systems is the Proportional–Integrate–Derivative (PID) controller [46]-[53]. The PID controller has also been implemented with fuzzy rules for the tuning of the controller parameters (k_p, k_i and k_d) to obtain a more effective HVAC system control [50], [51].

Optimal tuning of the three parameters has improved the control of the environmental parameters such as the temperature and humidity. Figure 2 shows the effect of optimizing the PID controller for a room temperature control obtained in [46]. It can be seen that by optimizing the PID controller parameters, overshoots have been reduced and the time taken for the room temperature to reach the desired values have been shortened, thus increasing the system's energy efficiency. In [47] the optimized PID controller was able to reduce the energy consumption of the HVAC system by up to 20%.

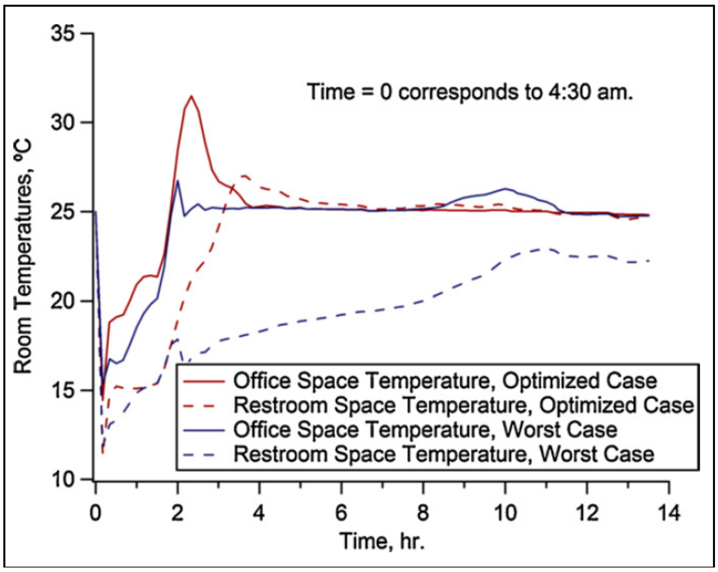

Fig. 2. Transient response of room temperature for optimized and worst case PID parameter values [46].

In [54], an adaptive neural network control strategy was proposed to obtain an efficient control of the HVAC systems via the setpoint tracking of the supply air temperature. Simultaneous perturbation stochastic approximation (SPSA) algorithm was embedded as the optimizer to tune the neural network controller weights so it can be used for various environmental conditions. It has been shown that the neural network control strategy was able to respond well with the change of supply air temperature setpoint without too much time delay and overshoot compared to the fixed parameter PID controller. In another work on optimal neural network controller strategy, the particle swarm optimization (PSO) and the back-propagation (BP) algorithms were used to tune neural network weights for better temperature control [55]. In [56], the mean squared error was introduced as performance function to tune neural network weights of the HVAC heat setting predictive model in optimizing the energy consumption and occupants' comfort. Although no exact energy reduction number is provided, this method was able to maintain good comfort without affecting energy consumption.

Control of HVAC system response is very important because weak control will lead to discomfort to occupants inside the space and unnecessary use of electrical energy. The implementation of better controllers usually requires accurate mathematical models of the HVAC system but this approach has been proven to be very effective in reducing a considerable amount of electrical energy consumption. The inclusion of various optimization algorithms to find optimal controller parameter values has shown to improve the control system performance of the HVAC systems even further.

3.3. HVAC Building Design Optimization

Other than directly optimizing the operational parameters and local controllers, HVAC system energy consumption in buildings can be reduced by planning ahead way before the purchasing of the system and even before the construction of the building [57-60]. Designing a low-energy building not only requires the efficiency of HVAC system to be evaluated, but also the design combinations and thermal characteristics of the elements involved such as the wall thickness, wall material, window width, window material and types of window blinds used. These factors determine the energy demands, energy consumptions and the life cycle cost of the buildings. Energy demands can be reduced by increasing the envelope thermal quality of a building [61]. Buildings with better thermal environment are able to save up to USD160 billion annually [62]. In recent years, simulation-based optimization methods have been introduced for designing green building. In the optimization process, concerns such as HVAC system, building materials and building designs are included as factors for energy consumption [63]-[65].

An advanced version of a simulation tool called SEDICAE was introduced in [57]. SEDICAE is an expert system for the design of energy-efficient buildings, which minimizes the life cycle costs and maximizes the energy rating of a building by determining what type of construction materials and HVAC system should be used [66]. The construction materials are chosen based on the thermal properties of the materials such as the U-values, the solar factor and the g-value or their air-tightness. HVAC system is chosen based on the types of demand - cooling or heating. For the case study in [57], the original building design proposal is optimally improved or re-designed based on the energy rating by using the Tabu search algorithm. The tool was able to propose a building design with 30 years life cycle cost as low as EUR5840.

An optimized building design has also been determined in [58] by using the simulation tool, Exergy Analysis Model for Retrofit Optimization (EXRETOpt), introduced in [67] to minimize the building annual energy use, occupant discomfort and building annual exergy destructions. The optimized building design parameters include the types of HVAC system, insulation type and size for wall, roof and ground, sealing percentage of cracks, joints and hole, window glazing level, cooling/heating set points, and lighting system type. Figure 3 shows the impact of insulation types and thickness to the energy use and exergy destruction reduction. It can be seen that as the thickness of insulation increases, the energy usage will also increase but the exergy reduction will decrease. Meanwhile, Figure 4 shows the effect of HVAC system configuration to energy usage, exergy destruction and comfort level. The figure shows that as the HVAC configuration uses less energy with low exergy destruction, the building will be uncomfortable for a longer period. The method was able to find the optimized building characteristic and types of HVAC configuration and achieved improvements of 62.1% in annual energy use, 57.9% of exergy destructions and up to 29.3% thermal comfort.

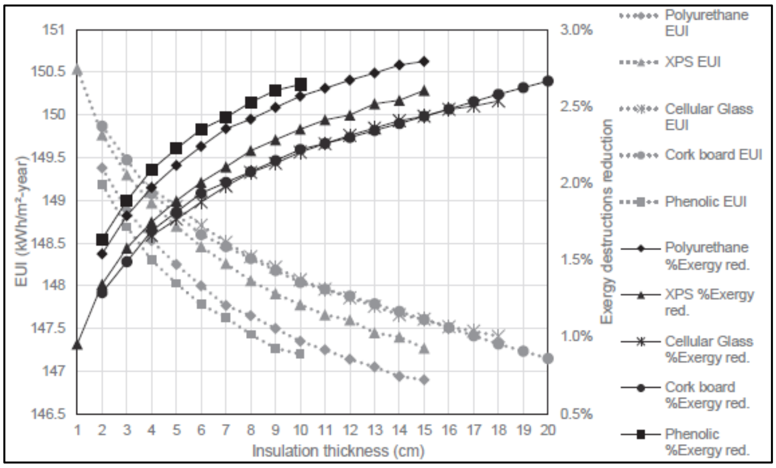

Fig. 3. Impact of insulation types and thickness on energy use and exergy destructions reduction [55].

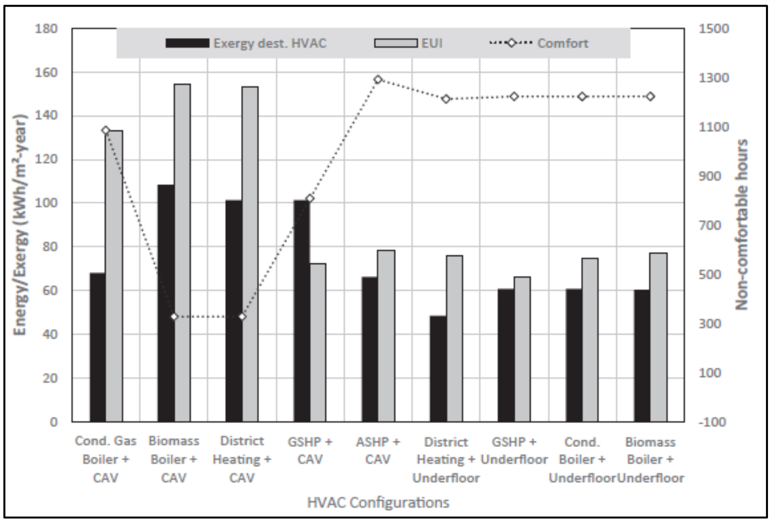

Fig. 4. Impact of HVAC configurations on energy use, exergy destructions reduction and comfort [55].

An energy efficient building design was achieved in [59] without compromising the occupants predicted percentage of dissatisfaction (PPD) by using the genetic algorithm (GA) optimization method. The PPD was evaluated using EnergyPlusTM simulation program that analyzed the building's comfort level and annual energy consumption. There are 80 design variables considered in this optimization work that revolved around the window design, wall design, floor design and HVAC schedule details with specific value constrains. A simpler work of building design optimization for low HVAC system energy consumption using

EnergyPlusTM has also been introduced in [60], which only optimizes the building direction, windows' width and the transmittance of the exterior shading device. Hooke-Jeeves pattern search algorithm was used to solve the single objective optimization problem. 14% of energy consumption reduction (heating, cooling and lighting) was achieved by [60].

4. CONCLUSIONS

This paper provides a review on optimization works related to buildings' HVAC systems to obtain an energy saving operation while maintaining occupants' comfort. The optimization works have been done on three different areas; HVAC operational parameters optimization, HVAC control system optimization and building design optimization. Operational parameters optimization is done to obtain the optimum operational parameter settings for the HVAC system that are able to reduce energy consumption while maintaining good comfort inside the buildings. In this category, the conventional energy consumption model and the predictive HVAC system models were the two recommended ways to reduce energy consumption. The use of the predictive HVAC system models was able to provide more energy consumption reduction compared to the conventional method. It has also been highlighted that the PMV approach has a better response than that of the IAQ with 46% reduction in the energy consumption. Controller optimization is done for the purpose of improving the response of HVAC system outputs in order to avoid unnecessary energy waste, while building design optimization involves determining a low energy building designs in terms of the type of HVAC system, construction material, building direction and window design used. Moreover, it seems that among the different controller optimizations approaches discussed in the paper, the fuzzy logic tuning optimization provides the best performance in reducing energy consumption. In conclusion, the combination of a predictive HVAC system approach with a fuzzy logic controller would provide the best result.

The review shows that the effort of reducing energy consumption of HVAC system through optimization not only can be done on the HVAC system itself, but also on the building design and building thermal dynamics. Operational parameters and controller optimization approaches are effective and can be applied on existing buildings but require the building's thermal and HVAC system dynamic model, which can be complicated. On the other hand, the building design optimization approach is more straightforward and can be incorporated during the building design stage but cannot be applied when buildings have been constructed without incurring high renovation costs. However, it is also important to notice that the conventional methods of optimizing HVAC operation are still used with some advance improvements in order to increase the effectiveness. The operational parameters and controller optimization approaches can provide up to 30% electrical energy consumption reduction while maintaining occupants' comfort compared to normal non-optimized HVAC operations. On the other hand, the building design parameters optimization approach alone can provide up to 62.1% electrical energy consumption reduction compared to buildings that are not designed for efficient energy usage. In conclusions, various optimization approaches have been used in obtaining optimal HVAC energy consumption and thermal comfort levels in buildings. Selections of building design parameters before building constructions will have a significant impact on the usage of HVAC electrical energy, and when combined with optimization approaches for the HVAC system used in the buildings via its operational parameters and control system which can be done based on the building thermal dynamics, further savings can be achieved.

Table 4. Summary of optimization approaches for HVAC systems.

Optimization Approach Category	Method/Tool	Reference	Number of Optimization Objective	Comfort Index Used	Energy Consumption Reduction	Advantages and Limitations
Operational Parameters Optimization	Conventional energy consumption model	[16]	1	-	10.00%	
		[17]		-	7.66%	
		[18]		-	11.82%	
		[19]		-	20.00%	
		[20]		-	12.00%	
		[21]		-	9.2%	
		[22]		-	15%	
	Predictive HVAC system models	[29]	1	-	17.24%	Effective and can be applied on existing buildings but requires the dynamic models of the buildings, which can be complicated and difficult to obtain.
		[23]	4	IAQ	12.4%	
		[28]	2	IAQ	18.55%	
		[30, 31]	4	IAQ	13.4%	
		[33], [34]	2	PMV	10%	
		[36]	2	PMV	46%	
		[37]	2	PMV	33%	
Controller Optimization	Reduce tracking errors	[42], [43]	3	-	10%	
	Fuzzy logic tuning optimization	[44]	2	PMV	18%	
		[45]	2	PMV	30%	
	PID tuning optimization	[46]	2	-	15,7% 4.8%	
		[47]	1	-	20%	
	Neural network tuning optimization	[54], [55]	1	-	Not provided	
		[56]	1	-	No provided	
Building Parameter and Design Optimization	SEDICAE	[57], [66]	2	PPD	Not provided	Straightforward and can be incorporated during the building design stage but cannot be applied when buildings have been constructed without incurring high renovation costs.
	EXRETOpt	[58]	3	PMV	62.1%	
	EnergyPlus	[59]	2	PPD	Not provided	
		[60]	4	-	Not available 14%	

* IAQ: Indoor Air Quality; PMV: Predicted Mean Vote; PPD: Predicted Percentage of Dissatisfaction

ACKNOWLEDGEMENT

The authors would like to thank the Ministry of Higher Education Malaysia, Universiti Tenaga Nasional (UNITEN), Universiti Teknologi Malaysia (UTM), Universiti Kuala Lumpur (UniKL) for their supports. This project is supported by the Research University Grant Vote Q.K130000.2409.04G18.

REFERENCES

[1] Haniff M.F. and H. Selamat. 2013. Review of HVAC scheduling techniques for buildings towards energy-efficient and cost-effective operations. *Renewable and Sustainable Energy Reviews* 27(1): 94–103.

[2] Rahman M.M. and M.G. Rasul. 2010. Energy conservation measures in an institutional building

in sub-tropical climate in Australia. *Applied Energy* 87(1): 2994–3004.

[3] Andrew K., Guanglin X., and Zijun Z., 2014. Minimization of energy consumption in HVAC systems with data-driven models and an interior-point method. *Energy Conversion and Management* 85(1): 146–153.

[4] Joseph C.L., Kevin K.W.W., and Liu Y., 2008. Sensitivity analysis and energy conservation measures implications. *Energy Conversion and Management* 49(11): 3170–3177.

[5] Zapater M. and P.Arroba. 2015. Energy Aware Policies in Ubiquitous Computing Facilities. In: Terzo, O. and L. Mossucca Cloud Computing With E-Science Applications. Boca Raton, Florida, United States: CRC Press, pages 267-286.

[6] Alves O., Monteiro E., Brito P., and Romano P., 2016. Measurement and classification of energy efficiency in HVAC systems. *Energy and Buildings* 130: 408–419

[7] Alibabaei N., Fung A., Raahemifar K., and Moghimi A., 2017. Effects of intelligent strategy planning models on residential HVAC system energy demand and cost during the heating and cooling seasons. *Applied Energy* 185: 29–43.

[8] Oropeza-Perez I., 2016 Comparative economic assessment of the energy performance of air-conditioning within the Mexican residential sector. *Energy Reports* 2(1): 147–154.

[9] Fanger P.O., 2017. *Thermal Comfort: Analysis and Applications in Environmental Engineering*. University of Michigan: Danish Technical Press.

[10] Bradshaw V., 2006. *The Building Environment: Active and Passive Control Systems. 3rd Edition*. Singapore: John Wiley and Sons.

[11] Ismail A.S. and R. Zulkifli. 2012. A review on thermal comfort assessment in Malaysian industries. *Jurnal Teknologi (Sciences & Engineering)* 59(2): 7–11.

[12] Kamaruzzaman, K. and Samsul M., 2013. Thermal comfort assessment of a classroom in tropical climate conditions. *Recent Advances in Energy, Environment and Development* 88–91.

[13] Azizpour F. and S. Moghimi. 2011. Objective and subjective assessments of thermal comfort in hot-humid region. In *Proceedings of 5th WSEAS international conferences on Recent Researches in Chemistry, Biology, Environment and Culture*, Montreux, Switzerland, pp. 207–210.

[14] American Society of Heating, Refrigerating, and Air- Conditioning Engineers, Inc., 2009. *Indoor Air Quality Guide*.

[15] American Society of Heating, Refrigerating, and Air- Conditioning Engineers, Inc., 2009. *Ventilation for Acceptable Indoor Air Quality*. Atlanta, GA.

[16] Lu L., Cai W., Xie L., Li S., and Soh Y.C., 2005. HVAC system optimization—in-building section. *Energy and Buildings* 37(1): 11–22.

[17] Kusiak A., Li M., and Tang F., 2010. Modeling and optimization of HVAC energy consumption. *Applied Energy* 87(10): 3092–3102.

[18] Wang J., Huang G., Sun Y., and Liu X., 2016. Event-driven optimization of complex HVAC systems. *Energy and Buildings* 133(1): 79–87.

[19] Zheng G.R. and M. Zaheer-Uddin. 1996. Optimization of thermal processes in a variable air volume HVAC system. *Energy* 21(5): 407–420.

[20] Du Z., Jin X., and Fan B., 2015. Evaluation of operation and control in HVAC (heating, ventilation and air conditioning) system using exergy analysis method. *Energy* 89: 372–381.

[21] Du Z., Jin X., Fang X., and Fan B., 2016. A dual-benchmark based energy analysis method to evaluate control strategies for building HVAC systems. *Applied Energy* 183: 700–714.

[22] He X., Zhang Z., and Kusiak A., 2014. Performance optimization of HVAC systems with computational intelligence algorithms. *Energy and Buildings* 81: 371–380.

[23] Wei X., Kusiak A., Li M., Tang F., and Zeng Y., 2015. Multi-objective optimization of the HVAC (heating, ventilation, and air conditioning) system performance. *Energy* 83: 294–306.

[24] Fiorentini M., Wall J., Ma Z., Braslavsky J., and Cooper P., 2017. Hybrid model predictive control of a residential HVAC system with on-site thermal energy generation and storage, *Applied Energy* 187: 465–479.

[25] Ruano A., Pesteh S., Silva S., Duarte H., Mestre G., Ferreira P.M., Khosravani H., and Horta R., PVM-based intelligent predictive control of HVAC systems. *IFAC-Papers On Line* 49(5): 371–376.

[26] Dobbs J. and B. Hencey. 2014. Model predictive HVAC control with online occupancy model. *Energy and Buildings* 82: 675–684.

[27] Risbeck M., Maravelias C., and Rawlings J., Real-time mixed-integer optimization for improved economic performance in HVAC systems. *Computer Aided Chemical Engineering* 44: 33–42.

[28] He X., Zhang Z., and Kusiak A., 2014. Performance optimization of HVAC systems with computational intelligence algorithms. *Energy and Buildings* 81: 371–380.

[29] Zeng Y., Zhang Z., and Kusiak A., 2015. Predictive modeling and optimization of a multi-zone HVAC system with data mining and firefly algorithms. *Energy* 86: 393–402.

[30] Kusiak A., Tang F., and Xu G., 2011. Multi-objective optimization of HVAC system with an evolutionary computation algorithm. *Energy* 36(5): 2440–2449.

[31] Kusiak A., Xu G., and Tang F., 2011. Optimization of an HVAC system with a strength multi-objective particle-swarm algorithm. *Energy* 36(10): 5935–5943.

[32] Kusiak A. and G. Xu. 2012. Modeling and optimization of HVAC systems using a dynamic neural network. *Energy* 42(1): 241–250.

[33] Cigler J., Prívara S., Váňa Z., Žáčeková E. and Ferkl L., 2012. On predicted mean vote optimization in building climate control. In *2012 20th Mediterranean Conference on Control & Automation (MED)*, Barcelona, Spain. pp. 1518–1523.

[34] Cigler J., Prívara S., Váňa Z., Komárková D. and Šebek M., 2012. Optimization of predicted mean vote thermal comfort index within model predictive control framework. In *2012 IEEE 51st IEEE Conference on Decision and Control (CDC)*, Maui, HI. pp. 3056–3061.

[35] Golshan M., Thoen H., and Zeiler W., 2018. Dutch sustainable schools towards energy positive. *Journal of Building Engineering* 19: 161–171.

[36] Haniff M.F., Selamat H., Khamis H., and Alimin, A.J., 2018. Optimized scheduling for an air-conditioning system based on indoor thermal comfort using the multi-objective improved global particle swarm optimization. *Energy Efficiency*: 1–19.

[37] Mei J., Xia X., and Song M., 2018. An autonomous hierarchical control for improving indoor comfort and energy efficiency of a direct expansion air conditioning system. *Applied Energy* 221: 450–463.

[38] Lee J.N., Lin T.M., and Chen C.C., 2014. Modeling validation and control analysis for controlled temperature and humidity of air conditioning system. *The Scientific World Journal*.

[39] Tashtoush B., Molhim M., and Al-Rousan M, 2005. Dynamic model of an HVAC system for control analysis. *Energy* 30(10): 1729–1745.

[40] NSW Government. Office of Environment and Heritage, 2015. *I Am Your Optimisation Guide: Heating, Ventilation and Air-Conditioning System*. Sydney, Australia.

[41] Aswani A, Master N., Taneja J., Culler D. and Tomlin C., 2012. Reducing transient and steady state electricity consumption in HVAC using learning-based model-predictive control. In *Proceedings of the IEEE* 100(1): 240–253.

[42] Asad H.S., Yuen R.K.K., and Huang G., 2017. Multiplexed real-time optimization of HVAC systems with enhanced control stability. *Applied Energy* 187: 640–651.

[43] Asad H.S., Yuen R.K.K., and Huang G., 2016. Degree of freedom based set-point reset scheme for HVAC real-time optimization. *Energy and Buildings* 128: 349–359.

[44] Hussain S, Gabbar H., Bondarenko D., Musharavati F., and Pokharel S., 2014. Comfort-based fuzzy control optimization for energy conservation in HVAC systems. *Control Engineering Practice* 32: 172–182.

[45] Homod R., Sahari K.S.M., Almurib H.A., and Nagi F.H., 2012. Gradient auto-tuned Takagi–Sugeno fuzzy forward control of a HVAC system using predicted mean vote index. *Energy and Buildings* 49: 254–267.

[46] Attaran S.M., Yusof R., and Selamat H., 2016. A novel optimization algorithm based on epsilon constraint-RBF neural network for tuning PID controller in decoupled HVAC system. *Applied Thermal Engineering* 99: 613–624.

[47] Wemhoff A.P., 2012. Calibration of HVAC equipment PID coefficients for energy conservation. *Energy and Buildings* 45: 60–66.

[48] Reynoso-Meza G., Blasco X., Sanchis J., and Martínez M., 2014. Controller tuning using evolutionary multi-objective optimisation: Current trends and applications. *Control Engineering Practice* 28: 58–73.

[49] Zajic I., Larkowski T. Burnham K.J., and Hill D., 2012. Control analysis and tuning of an industrial temperature control system. *IFAC Proceedings Volumes* 45(3): 679–684.

[50] Soyguder S., Karakose M., and Alli H., 2009. Design and simulation of self-tuning PID-type fuzzy adaptive control for an expert HVAC system. *Expert Systems with Applications* 36(3): 4566–4573.

[51] Moradi H., Setayesh H., and Alasty A., 2016. PID-Fuzzy control of air handling units in the presence of uncertainty. *International Journal of Thermal Sciences* 109: 123–135.

[52] Homod R., 2018. Analysis and optimization of HVAC control systems based on energy and performance considerations for smart buildings. *Renewable Energy* 126: 49–64.

[53] Attaran S.M., Yusof R., and Selamat H., 2016. A novel optimization algorithm based on epsilon constraint-RBF neural network for tuning PID controller in decoupled HVAC system. *Applied Thermal Engineering* 99: 613–624.

[54] Guo C., Song Q., and Cai W., 2007. A neural network assisted cascade control system for air handling unit. *IEEE Transactions on Industrial Electronics* 54(1): 620–628.

[55] Wei L. and Z. Junmin. 2012. Particle swarm optimization PID neural network control method in the main steam temperature control system. In *2012 International Conference on Computer Science and Electronics Engineering*, Hangzhou, China. pp. 137–140.

[56] Katić K., Li R., Verhaart J., and Zeiler W., 2018. Neural network based predictive control of personalized heating systems. *Energy and Buildings* 174: 199–213.

[57] Ruiz P.A., De La Flor F.S., Felix J.M., Lissén J.S., and Martín J.G., 2016. Applying the HVAC systems in an integrated optimization method for residential building's design. A case study in Spain. *Energy and Buildings* 119: 74–84.

[58] Kerdan I.G., Raslan R., and Ruyssevelt P., 2016. An exergy-based multi-objective optimisation model for energy retrofit strategies in non-domestic buildings. *Energy* 117(2): 506–522.

[59] Wright J. and A. Alajmi. 2016. Efficient genetic algorithm sets for optimizing constrained building design problem. *International Journal of Sustainable Built Environment* 5(1): 123–131.

[60] Wetter M., 2000. Design optimization with GenOpt. *Building Energy Simulation User News* 21: 19–28.

[61] Lai K., Wang W., and Giles H., 2014. Performance analysis of an energy efficient building prototype by using TRNSYS.

[62] Arcangeli G., 2008. Advanced tools for building simulation: Energy and airflow.

[63] Shi X., Tian Z., Chen W., Si B., and Jin X., 2016. A review on building energy efficient design optimization from the perspective of architects. *Renewable and Sustainable Energy Reviews* 65:

872–884.

[64] Yigit S. and B. Ozorhon. 2018. A simulation-based optimization method for designing energy efficient buildings. *Energy and Buildings* 178: 216–227.

[65] Gou S., Nik V.M., Scartezzini J.L., Zhao Q., and Li Z., 2018. Passive design optimization of newly-built residential buildings in Shanghai for improving indoor thermal comfort while reducing building energy demand. *Energy and Buildings* 169: 484–506.

[66] Ruiz P.A, Martín J.G., Lissén J.M.S., and de la Flor F.J., 2014. An integrated optimisation method for residential building design: A case study in Spain. *Energy and Buildings* 80: 158–168.

[67] Kerdan I.G., Raslan R., Ruyssevelt P., and Gálvez D.M., 2016. An exergoeconomic-based parametric study to examine the effects of active and passive energy retrofit strategies for buildings. *Energy and Buildings* 133: 155–171.