



# A Comprehensive Review on HVAC Systems

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**Abstract:** This paper explores the role of HVAC in achieving indoor thermal comfort for occupants. The performance of HVAC systems is measured using the coefficient of performance (COP), which indicates lower energy consumption and higher efficiency. Indoor thermal comfort levels are determined using expected mean vote (PMV) or indoor air quality (IAQ). Building energy flexibility is achieved through changes in HVAC system operation and human thermal comfort. Single-objective optimization aims to lower energy consumption while still providing acceptable occupant comfort, leading to higher comfort but lower efficiency. Multi-objective optimization aims to optimize energy use with minimum occupant complaints, resulting in a balance between energy conservation and human-centric control, resulting in low operational costs and happy occupants. The paper reviews various optimization methods for HVAC systems, including data-driven, physics-based, and grey box models, and discusses the development of Supervisory and Local Level ANN-MPC for HVAC systems in various buildings. The paper concludes by providing an overview of various HVAC system optimization approaches, including ANN-based MPC and optimization research, and their potential energy and cost savings.

**Keywords** - HVAC systems, Heating Efficiency, cost-effective, environment, cooling, air handling, algorithms

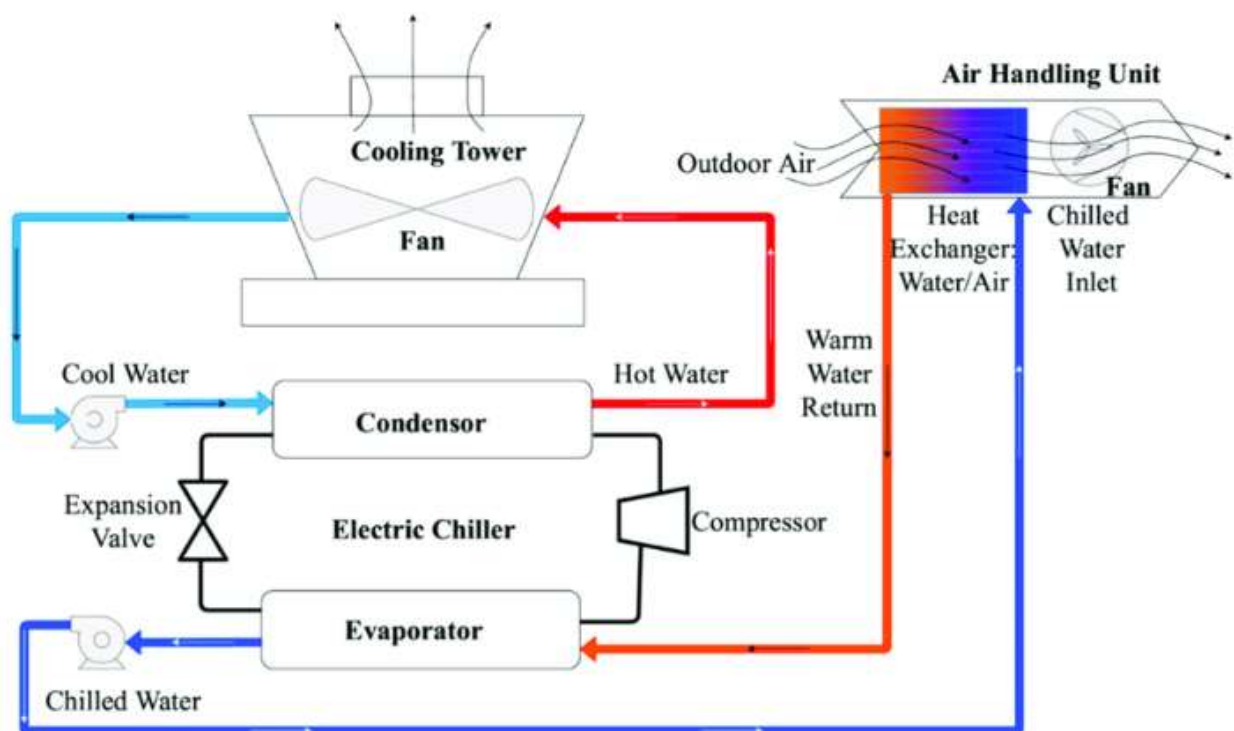
## I. INTRODUCTION

The Heating, ventilation and air-conditioning (HVAC) systems are crucial in providing comfortable indoor temperatures for building occupants, regardless of outdoor temperatures. The coefficient of performance (COP) is used to assess the energy performance of these systems globally.<sup>[1]</sup> The COP (Cooling/Heating Efficiency) is the ratio between the produced energy and the input, and higher COP results in lower energy consumption and higher system efficiency. HVAC systems, based on Carnot's Theorem, depend on the difference between indoor and outdoor temperatures. To increase COP for lower energy consumption, indoor

temperatures can be adjusted to provide a comfortable environment without excessive electrical energy consumption.<sup>[2]</sup> This paper focuses on indoor thermal comfort, specifically the effects of HVAC systems in buildings. Thermal comfort levels can be measured using indicators like the predicted mean vote (PMV) or indoor air quality (IAQ). PMV, introduced by Fanger, is widely used in optimization of comfort levels produced by HVAC systems. It predicts the mean value of votes on a 7-point thermal sensation scale, ranging from -3 to +3. The recommended PMV range is between -0.5 and +0.5. PMV values are determined based on air temperature, radiant temperature, activity rate, air velocity, relative air humidity, and clothing insulation. To achieve a good PMV value, several combinations of these six parameters can be manipulated, but the combination must not consume too much electrical energy.<sup>[3,4]</sup>

The HVAC system operation needs optimization to reduce building energy usage and provide thermal comfort. This can be achieved through single-objective optimization, which focuses on minimizing electrical energy consumption while ensuring minimum comfort levels for occupants. Multi-objective optimization, on the other hand, finds a balance between minimizing energy consumption and maximizing comfort for occupants.<sup>[5]</sup> This paper reviews various HVAC system optimization approaches to achieve a balance between building electrical energy consumption and thermal comfort. It discusses three broad approaches: manipulating energy consumption and predictive models, controlling parameters, and building design parameters. The paper also discusses the advantages and limitations of each approach and recommends suitable scenarios for each. It covers classic and advanced techniques, as well as recent and advanced techniques.<sup>[6,7]</sup>

This paper reviews data-driven, physics-based, and grey box models for HVAC systems. ASHRAE has published handbooks and energy calculation toolkits for primary and secondary components, including dynamic, steady-state, and quasi-steady state models. Technical documentation of building energy simulation programs like TRNSYS, EnergyPlus, and HVACSIM+ provide models of common HVAC system



Heating, ventilation and air-conditioning (HVAC) system layout.

components. The U.S. Department of Energy maintains a listing of building energy simulation software tools, including popular tools like BLAST, BSim, ESP-r, and DOE-2. Several toolboxes for Matlab Simulink have been developed to simulate building and HVAC systems, including international building physics toolbox (IBPT), SIMBAD toolbox, CARNOT toolbox, HAM-tools, and ASTECCA toolkit. [8] The Recent literature reports on various modeling approaches, such as fuzzy logic (FL) modeling for HVAC systems, software for HVAC component simulation, and Matlab Simulink use in HVAC systems research. However, no comprehensive survey of HVAC systems models covering data-driven, physics-based, and grey box modeling approaches has been reported, despite significant progress in HVAC system modeling.[9]

### **Evaluation of ANN-based MPC and HVAC system optimization :-**

This section reviews ANN-based MPC and optimization research for HVAC systems, focusing on different building types, control objectives, modeling data generation, ANN architecture, and optimization method selection. It discusses each factor with specific examples from literature and presents the potential energy and cost savings of these approaches.

### **Structure and HVAC structure**

The paper discusses the development of Supervisory and Local Level ANN-MPC for HVAC systems in various buildings, including public universities, commercial universities, commercial airports, experimental research facilities, automotive applications, integrated day lighting HVAC systems, warehouse and manufacturing areas, and schools. Despite its application in various buildings, ANN-MPC has not been used for residential buildings, particularly houses. Many commercial buildings have supervisory control, but most houses lack such control. This presents an opportunity to develop such controllers for residential HVAC systems to reduce energy consumption and operating costs.[10]

The paper discusses the development of ANN-MPC for the residential HVAC system of a house, focusing on the need to develop a controller that can reduce energy consumption and operating costs. The paper also discusses the potential of ANN-MPC in commercial buildings, where most buildings lack any form of supervisory control.[11]

In conclusion, the paper highlights the importance of developing ANN-MPC for residential HVAC systems to reduce energy consumption and operating costs. By implementing ANN-MPC in commercial buildings, researchers can develop more efficient and cost-effective HVAC systems for residential buildings.[12]

### **Control objective**

MPC is frequently used at the supervisory level to maximize energy consumption on a building-by-building basis. The notion of supervisory control is the source of the concept of employing MPC to conserve building energy. Generally speaking, the control objective is to reduce tracking error and control effort when MPC is used in the local level controller. However, the control aim is often expressed as one or a mix of the following when ANN-MPC is applied at the supervisory layer.[13]

1. Reduce your electricity use
2. Ensure comfort in terms of heat
3. Keep the quality of the indoor air (IAQ) at a respectable level.
4. Reduce operational expenses

5. Keep visual comfort at a respectable level.
6. Cut down on retrofit expenses
7. Cut down on hours of thermal discomfort<sup>[14]</sup>

A single objective optimization is achieved when only one of the following statements is stated, while a multi-objective optimization aims to achieve multiple objectives simultaneously. HVAC systems typically consist of multiple subsystems, and energy consumption is calculated and minimized simultaneously. Thermal comfort is calculated using the predicted mean vote (PMV) index, which predicts the mean response of a group of people according to the ASHRAE thermal sensing scale. The neutral value is 0, where most people will feel comfortable.<sup>[15]</sup>

Indoor air quality (IAQ) refers to indoor air temperature, humidity, and carbon dioxide (CO<sub>2</sub>) level. These factors depend on internal and external disturbances acting on the system. HVAC systems use heating/cooling, humidification/dehumidification, and ventilation systems to control these factors. A comfortable indoor temperature and humidity can be adjusted according to ANSI/ASHRAE standards, which range from 19.5 to 27.8 degrees Celsius. Relative humidity in occupied spaces should be controlled less than 65%, as higher humidity can increase the likelihood of conditions leading to microbial growth. The ventilation rate is determined based on the CO<sub>2</sub> generation rate in the space.<sup>[16]</sup>

### Modeling data

To develop data-driven models like Artificial Neural Networks (ANN), a rich data set is required, which includes all possible working conditions. Data can be measured from the site under normal operation or under special data gathering test conditions using the pseudo-random binary sequence (PRBS). Building energy simulation programs such as Transient System Simulation Tool (TRNSYS) and Energy Plus Energy Simulation Software can generate data sets for training and validation. In this study, over 500 parameters including air temperature, humidity, flow rate, and energy consumption were recorded at 1 minute intervals for 17 days. The database was generated by the EnergyPlus model, with 75% used for training and 25% for testing. A comprehensive building model was developed in TRNSYS, and a simulation database was generated to train and validate the ANN models.<sup>[17]</sup>

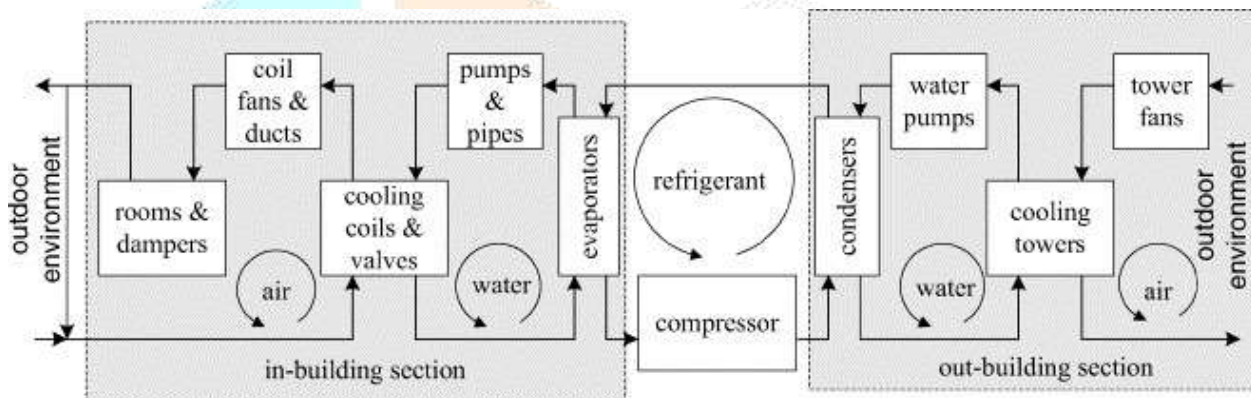
Forecasting weather parameters can be estimated using prediction models or downloaded from government servers where available. Three auto-regressive predictive models were used to predict outdoor air temperature, humidity, and global solar radiation. In this study, the outdoor air temperature and solar radiation were forecasted for 8 hours into the future based on previous day values corrected by current values. Occupancy can be forecasted using schedules and occupancy sensors, such as passive infrared (PIR) sensors. Occupancy can also be estimated through the CO<sub>2</sub> generation rate in the indoor space. Real-time occupancy was measured using PIR sensors, and a movement signal was calculated based on PIR sensors to be used in predictive control. Variable electricity price is generally known in advance, with prices having a fixed structure consisting of four periods of taxation. In Toronto, electricity price has a three-tiered structure, which was used in the next part of this paper.<sup>[18]</sup> All input/output data should be scaled to a [-1,1] range prior to the training of ANN to improve the efficiency of training. Data normalization gives equal weight to all variables in the model.<sup>[19]</sup>

## Optimization of HVAC Operational Parameters

By optimizing the parameters of the HVAC system models, an appropriate operational parameter setting may be found that will provide a desirable interior environment without requiring HVAC systems to consume a significant amount of electrical energy. The majority of HVAC system models show how different operational factors, such as temperature, humidity, and energy usage, relate to the system's output parameters. As elucidated in the subsequent sections, the optimization of these operational parameters may rely on either the predictive or the traditional energy consumption models.<sup>[20]</sup>

### Optimizing operational parameters with the use of traditional energy consumption models

The method of optimizing operational parameters of an HVAC system is based on a model that relates these parameters, such as air temperature, airflow rate, and air static pressure, with the energy consumption of the system. Energy consumption is defined as the total power usage from its components, such as the chiller, fan, pump, and cooling tower. Many parameters affect the amount of energy used by these components, and several are used as optimization variables.<sup>[21]</sup>



Some works consider two operational parameters to minimize energy consumption: the temperature of the chilled water supply and the supply airflow rate, while others use the supply air temperature set point and the air static set point. For example, in, the optimization variables included the cooling water temperature, the chilled water temperature from primary chillers, the chilled water temperature from secondary chillers, and the supply air temperature.<sup>[22]</sup>

Other optimization parameters include two zone temperatures, humidity ratios, discharge-air temperature, the temperature of chilled water, outdoor airflow rates, supply airflow rates, and static pressure in the duct system. The optimized operational parameters are then sent to local control loops like the fan speed control loop to achieve optimized HVAC performances.

The HVAC system can be optimized by minimizing energy consumption, resulting in optimized operational parameters and energy savings. These savings can be up to 10%, 7.66%, 11.82%, and 20% compared to the non-optimized, fixed-setting operation method. To reduce energy usage, some works aim to minimize total exergy loss, which is the energy available to be used. High exergy loss indicates low efficiency, while low exergy loss indicates high efficiency. Total exergy loss is defined by Equation and includes energy loss from

cooling tower water flow, cooling tower energy consumption, chillers, air handling units, and outflow exergy. Reducing energy consumptions of chiller, fan, pump, and cooling tower can also reduce total exergy loss.<sup>[23]</sup> The proposed approach optimizes parameters such as supply cooling water temperature setpoints, supply chilled water temperature, and outdoor air flow rate to reduce energy consumption in HVAC systems. The optimized parameters can achieve up to 12% and 9.2% reductions compared to non-optimized techniques. Particle swarm optimization and harmony search algorithms are used to minimize HVAC energy consumption and room temperature ramp rate. The proposed method results in 15% energy saving, which is significantly higher due to building thermal dynamics. This shows that modeling the energy consumption model of HVAC systems can be done based on both the system itself and building temperature dynamics, resulting in significant energy savings. Table summarizes works on operational parameters optimization based on the conventional energy consumption model.<sup>[24]</sup>

### **Optimizing operational parameters using predicted energy consumption models**

Predictive control models have been introduced to make HVAC systems more energy-efficient and comfortable. These models are simpler and easier to apply in real-time compared to other models like dynamic and physical-based ones. They can predict system outputs like temperature, humidity, CO<sub>2</sub> concentration level, and occupancy levels. Predictive models have been used in optimization works on HVAC system operation in recent years. The prediction of the desired output is based on the current and/or previous values of controlled parameters ( $x$ ) and uncontrolled parameters ( $v$ ). Equation provides a time interval, supply air static pressure setpoint, and supply air temperature setpoint. The controlled parameters to be optimized can be the supply air temperature set point, supply air static pressure set point, and the air and mean radiant temperature of the space affected by building thermal dynamics.<sup>[25]</sup>

Single-objective optimization of HVAC systems has been successful in reducing energy consumption by about 17.24%. Multi-objective optimization uses multiple predictive models to reduce energy consumption without negatively impacting indoor air quality (IAQ). The predictive energy consumption model, air temperature, air humidity, and CO<sub>2</sub> concentration were used as objective functions to determine the optimized parameter settings for  $x_1$  and  $x_2$ . One multi-objective approach combines all objective values into a single function to minimize them, such as Equation. The values of four objectives correspond to total energy, temperature, humidity, and CO<sub>2</sub> concentration. Violations of parameters are usually caused by a lack of knowledge to set the HVAC system to satisfy the building's thermal dynamics. The minimum and maximum values of these objectives were utilized, along with the weight of the system.<sup>[26]</sup>

The study focuses on optimizing energy consumption in buildings by reducing energy consumption without violating Indoor Air Quality (IAQ) constraints. The weights associated with each objective are based on user priorities or biases. The method has been reported to reduce energy consumption by about 12.4% without significantly violating IAQ constraints. The higher the weight value, the lower the violation level. Omitting IAQ in objectives weight reduces energy consumption but results in a major violation of IAQ levels. By including IAQ violations as an optimization objective, the system can satisfy building comfort needs without causing high energy consumption.

The HVAC optimization works based on manipulating operational parameters were similar to those in Equation 4, but with three objective functions instead of four. The multiobjective formulation showed energy reduction potential of 13.4% without violating IAQ constraints. Another work used predictive models of energy and temperature, reducing energy consumption by 18.5%. As more objectives were included in the optimization problem formulation, energy saving potentials decreased due to the need to compromise energy consumption with IAQ requirements.<sup>[27]</sup>

In Equations 5 to 11, the comfort index (PMV) was used instead of the IAQ. The PMV value is determined by air temperature, mean radiant temperature, activity rate, air velocity, relative air humidity, and clothing insulation. Not all six parameters can be controlled, so only some are used as variable parameters. Parameters such as clothing types, humidity, and air speed can be set to a certain normalized or average value depending on the building and activity.

The optimization objective was to minimize violation of PMV while reducing energy consumption. The operating parameters needed to be optimized and controlled were supply water temperature, air temperature, and mean radiant temperature. This approach reduced HVAC system energy consumption by up to 10% while maintaining occupants' comfort. Recent energy-comfort optimization based on the PMV model increased energy saving potential to 46% and 33%.<sup>[28]</sup>

The conventional energy model for optimizing HVAC systems can reduce energy consumption, but more models are needed for efficient operation. IAQ and PMV are used to achieve low energy consumption while maintaining thermal comfort. Predictive models are used in multi-objective optimization, but they require system identification, which can be time-consuming if the models need to be accurate. Despite these limitations, the basic method is still used and improved to more advanced versions.

### **HVAC Controller Enhancement**

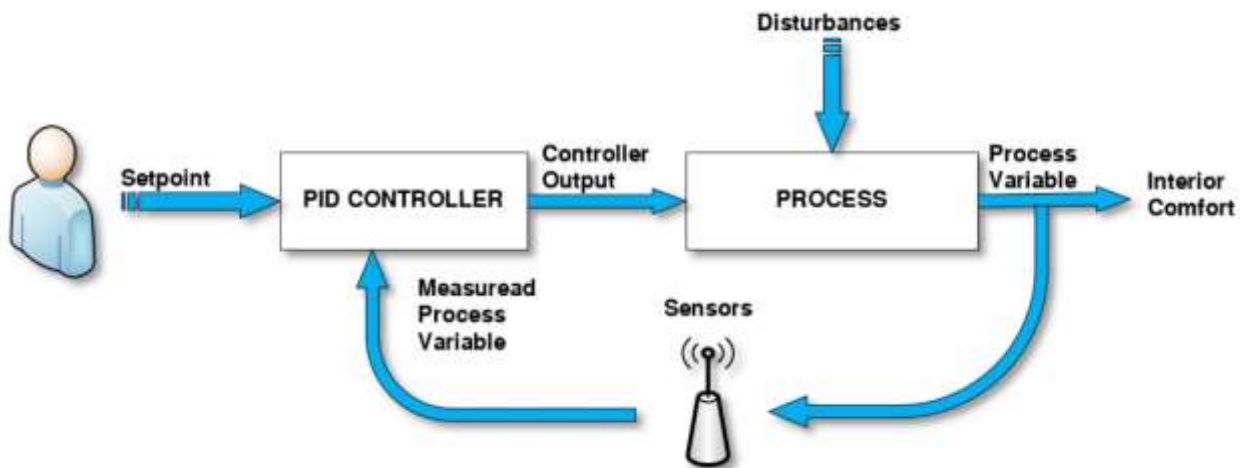
The control system of a HVAC system is crucial for improving its dynamic performance. Overshoot of the supply air temperature is a significant parameter, as high overshoot can lead to electrical energy wastage. To reduce overshoot, real-time optimization techniques have been used to minimize tracking errors of the system response. This has reduced tracking errors by over 26% and energy consumption by 10%. However, high tracking error occurrences occur when the setpoint temperature changes.<sup>[29]</sup>

Genetic algorithm (GA) has been used to optimize fuzzy control rules and membership functions in controlling set point temperature, aiming to minimize energy consumption while providing comfortable PMV values. This method has reduced cooling and heating energy consumption by up to 16% and 18%, respectively, compared to the performance of a widely used control tool EnergyPlus™.

Another work related to fuzzy logic control optimization for a HVAC system involves setting the fuzzy controller to be self-tuned using the GaussNewton method for nonlinear regression models with the PMV model to avoid discomfort to occupants while reducing energy consumption.<sup>[30]</sup>

The Proportional–Integrate–Derivative (PID) controller is a widely used control method for HVAC systems, which can reduce electrical energy usage by at least 30%. By optimizing the parameters, environmental parameters like temperature and humidity can be improved. This approach reduces overshoots and shortens the time taken for room temperature to reach desired values, increasing energy efficiency. The optimized PID

controller can reduce the energy consumption of the HVAC system by up to 20%. This approach has been implemented with fuzzy rules for tuning parameters, resulting in improved control of environmental parameters.



An adaptive neural network control strategy was proposed for efficient HVAC system control using setpoint tracking of supply air temperature. The strategy uses the simultaneous perturbation stochastic approximation (SPSA) algorithm to tune controller weights for various environmental conditions. The strategy responds well to changes in supply air temperature setpoints without significant time delay or overshoot compared to a fixed parameter PID controller. Particle swarm optimization (PSO) and back-propagation (BP) algorithms were used to improve temperature control. The mean squared error was introduced as a performance function to optimize energy consumption and occupant comfort in the HVAC heat setting predictive model. This method maintains good comfort without affecting energy consumption. Control of HVAC system response is crucial as weak control can lead to discomfort and unnecessary use of electrical energy. Accurate mathematical models are required for better controller implementation, but this approach has proven effective in reducing electrical energy consumption. Including optimization algorithms for optimal controller parameter values further improves HVAC system performance.<sup>[31]</sup>

### Optimizing HVAC Building Design

Energy consumption in buildings can be reduced by planning ahead, evaluating the efficiency of HVAC systems, and considering design combinations and thermal characteristics of elements like wall thickness, wall material, window width, and window blinds. These factors determine energy demands, consumptions, and life cycle costs. Buildings with better thermal environments can save up to USD160 billion annually. Simulation-based optimization methods have been introduced for designing green buildings, considering factors like HVAC system, building materials, and designs. An advanced version of a simulation tool called SEDICAE was introduced, which is an expert system for designing energy-efficient buildings. By focusing on these factors, buildings can save up to USD160 billion annually.<sup>[32]</sup>

The study focuses on optimizing the energy rating of buildings by determining the type of construction materials and HVAC system. The materials are chosen based on their thermal properties, such as U-values, solar factor, and g-value, and the HVAC system is chosen based on the types of demand - cooling or heating. The Tabu search algorithm was used to optimize the original building design proposal, resulting in a 30-year

life cycle cost as low as EUR5840. The Exergy Analysis Model for Retrofit Optimization (EXRETOpt) was used to determine the optimized building design parameters, including HVAC system types, insulation type and size, sealing percentage of cracks, joints, holes, window glazing level, cooling/heating set points, and lighting system type. The study found that increasing insulation thickness increases energy usage but decreases exergy reduction. The HVAC system configuration also affects energy usage, exergy destruction, and comfort level. The method achieved improvements of 62.1% in annual energy use, 57.9% of exergy destructions, and up to 29.3% thermal comfort.

A genetic algorithm (GA) optimization method was used to create an energy-efficient building design without compromising occupants' predicted percentage of dissatisfaction (PPD). The EnergyPlus™ simulation program evaluated the building's comfort level and annual energy consumption. 80 design variables were considered, including window design, wall design, floor design, and HVAC schedule details. A simplified work for low HVAC system energy consumption was introduced using EnergyPlus™. The Hooke-Jeeves pattern search algorithm was used to solve the single objective optimization problem, resulting in 14% energy consumption reduction.<sup>[33]</sup>

## CONCLUSIONS

This paper reviews optimization works related to buildings' HVAC systems to achieve energy-saving operation while maintaining occupant comfort. The optimization works focus on three areas: HVAC operational parameters optimization, HVAC control system optimization, and building design optimization. Operational parameters optimization aims to obtain optimal operational parameter settings for the HVAC system, reducing energy consumption while maintaining comfort. Two recommended methods are conventional energy consumption models and predictive HVAC system models. The PMV approach has a better response than the IAQ with a 46% reduction in energy consumption.

Controller optimization improves the response of HVAC system outputs to avoid unnecessary energy waste. Building design optimization focuses on determining low-energy building designs based on the type of HVAC system, construction material, building direction, and window design. Fuzzy logic tuning optimization provides the best performance in reducing energy consumption. Combining a predictive HVAC system approach with a fuzzy logic controller is suggested as the best result.<sup>[34]</sup>

The review shows that optimizing HVAC systems can be done on both the HVAC system itself and building design and thermal dynamics. Operational parameters and controller optimization approaches can provide up to 30% electrical energy consumption reduction while maintaining occupant comfort, while building design parameters optimization can provide up to 62.1% reduction.

Various optimization approaches have been used to achieve optimal HVAC energy consumption and thermal comfort levels in buildings. Selection of building design parameters before construction significantly impacts the usage of HVAC electrical energy. When combined with optimization approaches for the HVAC system, based on building thermal dynamics, further savings can be achieved.<sup>[35]</sup>

**REFERENCES :-**

1. 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.
2. 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.
3. Ismail A.S. and R. Zulkifli. 2012. A review on thermal comfort assessment in Malaysian industries. *Jurnal Teknologi (Sciences & Engineering)* 59(2): 7–11.
4. 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.
5. 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.
6. 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.
7. Kusiak A., Tang F., and Xu G., 2011. Multi objective optimization of HVAC system with an evolutionary computation algorithm. *Energy* 36(5): 2440–2449.
8. Afram, A. and Janabi-Sharifi, F., 2014. Review of modeling methods for HVAC systems. *Applied thermal engineering*, 67(1-2), pp.507-519.
9. P. Riederer, Matlab®/Simulink® for building and HVAC simulation-State of the art, in: Ninth Int IBPSA Conf, IBPSA, Montreal, Canada, 2005, pp. 1019-1026.
10. Ruano, A.E., Pesteh, S., Silva, S., Duarte, H., Mestre, G., Ferreira, P.M., Khosravani, H.R. and Horta, R., 2016. The IMBPC HVAC system: A complete MBPC solution for existing HVAC systems. *Energy and Buildings*, 120, pp.145-158.
11. X. He, Z. Zhang, A. Kusiak, Performance optimization of HVAC systems with computational intelligence algorithms, *Energy Build.* 81 (2014) 371–380.
12. Ng, B.C., Darus, I.Z.M., Jamaluddin, H. and Kamar, H.M., 2014. Application of adaptive neural predictive control for an automotive air conditioning system. *Applied Thermal Engineering*, 73(1), pp.1244-1254.
13. Huang, H., Chen, L. and Hu, E., 2015. A new model predictive control scheme for energy and cost savings in commercial buildings: An airport terminal building case study. *Building and environment*, 89, pp.203-216.
14. Asadi, E., Da Silva, M.G., Antunes, C.H., Dias, L. and Glicksman, L., 2014. Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application. *Energy and buildings*, 81, pp.444-456.
15. Ferreira, P.M., Ruano, A.E., Silva, S. and Conceicao, E.Z.E., 2012. Neural networks based predictive control for thermal comfort and energy savings in public buildings. *Energy and buildings*, 55, pp.238-251.

16. Goel, S., Rosenberg, M.I. and Eley, C., 2017. *Ansi/ashrae/ies standard 90.1-2016 performance rating method reference manual* (No. PNNL-26917). Pacific Northwest National Lab.(PNNL), Richland, WA (United States).
17. Kusiak, A., Xu, G. and Tang, F., 2011. Optimization of an HVAC system with a strength multi-objective particle-swarm algorithm. *Energy*, 36(10), pp.5935-5943.
18. Ning, M. and Zaheeruddin, M., 2010. Neuro-optimal operation of a variable air volume HVAC&R system. *Applied Thermal Engineering*, 30(5), pp.385-399.
19. Asadi, E., Da Silva, M.G., Antunes, C.H., Dias, L. and Glicksman, L., 2014. Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application. *Energy and buildings*, 81, pp.444-456.
20. Cigler J., Přívara 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.
21. Golshan M., Thoen H., and Zeiler W., 2018. Dutch sustainable schools towards energy positive. *Journal of Building Engineering* 19: 161–171.
22. Haniff M.F., Selamat H., Khamis H., and Alimin, A.J., 2018. Optimized scheduling for an airconditioning system based on indoor thermal comfort using the multi-objective improved global particle swarm optimization. *Energy Efficiency*: 1–19.
23. 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.
24. 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*.
25. Tashtoush B., Molhim M., and Al-Rousan M, 2005. Dynamic model of an HVAC system for control analysis. *Energy* 30(10): 1729–1745.
26. NSW Government. Office of Environment and Heritage, 2015. *I Am Your Optimisation Guide: Heating, Ventilation and Air-Conditioning System*. Sydney, Australia.
27. 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.
28. 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.
29. 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.
30. Hussain S, Gabbar H., Bondarenko D., Musharavati F., and Pokharel S., 2014. Comfortbased fuzzy control optimization for energy conservation in HVAC systems. *Control Engineering Practice* 32: 172–182.

31. 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.
32. 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.
33. Wemhoff A.P., 2012. Calibration of HVAC equipment PID coefficients for energy conservation. *Energy and Buildings* 45: 60–66.
34. 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.
35. 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.
36. 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.
37. 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.
38. Homod R., 2018. Analysis and optimization of HVAC control systems based on energy and performance considerations for smart buildings. *Renewable Energy* 126: 49–64.
39. 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.
40. 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.
41. 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.
42. 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.
43. 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.
44. Kerdan I.G., Raslan R., and Ruyssevelt P., 2016. An exergy-based multi-objective optimisation model for energy retrofit strategies in nondomestic buildings. *Energy* 117(2): 506–522.
45. 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.
46. Wetter M., 2000. Design optimization with GenOpt. *Building Energy Simulation User News* 21: 19–28.
47. Lai K., Wang W., and Giles H., 2014. Performance analysis of an energy efficient building prototype by using TRNSYS.

48. Arcangeli G., 2008. Advanced tools for building simulation: Energy and airflow.
49. 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.

